

VOLUME LXXX – N. 3

LUGLIO – SETTEMBRE 2026

RIVISTA ITALIANA DI ECONOMIA DEMOGRAFIA E STATISTICA



EDITOR IN CHIEF

CHIARA GIGLIARANO

ASSOCIATE EDITORS

MARIATERESA CIOMMI, ALESSIO GUANDALINI

JOURNAL MANAGER

ILARIA BOMBELLI

SCIENTIFIC COMMITTEE

GIORGIO ALLEVA, GIAN CARLO BLANGIARDO, CLAUDIO CECCARELLI, FRANCESCO M. CHELLI, CONCHITA D'AMBROSIO, CASILDA LASSO DE LA VEGA, MIKHAIL DENISENKO, PIERPAOLO D'URSO, ALESSIO FUSCO, MAURO GALLEGATI, ANTONIO GIMENEZ MORENO, RARES HALBAC COTOARA ZAMFIR, ALBERTO QUADRIO CURZIO, CLAUDIO QUINTANO, JESUS RODRIGO COMINO, KOSTAS RONTOS, SILVANA SCHIFINI D'ANDREA, SALVATORE STROZZA, PHILIPPE VAN KERM, PAOLO VENERI, PAOLO VERME, ROBERTO ZELLI

SECTION EDITORS

DEMOGRAPHY: ALESSIO BUONOMO, GIUSEPPE GABRIELLI, CECILIA REYNAUD, STEFANIA RIMOLDI

ECONOMICS: MARINA ALBANESE, ANDREA CUTILLO, GLORIA POLINESI, LUCA SALVATI

SOCIAL STATISTICS: LIVIA CELARDO, ANTONELLA D'AGOSTINO, EMILIANO SIRONI

STATISTICS: ANNAMARIA BIANCHI, CLAUDIO CECCARELLI, FRANCESCA MARIANI, MATTEO MAZZIOTTA, ADRIANO PARETO

EDITORIAL BOARD

OHIANA ARISTONDO, LIDIA CERIANI, DANIELE GRECHI, ENRICO MORETTO, SIMONA PACE, FAUSTO PACICCO, GIUSEPPE RICCIARDO LAMONICA, ANGELES SÁNCHEZ, ANDREA SPIZZICHINO, ANDREA VENEGONI

SIEDS
SOCIETÀ ITALIANA
DI ECONOMIA DEMOGRAFIA E STATISTICA

CONSIGLIO DIRETTIVO

Presidenti Onorari: FRANCESCO MARIA CHELLI

Presidente: SALVATORE STROZZA

Vice Presidenti: LEONARDO BECCHETTI, CHIARA GIGLIARANO,
VENERA TOMASELLI

Segretario Generale: ALESSIO GUANDALINI

Consiglieri: MARINA ALBANESE, MARCO ALFÒ, GIUSEPPE GABRIELLI,
MARGHERITA GEROLIMETTO, MATTEO MAZZIOTTA, SIMONE POLI,
MARIA CRISTINA RECCHIONI, LAURA TERZERA

Segretario Amministrativo: FABIO FIORINI

Revisori dei conti: MICHELE CAMISASCA, GIUSEPPE NOTARSTEFANO, DOMENICO SUMMO

Revisori dei conti supplenti: CLAUDIO CECCARELLI, CECILIA REYNAUD

SEDE LEGALE:

C/O Studio Associato Cadoni, Via Ravenna n. 34 – 00161 ROMA

info@sieds.it

rivista@sieds.it

VOLUME FUORI COMMERCIO

INDICE

Lucia Mongelli, Paola Perchinunno, Samuela L' Abbate, Antonella Massari <i>Statistical indicators for the analysis of social inequalities in Italy</i>	9
Monica Carbonara, Giuseppe Lecardane, Adriano Pareto <i>Women, territories and inequality. A multidimensional analysis of the well-being gender gap in the Italian provinces</i>	21
Francesca Ceccato, Marilena Angela Ciarallo, Paola Conigliaro <i>Determinants of Hourly Earnings and Earnings Inequality: Analyses on Italian Data from the Structure of Earnings Survey</i>	33
Fabrizio Sbicca <i>Corruption, inequality and poverty</i>	45
Elisabetta Segre, Alessandra Tinto, Miria Savioli, Anna Villa, Romina Fraboni <i>Multidimensional well-being deprivation among Italian youth</i>	57
Marco Marsili, Martina Lo Conte, Marco Rizzo, Cristina Ocello, Andrea Spizzichino <i>Projecting Italy's labour market: assessing the sustainability of the workforce by 2050</i>	69
Simona Cafieri, Gianmarco Borrata <i>Poverty risk and territorial disparities in Europe: a clusterwise lasso regression approach</i>	81
Matilde Bonelli, Giancarlo Carbonetti, Elena Grimaccia, Debora Tronu <i>A machine learning approach for the analysis of demographic features of the socio-economic deprivation at sub-municipal level</i>	93
Gianni Corsetti, Sara Gigante, Anita Guelfi, Valentina Talucci <i>Employment patterns before and after childbirth in Italy: a counterfactual study using administrative data</i>	105

Stefania Badiglio, Luciano Seta <i>Social capital at school: a tool to measure students' endowments</i>	117
Francesca Abate, Adriano Cabras, Lucia Martina, Anna Pia M. Mirto, Adriano Pareto, Francesco P. Rizzo <i>Inequalities between Mediterranean countries on the North, South and East shores: a multidimensional analysis</i>	129
Alessandro Valentini, Francesca Paradisi <i>Demographic vitality in Italian municipalities: measurement and features of the most dynamic areas</i>	141
Francesca Allegra, Paola Francesca Cortese, Graziella Fusaro, Giuseppe Stassi <i>The different Italies of the demographic decline</i>	153
Mariangela Verrascina, Silvia Dardanelli, Antonio Guglielmi <i>A territorial reading of households and families changes in Italy over the last 50 years</i>	165
Venera Tomaselli, Margaret Antonicelli <i>Structural health inequalities and territorial disparities: drivers of healthcare migration</i>	177
Francesca Feoli <i>Income, environmental pollution and health inequalities in Italy: a regional perspective in the era of transitions</i>	189
Giuseppe Venere <i>Health mobility among the older adults in Italy: a regional inequality perspective.....</i>	201

Simona Ballabio, Arianna Carra, Paola Maddalena Chiodini, Daniela Corso, Stefania Quartarone, Elena Sorba, Flavio Verrecchia <i>Latent stereotypes in contemporary society: teachers' strategies to protect children from gender discrimination in Sicilian schools</i>	213
Alessandra Di Bello, Alex Pieroni <i>Do family, health and job perceptions shape workers' well-being? A job satisfaction analysis in Europe</i>	225
Simona Peia, Giuseppina Sola <i>Gender equality at the top management of the Italian National Institute of Statistics</i>	237
Paolo Consolini, Mariagloria Narilli, Angela Pepe <i>The impact of the “Assegno Unico e Universale” reform on family welfare</i>	249
Ilaria Bombelli, Giorgia Sacco <i>Optimizing stratification with data-driven approach: a case study</i>	261
Daniela Vacca, Enrico Olla, Giovanna Pala, Stefano Tersigni, Luigi Minerba <i>An experimental approach to mapping exposure in contaminated sites</i>	273
Sheila A. Chapman, Vito Pipitone <i>Resilience in Italian LLMA: The role of specialization and diversification patterns in two recent crises</i>	285
Samanta Pietropaoli, Gabriella Fazzi <i>Automated ticket classification for training ISTAT's PUC chatbot</i>	297
Francesca Alonzi, Annarita Mancini, Caterina Viviano <i>The preliminary recoding procedure from Ateco 2022 to Ateco 2025</i>	309

Gianpiero Bianchi, Carlo Boselli, Mauro Bruno, Alessio Cardacino, Cecilia Colasanti, Mario Magarò, Emiliano Montefiori, Francesco Ortame, Serenella Ravioli, Francesco Rizzo	
<i>Use of Artificial Intelligence in Istat to improve the customer experience</i>	321
Margherita Gerolimetto, Stefano Magrini	
<i>Bootstrap double frequency dickey fuller test for unit roots</i>	331
Antonella Bianchino, Valeriana Leporanico, Angela Rosa, Giuseppe Stassi	
<i>Statistics and mass media: "writing with numbers"</i>	343
Emma Bellotti, Filippo Di Carlo, Cecilia Reynaud	
<i>Youth nightlife in Rome's VIII municipality: results from survey</i>	355
Gabriele Dore	
<i>Sentenced without evidence? An honest diff-in-diff evaluation of Italy's anti- depopulation national strategy for inner areas</i>	367
Francesca Bergamante, Gianni Corsetti, Francesca della Ratta-Rinaldi, Andrea Spizzichino	
<i>Innovations in the methodological design of the recurring INAPP Plus sample survey</i>	379
Diana Lampertico	
<i>Cognitive decline among older adults in Europe: an analysis of easySHARE data</i>	389
Gianpaolo Caprino, Viviana Amati	
<i>Exploring inequalities in co-authorship networks among Italian scholars</i>	401
Marina Albanese, Monica Varlese	
<i>Socio-economic implications of energy transition: the new role of human capital</i>	413

Gianni Carboni	
<i>A regional perspective on Italian life expectancy deceleration.....</i>	425
Gianni Carboni, Giambattista Salinari	
<i>Structural breaks in Italian age-specific mortality trends: assessing the cohort-effect hypothesis</i>	437
Maria Filomeno, Irene Rocchetti, Antonello Maruotti	
<i>The First Victory: An Empirical Survival Study of Career Dynamics in the Italian Judiciary</i>	449
Agata Maria Madia Carucci, Annamaria Fiore, Valeria Marzocca, Roberto Antonello Palumbo	
<i>Decoding Italy's commercial desertification: challenges, causes, and sustainable solutions</i>	461
Antonio Capiello , Claudio Ceccarelli	
<i>OECD PMR Indicators on professional services: top performances or outliers? The inhomogeneity of the civil law notaries' cluster may bias the assessment on the administration of the justice</i>	473

STATISTICAL INDICATORS FOR THE ANALYSIS OF SOCIAL INEQUALITIES IN ITALY¹

Lucia Mongelli, Paola Perchinunno, Samuela L'Abbate, Antonella Massari

Abstract. The analysis of social inequalities is a topic of growing academic and policy interest, recognized as a key dimension in assessing individual and collective well-being. A fundamental prerequisite for any rigorous statistical assessment of inequality is the adoption of a shared, multidimensional definition that captures the complex nature of social disadvantage. This study addresses the need to identify small-area territorial units or population subgroups affected by hardship or severe exclusion. A fuzzy logic approach (Totally Fuzzy and Relative) and a spatial clustering algorithm (DBSCAN) are adopted to construct and interpret indicators of social disadvantage. The analysis draws on 2024 data from the “*Equitable and Sustainable Well-being*” (BES) framework published by ISTAT, focusing on three domains: socio-demography, employment, and personal safety at the provincial level. This integrated methodology enables the detection of both the intensity and spatial configuration of disadvantage across Italian territories. It provides a robust foundation for evidence-based and place-sensitive policy interventions.

1. Introduction

Social inequalities are inherently complex and multidimensional phenomena, encompassing socio-demographic, economic, educational, and safety-related dimensions.

This study aligns with international initiatives such as the OECD Better Life Index and the UNDP Human Development Index, which promote a multidimensional and non-monetary conception of well-being.

The increasing availability of disaggregated territorial statistics enables a more rigorous and data-driven approach to these issues.

¹ The contribution is the result of joint reflections by the authors.

This study was carried out within GRINS - Growing Resilient, Inclusive and Sustainable and received funding from the European Union Next-Generation EU (NATIONAL RECOVERY AND RESILIENCE PLAN NRRP MISSION 4, COMPONENT 2, INVESTMENT 1.3 - D.D. 1558 11/10/2022, PE00000018 Spoke 8 Social Sustainability).

The aim of this study is to propose an integrated methodology capable of capturing both the intensity of social disadvantage and its spatial distribution across Italian territories, through the combined use of fuzzy logic and density-based clustering techniques.

The analysis relies on BES (Equitable and Sustainable Well-being) data, published by ISTAT (2024), and introduces a methodological framework that combines a fuzzy synthetic index and spatial clustering to enhance the understanding of multidimensional disadvantage.

2. Objectives and Methodological Strategy

The analysis of social inequalities requires statistical approaches capable of capturing the complexity and multidimensionality of the observed phenomena, moving beyond the traditional dichotomous perspective that rigidly distinguishes between inclusion and exclusion, well-being and deprivation.

The overarching objective of this study is to develop an integrated model that can measure, represent, and interpret social inequalities across Italian territories through a nuanced and spatially explicit representation of disadvantage.

The study has four main aims:

1. Construction of a synthetic index of social disadvantage
 - The index reflects the multifaceted nature of the phenomenon by aggregating multiple thematic indicators.
 - It employs fuzzy membership functions, allowing for a gradual rather than binary measurement of deprivation.
2. Overcoming limitations of traditional thresholds
 - We employ the Totally Fuzzy and Relative method, which assigns each territorial unit a score within the $[0,1]$ interval, reflecting its relative degree of disadvantage with respect to the national distribution.
3. Application of spatial clustering techniques
 - The DBSCAN algorithm is applied to identify homogeneous areas in terms of social distress intensity.
 - DBSCAN is particularly suitable for irregular spatial distributions, as it identifies clusters and outliers without requiring a predefined number of groups.
4. Support for evidence-based public policy
 - The methodology provides a robust basis for designing targeted interventions and moving beyond uniform strategies, which often prove ineffective in capturing local disparities.

The methodological strategy consists of two main and complementary phases. In the first phase, the social disadvantage index is constructed using the Totally Fuzzy and Relative method based on data from the BES (Equitable and Sustainable Well-being) framework. Key indicators are selected from three domains deemed particularly relevant in explaining social sustainability: demography, employment, and personal safety. The indicators are statistically standardized to ensure comparability before being aggregated into a fuzzy synthetic index. In the second phase, territorial clusters are identified through the DBSCAN algorithm, using as input both the synthetic Totally Fuzzy and Relative scores and, in a subsequent step, the raw values of the individual indicators. This choice facilitates a comparative assessment of clustering strategies: one based on the synthesized information using the Totally Fuzzy and Relative method and the other more closely aligned with the original multidimensional structure of the phenomenon.

This integrated approach, which combines fuzzy measurement and spatial clustering, allows for a deeper and more nuanced understanding of social inequalities. It supports a more accurate representation of reality and provides a solid foundation for more informed, differentiated, and sustainable policy interventions.

3. Data Sources and Indicator Selection

The primary data source used for this analysis is the system of territorial indicators from the BES framework (Benessere Equo e Sostenibile - Equitable and Sustainable Well-being) developed and published annually by ISTAT, the Italian National Institute of Statistics. Specifically, the study refers to the most recent 2024 edition, which compiles and disseminates a structured set of indicators disaggregated at the provincial level (NUTS-3), covering all 107 Italian provinces and metropolitan cities.

The BES dataset provides a multidimensional information base aimed at evaluating well-being not only in economic terms, but also from social, environmental, and relational perspectives. It represents both a conceptual and operational framework inspired by the principles of integrated progress measurement beyond GDP, as recommended by the Stiglitz-Sen-Fitoussi Commission (2009), and aligned with the goals of the United Nations 2030 Agenda. It reflects the commitment of statistical institutions to represent territorial inequalities through comparable, timely, and policy-relevant data.

For the purposes of this analysis, three thematic domains were selected as particularly relevant for examining territorial social inequalities. These domains were chosen based on the existing scientific literature and consolidated empirical experience in the socio-economic field.

A) *Socio-demography*: includes three socio-demographic indicators reflecting population structure and health conditions. These variables highlight the entrenched and cumulative nature of disadvantage over time and across generations:

- life expectancy at birth (inverted to reflect higher disadvantage),
- avoidable mortality in the 0–74 age group,
- share of individuals aged 25–64 who have not completed upper secondary education.

B) *Employment*: this domain includes indicators related to labour market participation and the economic sustainability of households. The selected indicators are the following:

- non-participation rate in the labour force among the active population,
- share of NEET youth (Not in Education, Employment or Training) aged 15–29,
- percentage of pensioners receiving incomes below the minimum threshold (as an indicator of economic vulnerability among the elderly population).

C) *Personal Security*: encompasses dimensions related to both perceived and actual exposure to risk. These elements significantly affect urban quality of life and the sense of individual safety. Selected indicators include the following:

- prison overcrowding rate,
- homicide and violent crime frequency,
- number of residential burglaries,
- reported incidents of pickpocketing.

All indicators were subjected to a process of statistical normalization, essential to ensure comparability across variables and to allow for accurate aggregation in subsequent phases of the analysis. Each indicator was also assessed in terms of temporal robustness, complete territorial coverage, and discriminative capacity within the national distribution.

The use of the NUTS-3 territorial level proves particularly suitable for the type of analysis proposed, as it allows for sufficient granularity to capture local specificities, while maintaining adequate sample robustness for advanced statistical elaboration. This balance is crucial for supporting empirically grounded, territorially targeted public policy design.

4. Adopted Statistical Methods

4.1. The Fuzzy approach

The Totally Fuzzy and Relative method, introduced by Cheli and Lemmi (1995), extends the concept of fuzzy sets originally formulated by Zadeh (1965). It allows

the assignment of a continuous membership degree in the interval $[0,1]$ to each territorial unit, representing its level of inclusion in the fuzzy set of social disadvantage. This continuous representation overcomes the limitations of traditional binary classification (e.g., inclusion vs. exclusion), offering a more nuanced, realistic, and accurate interpretation of social vulnerability as a gradual phenomenon.

The weights associated with each indicator are calculated based on their discriminative power within the observed distribution, following the approach proposed by Cerioli and Zani (1990). These weights reflect the relative contribution of each factor to the overall determination of disadvantage.

Assuming that k indicators are observed for each unit (e.g., a household or a territorial entity), the membership function for the i -th unit to the fuzzy set of disadvantage can be formally expressed as follows:

$$f(x_i) = \frac{\sum_{j=1}^k g(x_{ij}) \cdot w_j}{\sum_{j=1}^k w_j} \quad i = 1, \dots, n \quad (1)$$

where $g(x_{ij})$ represents the degree of membership of unit i to the fuzzy subset associated with indicator j , while w_j is a weight reflecting the relative importance of indicator j .

The weighting system w_j is derived from a generalized extension of the method originally proposed by Cerioli and Zani (1990). It is based on the discriminatory power of each indicator in distinguishing among different observed conditions of disadvantage:

$$w_j = \ln[1/\overline{g(x_j)}], \quad \text{where} \quad \overline{g(x_j)} = \frac{\sum_{i=1}^n g(x_{ij})}{n} \quad j = 1, 2, \dots, k \quad (2)$$

When the average function $\overline{g(x_j)} = 1$ the corresponding weight w_j is equal to zero, while when $\overline{g(x_j)} = 0$, w_j is not defined, or rather X_j is not an appropriate indicator for that collective.

This formulation ensures that indicators contributing more substantially to the differentiation of units within the observed distribution receive higher weights, thereby enhancing the sensitivity of the composite index to real disparities in social conditions.

4.2 The DBSCAN approach

After the construction of the fuzzy index, the second phase of the analysis involves the application of the DBSCAN algorithm (Density-Based Spatial Clustering of Applications with Noise), originally developed by Ester *et al.* (1996), to identify clusters of provinces with similar levels of social disadvantage and to detect potential outlier units. DBSCAN relies on local density estimation, defining a cluster as a set of points that are all reachable from each other through areas of sufficiently high point density. Unlike conventional clustering methods such as k-means, DBSCAN does not require the number of clusters to be specified a priori and is particularly well-suited to irregular or non-convex spatial distributions, making it ideal for complex territorial contexts.

The algorithm relies on two key parameters: ϵ (epsilon), which represents the maximum distance within which two points are considered neighbors, and *MinPts*, which indicates the minimum number of neighboring points required to form a dense region. To calibrate these parameters, parameter calibration was conducted via k-distance plot analysis. This technique identifies the "elbow point" of the curve, which corresponds to the empirically optimal value for ϵ . In contexts characterized by high dimensionality or strong territorial heterogeneity, the selection of ϵ and *MinPts* significantly affects clustering quality, requiring a careful balance between accurately identifying groups and minimizing the number of noise points.

In this study, DBSCAN was applied in two configurations: first, on the aggregated Totally Fuzzy and Relative index to detect clusters of overall social disadvantage; and second, on the standardized values of individual indicators to reveal more detailed clusters specific to the individual domains of demography, employment, and personal security. The integration of the Totally Fuzzy and Relative methodology with spatial clustering via DBSCAN provides a representation of both the intensity ("how much") and the spatial localization ("where") of social disadvantage. This integrated approach provides a robust tool to inform public policy, guide local planning, and evaluate high-impact territorial interventions.

5. Analysis Results

The following section presents the empirical findings emerging from the combined application of the Totally Fuzzy and Relative methodology and DBSCAN clustering. Results are presented by thematic domain: demography, employment, and personal security and by spatial configuration, highlighting both aggregated and domain-specific results. The analysis reveals a complex and fragmented geography

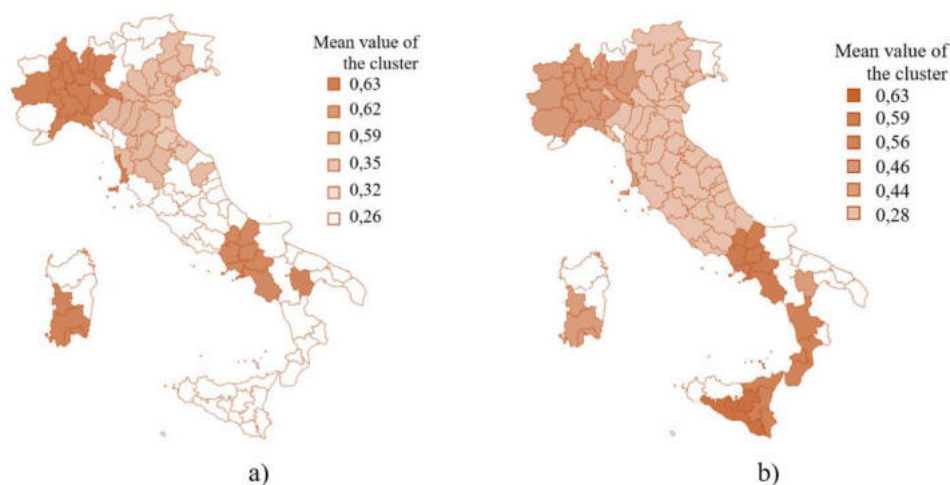
of social disadvantage across Italian provinces, challenging linear narratives and calling for nuanced, territorial policy responses.

The provinces were grouped using the DBSCAN algorithm. On the maps, the provinces shown in white were classified by the algorithm as noise points. This does not mean they lack a high fuzzy value, but rather that they are surrounded by fewer than MinPts provinces, and none of those are core points. In other words, noise provinces are located at a distance greater than ϵ from any core province.

5.1. Socio-Demographic Domain

For the first set, socio-demographic inequality, six clusters were obtained in both configurations mentioned above. The legend shows the average fuzzy values for each resulting cluster; darker colours indicate higher levels of disadvantage among the grouped provinces.

Figure 1 – Socio-demographic inequality with DBSCAN a) based on the fuzzy value ($\epsilon=0.7$ MinPts=4); b) directly on the three indicators ($\epsilon=0.87$ MinPts=4).



Clusters of significant socio-demographic disadvantage are mostly found in the South, particularly in provinces of Calabria, Sicilia, and Campania. However, signs of critical conditions also appear in certain inland provinces, such as Molise and the Abruzzo hinterland.

A notable divergence emerges between the two DBSCAN configurations: the first configuration, based on the aggregated Totally Fuzzy and Relative index,

identifies clusters broadly aligned with overall disadvantage levels; the second configuration, based on the three raw indicators, highlights more compact areas.

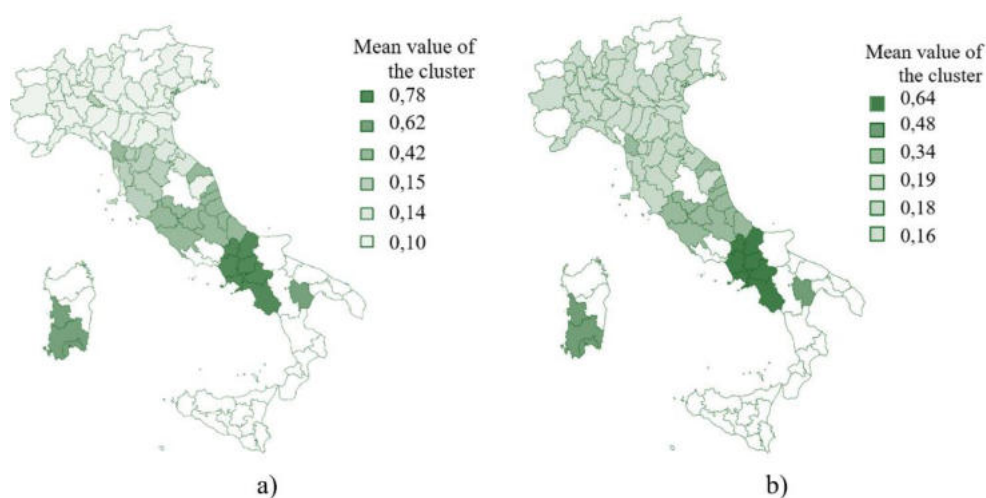
This divergence is largely explained by the presence of southern provinces where educational attainment levels are relatively high, but demographic conditions are poor (e.g., ageing, avoidable mortality).

Therefore, the second configuration better captures these localized mixed conditions of disadvantage. Therefore, the second configuration better captures these mixed localized conditions of disadvantage, also including the inland areas of Molise and Abruzzo.

5.2. Employment Domain

For the employment inequality analysis, six clusters were also identified in both DBSCAN configurations, revealing notable territorial disparities across Italy.

Figure 2 – *Employment inequality with DBSCAN a) based on the fuzzy value ($\epsilon=0.64$ MinPts=4); b) directly on the three indicators ($\epsilon=0.745$ MinPts=4).*



The findings indicate that the highest concentration of employment-related disadvantage emerges in the regions of Basilicata and Campania, where structural weaknesses in the labour market and persistent socio-economic challenges contribute to elevated levels of vulnerability.

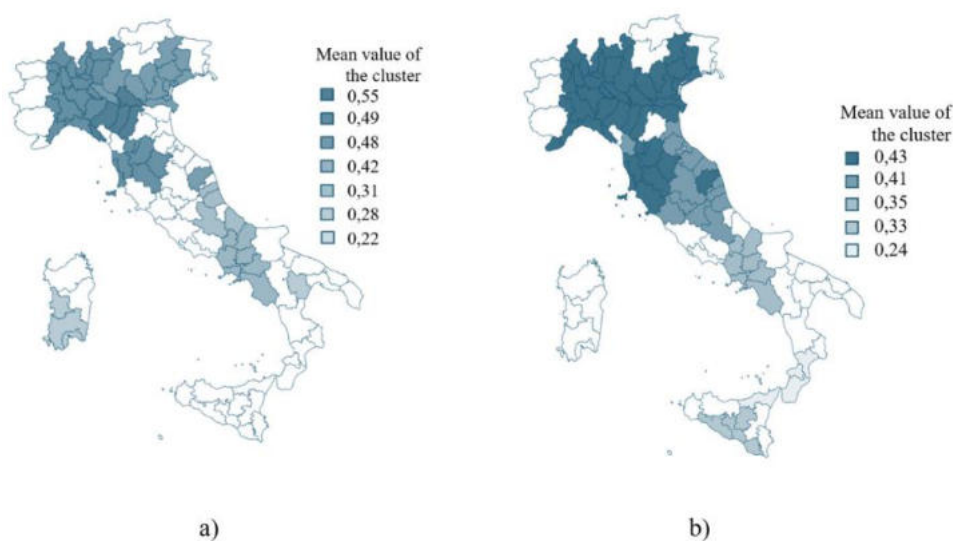
Significant levels of disadvantage are also evident in Molise and in several provinces of Puglia, suggesting the presence of broader economic difficulties within parts of Southern Italy.

Conversely, the northern regions are generally characterized by fewer high-density clusters, a pattern that reflects a stronger overall performance in terms of labour market participation and economic stability, with more resilient local economies mitigating the intensity of employment-related inequalities.

5.3 Personal Security Domain

For the personal safety domain, DBSCAN produced seven clusters when applied to the Totally Fuzzy and Relative composite index, while five clusters were obtained when the algorithm was applied using the raw indicator values.

Figure 3 – *Personal safety inequality with DBSCAN a) based on the fuzzy value ($\epsilon=0.75$ MinPts=4); b) directly on the four indicators ($\epsilon=0.855$ MinPts=4).*



The results indicate that disadvantage clusters are primarily concentrated around major metropolitan areas such as Naples, Milan, and Rome. Additionally, several central-northern provinces exhibit critical conditions, particularly when analyzing the raw indicators.

Furthermore, some border and coastal provinces in the central-southern regions are also affected, although the distribution in this domain appears to be more fragmented compared to the others.

6. Conclusions and Future Developments

The findings of this study highlight the effectiveness of integrating fuzzy logic and spatial clustering techniques in measuring social inequalities at the territorial level. The combination of the Totally Fuzzy and Relative method with the DBSCAN algorithm allowed for a multidimensional and spatially explicit representation of disadvantage, thereby overcoming the binary logic that traditionally segments populations into “included” and “excluded” groups.

The Totally Fuzzy and Relative method makes it possible to assign a relative score to each territorial unit, reflecting its position within the national distribution of social disadvantage through gradual measurement. This is complemented by DBSCAN, which effectively identifies clusters of similar intensity and territorial outliers, bringing to light situations that might otherwise remain hidden in analyses. This dual perspective, both quantitative and spatial, adds significant value to policy design by enabling place-based public interventions, in line with the European Commission’s guidelines on economic, social, and territorial cohesion.

These findings are consistent with international literature that emphasizes the crucial role of institutional quality and administrative impartiality in shaping territorial disparities in well-being. In particular, Charron, Lapuente, and Rothstein (2013) stress how the quality of government, defined by efficiency, transparency, and absence of corruption, is a structural determinant of socio-economic inequalities across European regions. Integrating governance-related indicators into future iterations of this model may thus enhance its explanatory power and provide further insights for evidence-based policymaking.

Moreover, future methodological developments may include the adoption of more advanced clustering techniques. Recent innovations, such as the HDBSCAN algorithm (Campello, Moulavi & Sander, 2013), offer the ability to detect clusters of varying densities and require fewer parameter specifications than DBSCAN. HDBSCAN’s flexibility makes it particularly suitable for heterogeneous spatial distributions and for identifying complex or irregular cluster structures, which are common in socio-territorial data.

The results show that social inequalities are not exclusively concentrated in Southern Italy but are instead present throughout the entire country, including areas in Central and Northern Italy. This evidence underscores the need for differentiated

policy strategies capable of capturing local dynamics and responding through flexible, multi-level approaches.

Several avenues for future development are suggested to further strengthen this line of research. One possible direction is the adoption of HDBSCAN (Hierarchical Density-Based Spatial Clustering of Applications with Noise), an advanced version of DBSCAN that can detect clusters with variable density while requiring only one parameter (*MinPts*); this could simplify adaptability to heterogeneous spatial distributions and improve outlier detection. Another avenue involves expanding the range of BES domains considered: beyond demography, employment, and personal safety, future studies could integrate indicators related to the environment, education, social cohesion, and the quality of public services, thereby broadening the interpretative capacity of the model. Additionally, adopting a longitudinal perspective would allow for the analysis of temporal dynamics in inequality trends and enable the monitoring and evaluation of policy impacts over time. Finally, comparative integration with international frameworks, such as EU-SILC (European Union Statistics on Income and Living Conditions) and the United Nations' Sustainable Development Goals (SDGs), would further enhance international comparability and support the interpretation of results across different territorial and governance scales.

Overall, the proposed approach offers a replicable, flexible, and scalable model that can effectively support territorial policies aimed at reducing social inequalities and advancing sustainable development goals.

References

- BARCA F. 2009. *An agenda for a reformed cohesion policy*. European Commission. https://ec.europa.eu/regional_policy/archive/policy/future/pdf/report_barca_v0306.pdf
- CAMPELLO R. J. G. B., MOULAVI D., SANDER J. 2013. Density-based clustering based on hierarchical density estimates. In J. Pei, V. S. Tseng, L. Cao, H. Motoda, G. Xu (Eds.), *Advances in knowledge discovery and Data Mining. PAKDD 2013. Lecture Notes in Computer Science* (Vol 7819, pp. 160–172). Springer. https://doi.org/10.1007/978-3-642-37456-2_14
- CERIOLO A., ZANI S. 1990. A Fuzzy Approach to the Measurement of Poverty. In Dagum, C., Zenga, M. (Eds.), *Income and wealth distribution, inequality and poverty* (pp. 272–283). Springer. https://doi.org/10.1007/978-3-642-84254-1_14
- CHELI B., LEMMI A. 1995. A Totally Fuzzy and Relative Approach to the Multidimensional Analysis of Poverty. *Economic Notes*, Vol. 24, No. 1, pp. 115–134.

- CHARRON N., LAPUENTE V., ROTHSTEIN B. 2013. *Quality of government and corruption from a European perspective*. Edward Elgar Publishing. <https://doi.org/10.4337/9781782545591>
- ESTER M., KRIEGEL H. P., SANDER J., XU X. 1996. A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise. In *Proceedings of the second international conference on knowledge discovery and Data Mining (KDD'96)*, (pp.226–231). AAAI Press.
- ISTAT 2024. *Il benessere equo e sostenibile in Italia – Indicatori territoriali*. <https://www.istat.it/it/archivio/benessere-e-sostenibile>
- OECD 2020. *How's Life? Measuring Well-being*. OECD Publishing. <https://doi.org/10.1787/9870c393-en>
- STIGLITZ J. E., SEN A., FITOUSSI J. P. 2009. *Report by the Commission on the Measurement of Economic performance and social progress*. Commission on the Measurement of Economic Performance and Social Progress. <https://ec.europa.eu/eurostat/documents/118025/118123/Fitoussi+Commission+report>
- UNDP 2023. *Human Development Report: Breaking the Gridlock*. UNDP. <https://hdr.undp.org>
- ZADEH L. A. 1965. Fuzzy Sets. *Information and control*, Vol. 8, No. 3, pp. 338–353. [https://doi.org/10.1016/S0019-9958\(65\)90241-X](https://doi.org/10.1016/S0019-9958(65)90241-X)

Lucia MONGELLI, Istat, Italian National Institute of Statistics, Department for the Development of Methods and Technologies for the Production and Dissemination of Statistical Information, Directorate for Data Collection, mongelli@istat.it
Paola PERCHINUNNO, Department of Economics, Management and Business Law, University of Bari Aldo Moro, Italy, paola.perchinunno@uniba.it
Samuela L'ABBATE, Department of Humanities Research and Innovation, University of Bari Aldo Moro, Italy, samuella.labbate@uniba.it
Antonella MASSARI, Department of Economics, Management and Business Law, University of Bari Aldo Moro, Italy, antonella.massari@uniba.it

WOMEN, TERRITORIES AND INEQUALITY. A MULTIDIMENSIONAL ANALYSIS OF THE WELL-BEING GENDER GAP IN THE ITALIAN PROVINCES¹

Monica Carbonara, Giuseppe Lecardane, Adriano Pareto

Abstract. The analysis of the well-being gender gap in the Italian provinces highlights the persistent socio-economic inequalities between men and women and the territorial differences in the distribution of well-being. In this study, a multidimensional statistical analysis of the well-being gender gap in the Italian provinces is proposed to identify latent structures and recurring territorial patterns. Using data from official sources such as Italian National Institute of Statistics (Istat) and in particular the report on “Equitable and Sustainable Well-being in Italy” (BES)², a set of indicators was selected that represent three dimensions of well-being - Knowledge, Work and Wealth - disaggregated by gender. The study provides ideas for the design of targeted territorial policies that can address inequalities in an integrated way and promote more equitable and inclusive development at local level.

1. Introduction

Gender equality is a fundamental human right and a strategic goal for individual economic and social well-being. Ensuring equal opportunities for men and women promotes economic growth, strengthens democracy and improves social cohesion, which benefits society as a whole.

Goal 5 of the United Nations Sustainable Development Goals (SDGs)³ focuses on reducing the gender gap with the aim of achieving gender equality and empowering all women and girls. However, despite the progress made in recent years, gender inequalities persist in our country and manifest themselves in many areas of life.

¹ The paper is the result of the common work of the authors. In particular, the sections are attributed as follows: M. Carbonara sections 1, 2.1 and 3.2, G. Lecardane sections 3, 3.1, 3.3, 3.4 and 4, A. Pareto sections 2.2. and 3.5.

² ISTATa. 2024. Rapporto Bes 2023: il Benessere Equo e Sostenibile in Italia. <https://www.istat.it/wp-content/uploads/2024/04/Bes-2023-Ebook.pdf>.

³ The 2030 Agenda for Sustainable Development, adopted by all United Nations Member States in 2015, provides a shared blueprint for peace and prosperity for people and the planet, now and into the future. ISTATb. 2024. Rapporto SDGs 2024: informazioni statistiche per l'Agenda 2030 in Italia. <https://www.istat.it/produzione-editoriale/rapporto-sdgs-2024/>.

According to the World Economic Forum's Global Gender Gap Report 2024⁴, full gender equality could only be achieved in 134 years, i.e. in around five generations, well beyond the sustainable development goal set for 2030. In the global ranking of 146 countries, Italy is in 87th place, with a worrying drop of 8 positions compared to 2023.

The analysis of the BES indicators in Italy reveals significant differences between men and women. Although women achieve better school results, with fewer dropouts and higher skills, they encounter considerable difficulties on the labour market. The female employment rate is significantly lower, while non-participation in the labour market and involuntary part-time work are higher.

Gender inequality manifests itself in various areas, from professional life to family, from education to pay, up to the representation of women in leadership positions. This phenomenon is influenced by behavioural patterns or personal attitudes and the socioeconomic context. However, there is still much scope for policy measures aimed at building a more equitable system, improving work-life balance, strengthening services and promoting employment and employability.

In this paper, data from the "BES of Territories" indicator system are used to perform a multidimensional statistical analysis of inequalities between men and women in the Italian provinces, focussing on three key dimensions: Knowledge, Work and Wealth. The aim is to identify particularly vulnerable groups and provide elements of reflection for policies aimed at improving well-being in various aspects of life.

2. Data and method

2.1 Individual indicators and polarities

Every year, Istat publishes the update of the indicator system for the "Equitable and Sustainable Well-being of Territories" (BesT) for the Italian provinces and metropolitan cities, which is consistent and integrated with the BES framework adopted at national level. The BesT indicators provide a detailed overview of the distribution of well-being in the different territories of the country and allow a more accurate assessment of territorial inequalities and the definition of the specific well-being profiles of each territory.

From this system of indicators, 11 individual indicators updated until 2023 were selected and grouped into three dimensions:

⁴ The Global Gender Gap Index annually benchmarks the current state and evolution of gender parity across four key dimensions (Economic Participation and Opportunity, Educational Attainment, Health and Survival, and Political Empowerment).

1. *Knowledge*, which includes indicators related to educational attainment and skills development.
2. *Work*, which relates to employment and job security.
3. *Wealth*, which contains indicators related to income and economic well-being.

Table 1 describes, for each dimension, the indicators and their ‘polarity’, i.e. the sign of the relationship between the indicator and the phenomenon to be measured.

Table 1 – *Dimensions, individual indicators and polarities.*

Dimension	Label	Indicator	Polarity (+/-)
Knowledge	Ind1	Transition to university	+
	Ind2	Inadequate numerical competence (students in third year of secondary school)	-
	Ind3	Inadequate literacy skills (third year secondary school students)	-
Work	Ind4	Employment rate (20-64 years)	+
	Ind5	Non-participation rate at work	-
	Ind6	Rate of fatal and permanent disability accidents at work	-
	Ind7	Youth employment rate (15-29 years)	+
Wealth	Ind8	Youth Labour Market Non-Participation Rate (15-29 years)	-
	Ind9	Average annual wages of employees	+
	Ind10	Average annual per capita pension income	+
	Ind11	Retirees with low pension income	-

Source: Istat

2.2 Composite index construction

The challenge of this study is to compare the evolution of well-being in the Italian provinces by gender and over time.

In order to make comparisons by gender from 2018 to 2022, the individual indicators were normalized using the constrained Min-Max method of the AMPI (Adjusted Mazziotta-Pareto Index), which transforms the indicators in a similar way to the Min-Max method but uses a common reference base set equal to 100 (Mazziotta and Pareto, 2022).

For a generic province i , indicator j and gender k at time t , the normalized value is:

$$r_{ijk}^t = 100 \pm 60 \frac{x_{ijk}^t - x_{oj}}{\max_{itk}(x_{ijk}^t) - \min_{itk}(x_{ijk}^t)}$$

where:

- x_{ijk}^t is the original value;

- x_{oj} is the value of indicator j for Italy (males + females) in 2018 (base);
- $\min_{ik} (x_{ijk}^t)$ and $\max_{ik} (x_{ijk}^t)$ are the minimum and maximum of indicator j from 2018 to 2022 regardless of gender;
- the sign $\pm$ is the polarity of indicator j .

The normalized indicators were aggregated with a compensatory approach into 3 pillars (one for each dimension) using a simple arithmetic mean:

$$\text{KNOW}_{ik}^t = \frac{\sum_{j=1}^3 r_{ijk}^t}{3}; \quad \text{WORK}_{ik}^t = \frac{\sum_{j=4}^8 r_{ijk}^t}{5}; \quad \text{WEAL}_{ik}^t = \frac{\sum_{j=9}^{11} r_{ijk}^t}{3}.$$

The 3 pillars were then aggregated with a partially compensatory approach into the AMPI with a negative penalty (Mazziotta and Pareto, 2016). Therefore, the composite index of well-being for province i and gender k at time t is given by:

$$\text{AMPI}_{ik}^t = M_{ik}^t - S_{ik}^t \text{cv}_{ik}^t$$

where M_{ik}^t , S_{ik}^t , cv_{ik}^t are the mean, standard deviation, and coefficient of variation of the three pillars (KNOW, WORK and WEAL) for province i and gender k at time t , respectively.

Finally, the AMPI variation from 2018 to 2022 for province i and gender k was also calculated as follows:

$$\Delta(\text{AMPI})_{ik} = \text{AMPI}_{ik}^t - \text{AMPI}_{ik}^{t-1}$$

where $t=2022$ and $t-1=2018$.

If $\Delta(\text{AMPI})_{ik} > 0$, well-being has increased from 2018 to 2022; if $\Delta(\text{AMPI})_{ik} < 0$, well-being has decreased.

3. Results and discussions

3.1. Descriptive statistics of the individual indicators

Table 2 presents the descriptive statistics of the analysed indicators, disaggregated by gender and compared between 2018 and 2022. The data reveal marked gender differences that persist over time.

Regarding education, the transition to university (Ind1) shows a clear female advantage, with an average of 56.6% for women versus 44.6% for men in 2018, a gap that widens further in 2022 (59.8% vs. 46.2%). Conversely, indicators of inadequate basic education (Ind2 and Ind3) show worse performance for men, with higher coefficients of variation indicating greater territorial dispersion. The greatest inequalities can be observed on the labour market. The general employment rate

(Ind4) presents a substantial gender gap: 73% for men versus 53.4% for women in 2018, which persists in 2022 (74.9% vs. 55.4%). The phenomenon is even more pronounced in the youth cohort (Ind7), where the gap intensifies over time. Non-participation in the labour force (Ind5 and Ind8) confirms greater female exclusion from the labour market.

Table 2 – Descriptive statistics of the indicators. Male and Female. 2018 and 2022.

Indicator	Male			Female		
	Mean	Std	CV (%)	Mean	Std	CV (%)
2018						
Ind1	44.6	6.0	13.4	56.6	6.7	11.8
Ind2	37.2	10.5	28.3	40.5	11.0	27.1
Ind3	37.8	7.8	20.6	29.9	6.7	22.5
Ind4	73.0	8.9	12.2	53.4	13.2	24.7
Ind5	16.1	9.6	59.3	24.4	13.4	55.1
Ind6	18.4	5.9	32.2	7.7	3.8	48.7
Ind7	36.3	9.2	25.3	27.1	8.9	32.7
Ind8	32.9	16.4	49.7	39.6	17.5	44.2
Ind9	22,449.2	4,485.3	20.0	15,075.7	3,040.9	20.2
Ind10	21,053.8	2,626.4	12.5	15,401.9	1,273.2	8.3
Ind11	9.3	3.2	35.0	11.3	3.6	32.1
2022						
Ind1	46.2	6.0	13.0	59.8	6.5	10.9
Ind2	41.9	10.2	24.4	45.7	10.7	23.4
Ind3	43.7	7.3	16.8	33.4	7.1	21.1
Ind4	74.9	8.1	10.9	55.4	13.1	23.6
Ind5	13.2	8.4	64.0	20.4	12.5	61.4
Ind6	15.1	4.4	29.3	6.1	2.5	40.8
Ind7	39.6	8.6	21.8	29.6	9.5	32.1
Ind8	26.2	14.3	54.4	31.5	17.5	55.6
Ind9	23,534.3	4,503.9	19.1	16,037.9	3,065.6	19.1
Ind10	22,765.4	2,797.9	12.3	16,908.3	1,441.4	8.5
Ind11	8.1	2.7	33.6	10.2	3.2	31.9

Source: Istat data processing.

Economic indicators reveal further disparities: the average wage of employees (Ind9) and the average amount of pension income (Ind10) show higher values for men in both years. The percentage of pensioners with low-income benefits (Ind11) is systematically higher among women. The coefficients of variation highlight considerable territorial heterogeneity for all indicators, with particularly high values for labour participation indicators, suggesting marked differences across Italian provinces. Overall, the data confirm the persistence of significant gender inequalities in Italian territorial well-being, with slight improvements in some areas between 2018 and 2022, but without substantial structural changes.

3.2. Box plots of the individual indicators

The box plots in Figure 1 show the distribution of the eleven normalized well-being indicators across Italian provinces, disaggregated by gender in 2022. The graphical analysis reveals not only differences in medians between men and women, but also territorial variability and the presence of extreme values.

Knowledge indicators. The transition to university (Ind1) graphically confirms the female advantage, with a significantly higher median for women and a distribution more concentrated in the upper values. The inadequate basic education indicators (Ind2 and Ind3) show similar distributions between genders, with a slight tendency toward higher values for men, particularly evident in the upper outliers.

Work indicators. The box plots reveal the most pronounced disparities in the work market. The general employment rate (Ind4) and youth employment rate (Ind7) show markedly different distributions: for men, the medians are positioned at high levels with contained variability, while for women the distributions are systematically shifted toward lower values. Non-participation in work (Ind5 and Ind8) presents the opposite pattern, with women showing higher medians and greater territorial dispersion, evidenced by wider boxes and numerous outliers.

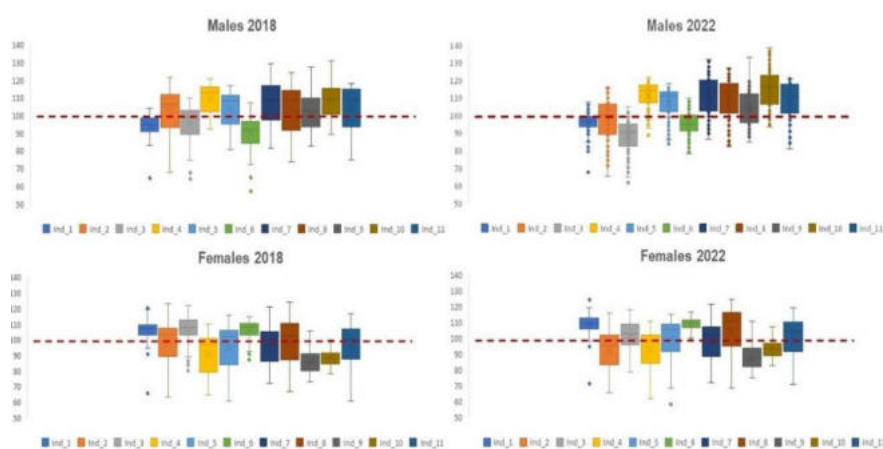
Wealth indicators. The wage indicators (Ind9 and Ind10) show distributions favourable to men, with higher medians and more contained variability. Particularly significant is the gap in pension income (Ind10), where the difference between medians is substantial. The indicator on low-income pensioners (Ind11) confirms greater female economic vulnerability, with a distribution shifted toward higher values.

The most significant aspects emerging from the analysis are:

- Persistence of the employment gap. Women continue to show systematic disadvantages in labour market-related indicators, both for general and youth employment.
- Female educational advantage. The transition to university represents an area where women excel, suggesting greater investment in human capital.
- Temporal stability of disparities. The 2018-2022 comparison shows that, despite some improvements, the fundamental patterns of the gender gap remain substantially unchanged.
- Territorial heterogeneity. The variability of the box plots highlights how gender disparities manifest differently across Italian provinces, requiring territorially differentiated approaches.
- Territorial variability. The box plots highlight how some indicators present considerable heterogeneity among provinces, with wide interquartile ranges and presence of outliers, particularly in female labour participation indicators. This variability suggests the existence of territorial contexts with very

different performances, emphasizing the importance of the geographical dimension in analysing gender inequalities. The presence of numerous outliers in several indicators indicates provinces with exceptional characteristics compared to the national pattern, deserving specific in-depth analysis to understand the factors underlying such differences.

Figure 1 – Normalized well-being indicators across Italian provinces by gender. 2018, 2022.



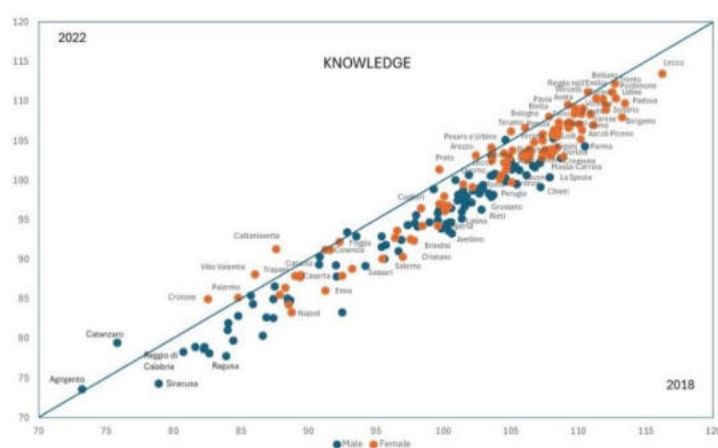
Source: Istat data processing

3.3. Transition diagrams of the Pillars

In this Section, the transition diagrams of the three pillars from 2018 to 2022 are discussed. The further away the points are from the main diagonal (the line of equation $y = x$), the more the values for 2018 and 2022 differ.

Knowledge Pillar. The diagram shows a prevalent concentration for northern Italy in the upper right quadrant (values >100 in both years), with particular prominence of Lombardia and Triveneto provinces, while in southern Italy, the concentration is present in the lower left quadrant, with values systematically below the national average (Fig. 2). The female advantage is marked, with systematically superior performance compared to men in all geographical areas. The gender gap persists and remains stable over time, with differences of approximately 5-10 points. Lecco is the province with absolute prevalence for women (>113), representing the best national case. Additionally, a generalized deterioration is recorded in the provinces as most of them are positioned below the bisector, indicating decreases from 2018 to 2022.

Figure 2 – Transition diagram of the Knowledge Pillar, Male and Female. 2018 vs 2022.



Source: Istat data processing

Work Pillar. The diagram highlights a pronounced territorial gap with higher performance for northern provinces, particularly for Bolzano/Bozen, which reaches the highest values approaching 120 for both genders (Fig. 3). The South shows a strong concentration in the lower quadrant, with acute criticalities for the provinces of Sicilia and Calabria. Contrary to the Knowledge pillar, there is a reversal of the gender advantage in favour of men, who generally show superior performance. Furthermore, women's results present higher dispersion. Between the two years, many provinces show substantial progress for both sexes, positioning themselves well above the reference bisector. A particular case is the province of Caltanissetta, which shows strong improvement for women. Additionally, the southern provinces, while improving, maintain critical values.

Wealth Pillar. Territorial stratification is more pronounced compared to other pillars, with an almost exclusive concentration of northern provinces above the value of 100 (Fig. 4). Southern values are systematically below 90, with Crotona and Agrigento in critical conditions (<80). A greater gender divergence is evident. Indeed, the differences between men and women are larger compared to the other pillars examined. Furthermore, rigidity in progress is highlighted with apparent temporal stability across territory and gender. The points concentrate closer to the bisector compared to the other pillars examined.

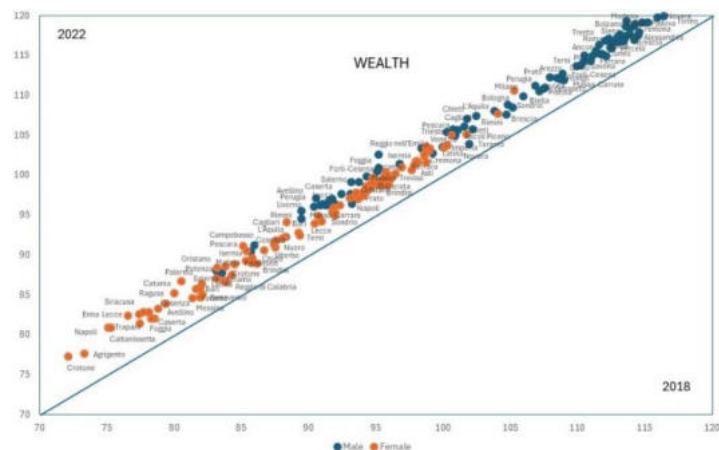
The analysis reveals how the three dimensions of well-being in the gender gap present distinct evolutionary dynamics and territorial patterns, requiring differentiated policy strategies for each pillar.

Figure 3 – *Transition diagram of the Work Pillar, Male and Female. 2018 vs 2022.*



Source: Istat data processing

Figure 4 – *Transition diagram of the Wealth Pillar, Male and Female. 2018 vs 2022.*



Source: Istat data processing

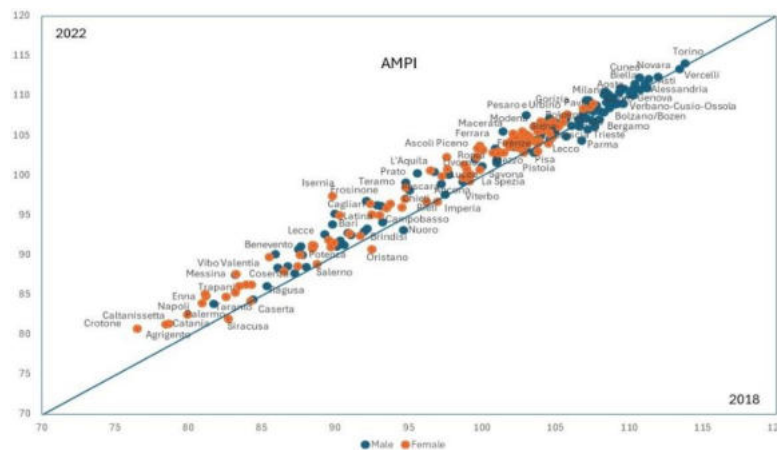
3.4 Transition diagram of the AMPI Index

Figure 5 illustrates the evolutionary dynamics of the AMPI, disaggregated by gender, across Italian provinces over the period 2018-2022, allowing for a visualization of the trajectory of change for each province. The data reveal a distribution spanning a wide range of values, with the AMPI varying from approximately 70 to 120 points in both reference years. A general upward trend is

observed during the period, with most data points located above the bisector, indicating a widespread improvement in multidimensional well-being for both sexes.

The partial overlap between gender clusters in the central segment of the distribution suggests that, while gender-specific disparities persist, there are provinces where the well-being gap between men and women is relatively limited. In contrast, at the extremes of the distribution, more distinct patterns emerge, suggesting that gender inequalities tend to intensify in territorial contexts characterized by either particularly high well-being levels in favour of men or particularly low levels for women. Despite the overall improvement observed between 2018 and 2022, the persistence of the gender gap indicates that progress towards gender equality remains slow and requires targeted policy interventions.

Figure 5 – Transition diagram of the AMPI, Male and Female. 2018 vs 2022.



Source: Istat data processing

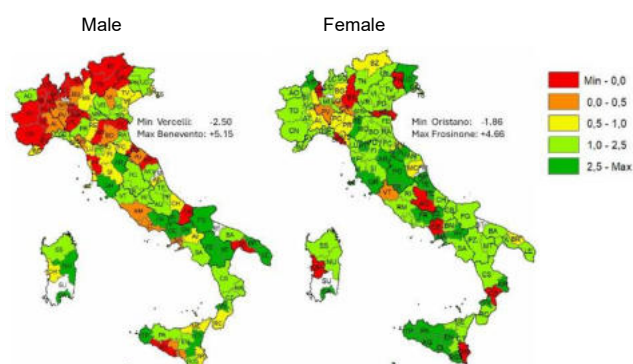
3.5. AMPI variations from 2018 to 2022

Figure 6 shows a comparative cartographic representation of AMPI changes by gender in the Italian provinces between 2018 and 2022. The aim is to identify the spatial dynamics of multidimensional well-being and gender-specific patterns in its territorial evolution.

The analysis of the map for the male population reveals a pronounced north-south territorial polarization of AMPI variation. The north regions show a widespread decline in the index, with negative changes in Piedmont, Western Lombardy and Liguria. In contrast, Central and Southern Italy shows a more heterogeneous but generally positive pattern, with several southern and island provinces showing

significant improvements, particularly in Eastern Sicily, Calabria and parts of Apulia. For the female population, the improvement appears to be widespread throughout almost the entire country, especially in the North-East, where several provinces report significant increases of between 1.0 and 2.5 points. This trend indicates progress in the integration of women into skilled labour markets and access to positions of higher responsibility, which has a positive impact on the dimensions of Work and Wealth. Emilia-Romagna and Veneto stand out with particularly favourable results, indicating the effectiveness of territorial policies to promote work-life balance and the empowerment of women. Southern Italy also shows generally positive results for women, although in some areas with slightly less intensity than for men. Nevertheless, there is a clear increase in Sicily, Calabria and Apulia, which indicates a stronger convergence process in the well-being of women in these regions.

Figure 6 - AMPI variation from 2018 to 2022*.



* The values for the provinces of Monza and Brianza, Fermo, Barletta-Andria-Trani and South Sardinia are not present because they are missing.

Source: Istat data processing

In summary, between 2018 and 2022, the dynamics of multidimensional well-being evolved differently between the genders. In the northern regions, traditionally characterized by a higher level of well-being, the trend seems to have been more favourable for women than for men, while in Southern Italy both genders have benefited from improvements, albeit with varying intensity.

4. Conclusions

The AMPI analysis reveals a complex picture in which the gender gap in multidimensional well-being exhibits strong territorial characteristics. While signs of improvement are evident, the persistence of the gap highlights the need for

integrated policies that simultaneously address the educational, labour market, and economic dimensions of women's well-being, with particular attention to Italy's territorial specificities. In the *Knowledge pillar*, the gender gap shows a tendency to narrow, with women continuing to outperform men, thereby consolidating the educational advantage acquired in previous decades. In the *Work pillar*, the results indicate a substantial reduction in the gender employment gap, although men still maintain an overall advantage and higher performance levels. Furthermore, women's outcomes show greater territorial dispersion between the North and South. In the *Wealth pillar*, the gender gap demonstrates divergent trends and remains strongly in favour of men. Although the growth in disposable income has benefited both genders, southern regions remain disadvantaged compared to the North, with persistent disparities that particularly penalize women. Unfortunately, recent improvements in female employment have not yet translated fully into pay equity.

This emerging configuration suggests that gender inequalities are being reconfigured rather than simply reduced. Consequently, policy responses must address both the emergence of new male disadvantages and the consolidation of female progress, with a nuanced focus on territorial and sectoral specificities.

References

- ISTATa. 2024. Rapporto Bes 2023: il Benessere Equo e Sostenibile in Italia. <https://www.istat.it/wp-content/uploads/2024/04/Bes-2023-Ebook.pdf>
- ISTATb. 2024. Rapporto SDGs 2024: informazioni statistiche per l'Agenda 2030 in Italia. <https://www.istat.it/produzione-editoriale/rapporto-sdgs-2024/>
- MAZZIOTTA M., PARETO A. 2016. On a Generalized Non-compensatory Composite Index for Measuring Socio-economic Phenomena, *Social Indicators Research*, Vol. 127, pp. 983–1003.
- MAZZIOTTA M., PARETO A. 2022. Normalization methods for spatio-temporal analysis of environmental performance: Revisiting the Min–Max method. *Environmetrics*, Vol. 33, No. 5. <https://doi.org/10.1002/env.2730>

Monica CARBONARA, Istat, mocarbon@istat.it
Giuseppe LECARDANE, Istat, lecardan@istat.it
Adriano PARETO, Istat, pareto@istat.it

DETERMINANTS OF HOURLY EARNINGS AND EARNINGS INEQUALITY: ANALYSES ON ITALIAN DATA FROM THE STRUCTURE OF EARNINGS SURVEY¹

Francesca Ceccato, Marilena Angela Ciarallo, Paola Conigliaro

Abstract. The study examines the differences in hourly earnings among employees, which can contribute to an unequal distribution of income with implications for equity and social cohesion. The analyses apply a log-linear regression model to data from the Structure of Earnings Survey (SES). The method allows highlighting whether and to what extent certain categories of employees are disadvantaged compared to others. The findings reveal substantial and persistent wage differentials associated with gender, education, occupation, contract type, firm size and geographical location. In particular, women earn significantly less than men even after controlling for observable factors, and higher educational attainment is strongly rewarded, though unevenly across sectors. Territorial gaps also remain pronounced, especially between the North-West and the South. These results underscore the importance of targeted labour market policies aimed at reducing structural disparities and improving wage equity across demographic groups and regions.

1. Introduction

Earnings gaps are one of the most evident expressions of inequality in modern labour markets. These disparities extend beyond mere pay comparisons, reflecting deeper structural dynamics influenced by individual, institutional, and geographic factors. Understanding the factors influencing earnings is essential for informing policies that promote fairness and social cohesion. Hourly earnings differentials, in particular, provide a clearer perspective on the relative advantages and disadvantages experienced by different groups of employees. These gaps can persist even among individuals with similar roles or contractual conditions, revealing subtle forms of labour market segmentation. In countries like Italy, which are characterised by significant territorial disparities and varied employment structures, analysing earnings differences is particularly important. Harmonised data sources, such as the Structure of Earnings Survey, allow for rigorous analysis of earnings inequality within a statistically robust and comparative framework.

This paper provides an empirical contribution by supplying updated evidence for 2022 and comparisons with 2018, and a methodological contribution by using a

¹ The article is the result of the joint work of the authors. §1 and §2 are attributed to Francesca Ceccato, §3 is attributed to Paola Conigliaro, §4, §5 and §6 are attributed to Marilena Ciarallo.

harmonised set of covariates that deepens our understanding of the structural drivers of earnings inequality.

2. Measuring hourly earnings according to the Structure of Earnings Survey

2.1. Data source and methodology

This paper relies on data from the Structure of Earnings Survey (SES) for the 2018 and 2022 editions related to Italy. In line with Regulation (EC) No 530/1999, the SES provides harmonised statistics every four years in each EU country. The target population comprises all enterprises and institutions in the private and public sectors with at least ten employees, engaged in industrial, construction and service activities (excluding the activities of households as employers and extra-territorial organisations and bodies) (NACE Rev. 2, sections B to S). Italy also covers public administration and defence, compulsory social security (section O), but these are still considered optional. The indicators released by Eurostat do not include section O, allowing for comparisons between Member States.

The statistical processes for the private and public sectors differ considerably. In the private sector, data from direct statistical survey are combined with data drawn from ad hoc processing on the Istat private-sector labour register (LR-Priv). The register supports all major phases of the process, such as sampling, variable pre-filling, editing and imputation and final estimates. In the Public sector, on the other hand, data completely derive from administrative and register data as the Istat public-sector labour register (LR-Pubb). Due to the recent development of its framework, it is worth spending some words describing LR-Pubb. In order to ensure a comprehensive coverage of public sector institutional units, their employees and all statistical variables on employment, earnings and social security contributions, it is necessary to integrate several administrative sources. With regards to economic units in the public sector, the frame list is compiled from the Register of Public Institutions (ISTAT, 2021). The target population of employees was drawn from these units and the statistical variables of interest are constructed from administrative variables, metadata and, in some cases, auxiliary sources. This process is complex and leads to the attribution to each reference unit of information on the characteristics of the job position (contractual qualification, professional qualification, etc.), labour input, working time (number of paid days, ordinary paid hours, etc.), earnings and contributions (for more details ISTAT, 2025).

2.2 Survey Scope and Focus of the Analysis

Employees who received remuneration for the reference month of the year are covered (October is conventionally used as it is characterised by low seasonality).

Of the approximately 11.698 million employees in the total population, about 268 thousand were selected for the sample. Of these, 59% belong to the private sector, which represents 71% of the target population.

This paper focuses on average hourly earnings in the reference month, which is one of the indicators derived from the SES. These are calculated using the arithmetic mean of the ratio of the remuneration received by employees in October (excluding remuneration in kind and non-regular components but including remuneration for overtime) to the hours paid by the employer (including ordinary and overtime hours worked, as well as paid and unpaid holiday hours, public holidays and employer-paid sick leave). As required by EU regulations, the indicators are calculated with reference to a specific month that is not exposed to seasonality. Furthermore the data is limited to enterprises and institutions with at least ten employees. It incorporates both the limits of representativeness relating to a population unbalanced towards large units (not faithful to the economic reality of the country) and the limits common to almost all surveys, linked to the information collected that fail to capture informality, relevant in our economic system. These, however, are common features of all the strategies for collecting these data adopted across EU countries. Starting from SES 2026 edition, according to the new regulation on Business Statistics, the sample will be expanded to enterprises under ten employees, significantly improving representativeness.

The richness of the sources allows however to produce comparable analyses of the relationships between remuneration levels and employee and employer characteristics. The survey collects information on economic units characteristics: sector of economic activity, geographical macro-area of the economic unit's location, size of the unit and form of economic and financial control. It also detects job characteristics, such as occupation, type of employment contract, contractual working time and length of service in the enterprise, as well as on personal characteristics of the employee, mainly sex, age and educational attainment. The following sections provide a detailed analysis of mean hourly earnings, combining all these aspects through descriptive and regression analyses.

3. Preliminary Analyses

Before introducing the multivariate analysis, it is useful to present main differences in hourly earnings resulting in SES 2022 survey, following a descriptive approach. Overall, data resulting from 2022 edition confirm the articulate landscape in term of average hourly earnings, as observed in previous editions. Gender difference in earnings remain evident, even considering average hourly earnings: in 2022 women earn on average 0.9 euro less than men (15.9 and 16.8 euro per hour respectively). Also the strong relationship between earnings and educational attainment is widely confirmed: the average hourly earnings is 12.4 euro for

employees with, at most, lower secondary education (G1), 15.0 euro for those with a upper secondary degree (G2), 16.5 euro in case of tertiary education with not more than 4 years (G3), and 24.2 euro for employees with the highest educational levels (G4). Furthermore, at any educational level, women earn less than men, with more pronounced differences for the highest levels (Table 1).

Part-time workers tend to have lower hourly earnings (12.0 euro) than full-time workers (17.3). The same happens for those with atypical contracts, e.g. employees on fixed-term contracts earn 24.6% less than those on indefinite duration contracts.

Table 1– *Average hourly earnings (€) by macro-section of economic activity, educational attainment and sex.*

ECONOMIC ACTIVITIES	Educational attainment				Total
	Basic	Secondary	Tertiary	Tertiary+	
Industry except construction (B-E)	12.9	15.1	17.0	23.1	15.4
Construction (F)	12.9	13.5	14.7	20.3	13.7
Services of the business economy (G-N)	11.2	13.8	15.1	22.3	14.6
Other Services (O-S)	14.3	16.9	17.3	25.6	19.6
SEX					
Female	11.1	14.0	15.5	22.3	15.9
Male	13.1	15.7	18.0	26.7	16.8
Total	12.4	15.0	16.5	24.2	16.4

Source: Istat, Structure of earnings survey, 2022

Company size and sector of economic activity also play relevant roles: the average hourly earnings is 12.8 euro in enterprises with 10 to 49 employees, while it amounts to 19.2 euro in those with at least 1,000 employees. In addition, certain sectors tend to offer higher earnings than others. Differences span from Accommodation and food services activities (10.9 euro per hour) to Financial and insurance activities (25.9 euro). Differences are evident also at macro sector level (Table 1). In units under private control average hourly earnings are lower (14.4 euro) than in units under public control (20.4 euro).²

Although the table clearly illustrates the well-known correlation between educational attainment and earnings, a closer look at the details reveals additional significant information, about the intertwining between educational attainment and other factors, as macro sector of activity or sex. It is, in fact, possible to observe that women with G3 level earn on average less than men with G2 and that the hourly

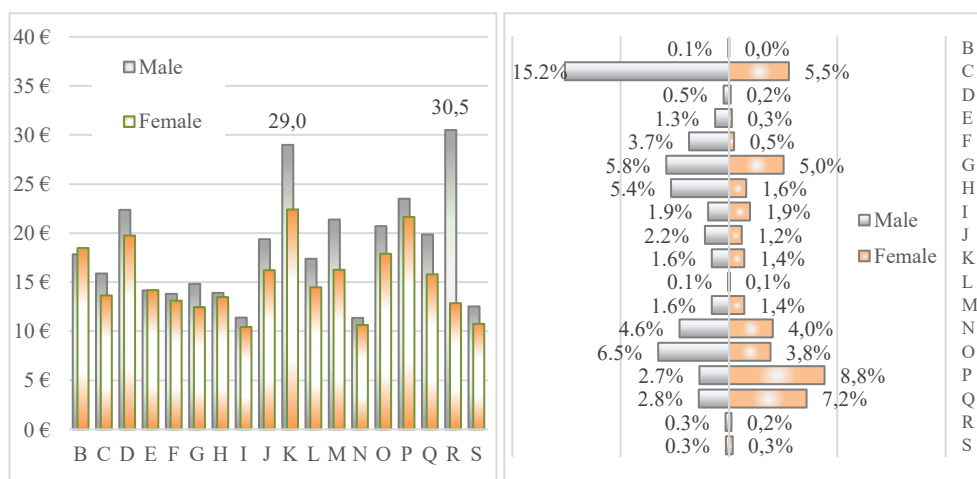
² For more detailed information, see ISTAT, 2025

earnings vary on a narrower range according to educational level in sector F (Construction) than in the other macro sectors.

A study applied to SES 2018 dataset, focusing on the gender pay gap (Ceccato *et al*, 2022), highlighted how differences in hourly earnings are strengthened or weakened according to the combined effect of multiple characteristics. This effect is commonly defined composition effect. Main foundational studies on wage discrimination (e.g. Blinder, 1973, Mincer, 1974) as well as on evolution on wages structure (Lemieux, 2006) devoted their attention on it. One of the goals of these studies is to ascribe the contribution of a character (usually gender) in determining earnings, by isolating it as much as possible from the effects attributable to other characteristics. They apply advanced methods to decompose earnings differences among subpopulations according to the main factors determining earnings.

It should also be noted that the average value of an indicator is determined by the frequency with which a combination of characteristics occurs in the target population (i.e. the relative number of units holding those characteristics). Figure 1 aims to clarify this statement: in the left side, it depicts the average hourly earnings in euro by sector of economic activity and sex, while in the right one it reports the share of employees by section and sex out of the total number of employees.

Figure 1 – Average hourly earnings by section and sex, and GPG (left chart). Share of employees on total employees by section and sex (right chart).



Legend axis: B - Mining and quarrying; C - Manufacturing; D - Electricity, gas, steam and air conditioning supply; E - Water supply; sewerage, waste management and remediation activities; F - Construction; G - Wholesale and retail trade; repair of motor vehicles and motorcycles; H - Transportation and storage; I - Accommodation and food service activities; J - Information and communication; K - Financial and insurance activities; L - Real estate activities; M - Professional, scientific and technical activities; N - Administrative and support service activities; O - Public administration and defence; compulsory social security; P - Education; Q - Human health and social work activities; R - Arts, entertainment and recreation; S - Other service activities

Source: Istat, *Structure of earnings survey*, 2022

It is evident that working in Section R (Arts, entertainment and recreation) is very remunerative for men, that earn on average 30.5 euro per hour, while it is not for women (12.8 euros), resulting in a *Gender Pay Gap* (GPG) jumping to 57.8%. Also in section K (Financial and insurance activities), the hourly earnings are on average high, but the differences between men (29.0 euro) and women (22.4) are smaller (GPG 22.7%). However, what happens in these two sections has little influence on average hourly earnings and overall GPG, since only 3.5% of employees work in them (right chart).

The right chart also shows the gender composition of each sector of economic activity. In Section C (Manufacturing), collecting over 20% of employees (within SES target population), three out of four are men, and average hourly earnings are not particularly high neither for men (15.9 euro), nor for women (13.7). Among 11.6% of employees working in Section P (Education), three quarter are women (over 20% of female employees).

The examples demonstrate that, while mean values are indeed substantial, they have a tendency to hide disparities in earnings among employees. Therefore, in order to explore the intensity of the disparities, it is necessary to identify the contribution of each relevant characteristic in determining the average value. In summary, it is imperative to explore the combined effect of any characteristic by applying multivariate analysis.

4. Methodological approach

Although the descriptive analysis conducted in the first part of the paper allows us to highlight some regularities in the distribution of hourly earnings, it is not sufficient to clearly identify the mechanisms underlying earnings formation. Indeed, univariate and bivariate statistics may reflect spurious correlations or overlaps between compositional and structural effects, without isolating the specific impact of each factor. To overcome these limitations and estimate the partial effects of different individual and job characteristics, a log-linear regression model is therefore used, an established approach in labour economics. As Mincer (1974) noted, “*the earnings function summarizes the net effects of various human capital investments on earnings*”. Specifically, the dependent variable is the natural logarithm of the hourly earnings, a functional transformation commonly used in the literature to smooth the skewness of the earnings distribution and allow for “*a straightforward interpretation of regression coefficients as approximate percentage changes*” (Blau & Kahn, 2017, p. 791). The multivariate model adopted allows controlling simultaneously for multiple covariates, returning a more accurate and robust representation of earnings determinants in the Italian labour market. The set of

explanatory variables includes both individual and job-related characteristics. These comprise age and length of service in enterprise (both entered as linear and squared terms), educational attainment (four levels from lower secondary to advanced tertiary, (Becker, 1964), gender, type of employment contract (permanent, temporary, apprenticeship), and working time arrangement (full-time vs. part-time). We also control for firm size, occupational category (ISCO classification), economic sector (NACE codes), ownership (public vs. private), and geographic macro-region (NUTS-1 level). As Wooldridge (2010, p. 135) emphasizes, “*using dummy variables with appropriate base categories is essential to avoid perfect multicollinearity and ensure meaningful interpretation of coefficients.*” Specifically, the reference groups are: upper secondary education, male, full-time employees, permanent contracts, clerks, firms with 10–49 employees, public sector, and the North-West macro-region. The model can be formally specified as follows: $\log(w_i) = \beta_0 + \sum \beta_k \cdot X_{ik} + \varepsilon_i$, where $\log(w_i)$ is the natural logarithm of hourly earnings for individual i , X_{ik} is the vector of explanatory variables, and ε_i is the error term.

5. Results

5.1. Model fit

The regression model explains approximately 56.7% of the variance in hourly earnings (adjusted $R^2 = 0.567$). This value is in line with similar earnings models in the literature (Lemieux, 2006) and confirms that the chosen specification captures the main determinants of wage differentials. While cross-sectional and not causal, the model offers a robust descriptive framework to analyze earnings structures and disparities in the Italian labor market. As Blau and Kahn (2017) argue, “*descriptive analyses of gender pay gaps and labor market inequalities remain crucial for informed policy responses*”. The main results are reported and interpreted in Section 5.2.

5.2. Regression results

Table 2 reports the estimated coefficients from the log-linear regression model of hourly earnings. All coefficients are interpreted in semi-elasticity terms, that is the approximate percentage change in earnings associated with a one-unit change in the covariate controlling for all other variables. Several factors show a strong and statistically significant association with earnings levels. In particular, higher educational attainment and professional occupational status are positively correlated with higher hourly earnings. Firm size and geographic location also contribute to earnings differences, with workers in larger firms and in certain territories earning more on average.

Table 2 – Main regression results on Hourly Earnings Determinants (Year 2022).

<i>Parameter</i>	<i>Estimate</i>	<i>StdErr</i>	<i>95% Confidence Interval</i>		<i>ChiSq</i>	<i>p-value</i>
Intercept	2,211	0,009	2,194	2,228	66183	<.0001
Higher Level of education and training						
G1: Lower Secondary	-0,051	0,002	-0,054	-0,048	1018	<.0001
G3:Tertiary(up to 4 years)	0,053	0,002	0,049	0,058	521	<.0001
G4:Tertiary (more than 4 years)	0,185	0,002	0,181	0,189	10485	<.0001
Sex						
Female	-0,110	0,001	-0,113	-0,107	6763	<.0001
Contractual Working Time						
Part Time	-0,077	0,002	-0,080	-0,073	1984	<.0001
Occupation						
Armed forces	0,405	0,004	0,396	0,414	8455	<.0001
Craft and related trades workers	-0,048	0,003	-0,053	-0,043	347	<.0001
Elementary occupations	-0,133	0,002	-0,138	-0,128	3121	<.0001
Managers	0,828	0,005	0,818	0,838	25062	<.0001
Service workers and shop and market sales workers	-0,009	0,002	-0,013	-0,004	12	0,0004
Plant and machine operators and assemblers	-0,027	0,003	-0,032	-0,022	97	<.0001
Professionals	0,371	0,002	0,366	0,375	26202	<.0001
Skilled agricultural and fishery workers	-0,038	0,014	-0,066	-0,010	7	0,0078
Technicians and associate professionals	0,139	0,002	0,135	0,143	4509	<.0001
Size class of the enterprise						
1000+	0,121	0,002	0,117	0,125	3920	<.0001
500-999	0,088	0,003	0,083	0,093	1047	<.0001
250-499	0,075	0,003	0,070	0,080	869	<.0001
50-249	0,048	0,002	0,044	0,051	720	<.0001
Geographic macro-area NUTS-1						
Center	-0,042	0,002	-0,045	-0,039	669	<.0001
Island	-0,061	0,003	-0,066	-0,057	615	<.0001
Northeast	-0,007	0,002	-0,010	-0,004	20	<.0001
South	-0,074	0,002	-0,078	-0,070	1602	<.0001
Effects of experience and length of service						
Age	0,010	0,000	0,009	0,011	596	<.0001
Agesquared	0,000	0,000	0,000	0,000	140	<.0001
Lenght of service	0,009	0,000	0,009	0,009	1956	<.0001
Lenght of service sq	0,000	0,000	0,000	0,000	276	<.0001

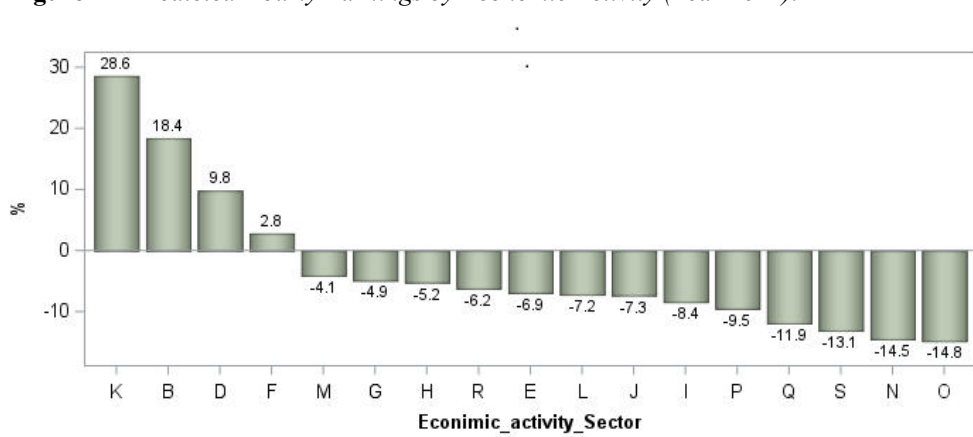
Note: Estimates are derived from a log-linear regression model bases on Structure of earnings data for Italy (Year 2022) . All categorical variables are included as dummy variables; reference categories are described in Section 5.1.

Moreover, contractual arrangements (e.g., part-time work) and individual characteristics such as age and length of service in the enterprise play a measurable role. Specifically, the inclusion of quadratic terms highlights a non-linear

relationship: earnings tend to increase with age and length of service, but at a decreasing rate. This pattern is consistent with human capital theory, according to which earnings rise with accumulated experience (Becker, 1964), but also reflects potential mechanisms of deferred compensation within enterprises. The significant and independent effects of both variables suggest that general labour market experience and firm-specific seniority contribute distinctly to earnings differentials.

Results for economic activity sections are not shown in the table but will be presented in the next paragraph. Compared to the reference category (Manufacturing), hourly earnings are notably higher in Financial Services and Energy, and lower in Hospitality and Administrative Support (Figure 2). A pronounced and statistically significant gender pay gap is also evident: women earn approximately 10.4% less than men, after controlling for all other characteristics.

Figure 2 – Predicted Hourly Earnings by Economic Activity (Year 2022).



Legend x-axis: B - Mining and quarrying; C - Manufacturing; D - Electricity, gas, steam and air conditioning supply; E - Water supply; sewerage, waste management and remediation activities; F - Construction; G - Wholesale and retail trade; repair of motor vehicles and motorcycles; H - Transportation and storage; I - Accommodation and food service activities; J - Information and communication; K - Financial and insurance activities; L - Real estate activities; M - Professional, scientific and technical activities; N - Administrative and support service activities; O - Public administration and defence; compulsory social security; P - Education; Q - Human health and social work activities; R - Arts, entertainment and recreation; S - Other service activities

Source: Istat, Elaboration based on Structure of earnings survey, 2022

As for occupational category, the reference group (clerks) is associated with mid-range earnings. Higher occupational levels—such as managers and professionals are linked to substantial “wage premiums” (+49.9% and +44.9%, respectively), while manual and elementary occupations show negative and significant earnings differentials, down to –13% for elementary occupations.

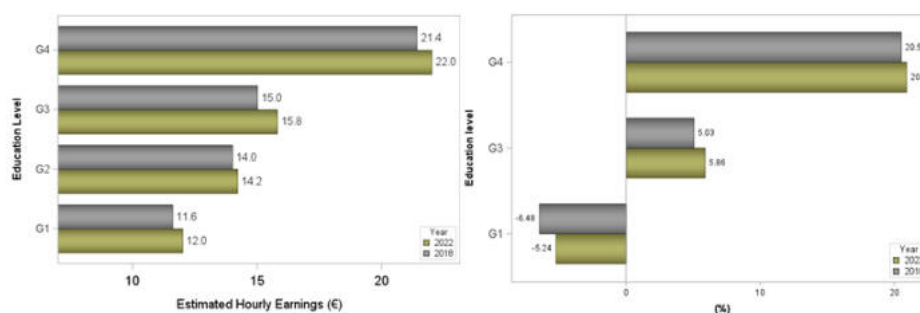
Firm size is also positively correlated with earnings. Employees in larger firms (250–499 and 500–999 employees) earn roughly 7.5% and 9.3% more, respectively, than those in smaller firms (10–49 employees).

Finally, territorial disparities are evident: all macro-areas show lower earnings compared to the North-West (reference area). The earnings gap is particularly pronounced in the South (–6.1%) and Islands (–7%), confirming long-standing territorial imbalances in the Italian labour market.

5.3. Comparative Analysis: 2022 vs. 2018

An increase in hourly earnings is observed across all educational groups between 2018 and 2022. The highest earnings are recorded among individuals with tertiary education longer than 4 years (G4), whose average hourly earnings rises from €21.4 in 2018 to €22.0 in 2022. The largest increase is seen among those with tertiary education up to 4 years (G3), with a gain of €0.8 (from €15.0 to €15.8). In contrast, individuals with upper secondary education (G2) experienced the smallest increase, of just €0.2 (from €14.0 to €14.2). The earnings gap between education levels remains wide, confirming the strong positive association between educational attainment and earnings levels. However, the relatively modest earnings growth suggests that returns to education, while persistent, have not substantially increased over the period considered.

Figure 3 – Predicted Hourly Earnings by Education Level (Year 2022 vs 2018) and Hourly Earnings Difference by Education Level (Relative to Upper Secondary Level %).



Source: Istat, Elaboration based on Structure of earnings survey, 2022

The estimated effects of education level on hourly earnings in 2022, using Upper Secondary education (G2) as the reference category are shown in the right of the Figure 3. Results show that individuals with tertiary education earn significantly more than those with upper secondary education. In particular, those with more than four years of tertiary education (G4) have the highest earnings premium (+20.9%),

followed by individuals with up to four years of tertiary education (G3, +5.86%). Conversely, individuals with lower secondary education (G1) earn approximately 5.24% less than the reference group. The interaction effects, though relatively modest, suggest that the earnings advantage associated with tertiary education slightly increased in 2022 compared to 2018. Interestingly, the smallest increase over time is observed for the highest education level (G4: +0.39%), while the largest relative improvement is found among workers with lower secondary education (G1: +1.24%). All coefficients are statistically significant at the 1% level.

These findings are consistent with previous research suggesting that the increase in earnings inequality is not evenly distributed across the earnings spectrum, but rather disproportionately concentrated at the top. In particular, studies such as Mincer (1997) highlight that the earnings–education relationship has become increasingly convex, with higher education levels yielding proportionally greater returns.

The persistence of sizeable earnings gaps across education levels between 2018 and 2022 indicates that returns to education remain a stable feature of the wage structure. Despite significant macroeconomic disruptions during this period, including the COVID-19 shock, relative wage advantages by education level changed only marginally. This suggests that short-term shocks primarily affected overall wage growth rather than the underlying education-related wage hierarchy. Institutional factors such as wage rigidities, collective bargaining, and rising inflation may help explain the modest temporal variation observed.

6. Conclusions

The proposed multivariate analysis of hourly earnings, using a log-linear regression provides robust empirical evidence of the main factors associated with differences in earnings, highlighting the relevance of both individual and job-related characteristics. Results confirm persistent earnings gaps by educational attainment, with higher returns to tertiary education, and a significant gender pay gap of around 10.4%. Temporal comparisons between 2018 and 2022 show modest overall wage growth, with slight increases in relative earnings advantages for some groups, while structural differentials remain largely unchanged. The analysis is based on a structural four-yearly survey, which, while rich in cross-sectional detail, does not allow for tracking individual earnings over time or establishing causal mechanisms. Therefore, the findings should be interpreted as descriptive associations rather than causal effects..

Looking ahead, further advancement of Labour Register and its integration with survey data, could support the analysis of dynamic phenomena such as earnings persistence, career mobility, and contract transitions.

In addition, the forthcoming revision of the statistical regulation governing the 2026 edition of the Structure of earnings survey, will extend the coverage to enterprises with fewer than ten employees. This expansion of the observation field is expected to improve the representativeness of the dataset and provide a stronger basis for targeted policy interventions, including measures to reduce gender wage gaps, address territorial disparities, and tackle contract segmentation.

References

- BECKER G. S. 1964. *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*. New York: Columbia University Press.
- BLAU F.D., KAHN L.M. 2017. The Gender Wage Gap: Extent, Trends, and Explanations. *Journal of Economic Literature*, Vol. 55, No. 3, pp. 789–865.
- BLINDER A. S. 1973. Wage Discrimination: Reduced Form and Structural Estimates. *Journal of Human Resources*, Vol. 8, No. 4, pp. 436–455.
- CECCATO F., CIARALLO M.A., CONIGLIARO P.. 2022. Exploring Earnings Differences Hidden Behind the Gender Pay Gap. *RIEDS - Rivista Italiana di Economia, Demografia e Statistica*, Vol. LXXVI, No. 1, pp.83-94.
- ISTAT. 2021. Registro ASIA Istituzioni pubbliche. Anno 2018. Statistiche Report. https://www.istat.it/wp-content/uploads/2021/01/Report_REGISTRO-ASIA-ISTITUZIONI-PUBBLICHE_PUBBLICATO.pdf
- ISTAT. 2025. Structure of earnings in Italy. Year 2022. Statistiche Report. https://www.istat.it/wp-content/uploads/2025/02/REPORT_SES_2022_ENG.pdf
- LEMIEUX T. 2006. Increasing residual wage inequality: Composition effects, noisy data, or rising demand for skill? *American Economic Review*, May 2006, Vol. 96, No. 3: pp 461-498
- MINCER J. 1974. *Schooling, Experience, and Earnings*, National Bureau of Economic Research, New York.
- MINCER J. 1997. The Production of Human Capital and the Life Cycle of Earnings: Variations on a Theme. *Journal of Labor Economics*, Vol. 15, No. 1, pp. S26–S47
- WOOLDRIDGE J.M. 2010. *Econometric Analysis of Cross Section and Panel Data*, Second Edition, MIT Press, Cambridge (MA).

Francesca CECCATO, Istat, paola.conigliaro@istat.it
Marilena Angela CIARALLO, Istat, ciarallo@istat.it
Paola CONIGLIARO, Istat, ceccato@istat.it

CORRUPTION, INEQUALITY AND POVERTY

Fabrizio Sbicca

Abstract. The UN 2030 Agenda for Sustainable Development identifies the reduction of corruption, inequality, and poverty as key goals. These three phenomena are, in fact, closely interconnected, and action in one area can significantly impact outcomes in the others. Recent developments in the measurement of corruption have led to the identification of a series of risk indicators based on the relationship between corruption and various cultural, legal, economic, social, and political-institutional factors that may influence its spread and persistence, including inequality and poverty. These factors are considered primarily for their social implications: greater economic inequality is associated with a higher likelihood of criminal behavior; moreover, when individuals perceive unfair treatment, their inclination to seek shortcuts to achieve economic well-being may increase.

1. Corruption, inequality, poverty and Sustainable Development Goals

The 2030 Agenda for Sustainable Development, adopted by all United Nations Member States in 2015¹ *“provides a shared blueprint for peace and prosperity for people and the planet, now and into the future. At its heart are the 17 Sustainable Development Goals (SDGs), which are an urgent call for action by all countries - developed and developing - in a global partnership. The 17 SDGs with 169 associated targets, which are integrated and indivisible, stimulate action over the next years in areas of critical importance for humanity and the planet. SDGs recognize that ending poverty and other deprivations must go hand-in-hand with strategies that improve health and education, reduce inequality, and spur economic growth, all while tackling climate change and working to preserve our oceans and forests”*².

The UN 2030 Agenda highlights that sustainable development cannot be achieved without peace and security and that these, in turn, will be at risk without sustainable development. In particular, Goal 16 aims to: *“Promote peaceful and inclusive societies for sustainable development, provide access to justice for all and*

¹ <https://sdgs.un.org/2030agenda>.

² <https://sdgs.un.org/goals>.

build effective, accountable, and inclusive institutions at all levels”. Among the main factors contributing to violence, insecurity, and injustice, the Agenda also identifies corruption, which is the focus of a specific target: “16.5 Substantially reduce corruption and bribery in all their forms”.

However, the Agenda also identifies Goal 1 “End poverty in all its forms everywhere” and Goal 10 “Reduce inequality within and among countries” as important objectives.

Regarding these three phenomena, there exists an extremely vast and diverse body of theoretical, empirical, and interdisciplinary literature, ranging from economics to statistics, and from philosophy to sociology (see, for example, the recent contribution by Chandler (2023) on inequality, which synthesizes previous research on the subject).

The SDGs are integrated, that is, they recognize that action in one area affects outcomes in others. Inequality is not just about money; it's about access to opportunity (for example, education and health). Poverty is not just low income; it's about multidimensional deprivation. And corruption isn't just about stealing, it erodes trust in others and in public institutions. It's a vicious cycle: these three problems feed into one another. Corruption leads to more inequality, inequality leads to more poverty, and poverty makes corruption harder to stop. Corruption reduces efficiency and disproportionately benefits elites. Inequality increases the perception of unfairness, encourages clientelism, and concentrates power. Poverty makes people more vulnerable to corruption and blocks social mobility.

2. Corruption risk indicators

Today, there is widespread consensus that corruption is one of the main obstacles to economic, political, and social development. It is also a factor that exacerbates poverty and inequality, and distorts the implementation of public policies. Corruption can undermine citizens' trust in institutions, lower the quality of life, and diminish overall well-being.

However, in order to prevent and combat corruption, it is essential to develop a deep understanding of this latent phenomenon, which is notoriously difficult to measure. Achieving any objective necessarily requires the most accurate possible understanding of the phenomenon in question. This calls for a multidisciplinary approach to examine the main methodologies and recent developments in the field of corruption measurement.

At the international level, however, there is a lack of structured data on corruption that goes beyond the measurement of so-called “perceptions” or ad hoc scientific studies, whose content and results are often difficult to generalize (Gnaldi and Ponti,

2018; Picci, 2024). Corruption is a hidden phenomenon, often compared to an iceberg: we only see the tip, while the submerged part is much larger than what appears on the surface. To improve understanding of the phenomenon, the United Nations itself has made significant efforts to develop a statistical framework to measure corruption and guide countries in the implementation of national information systems on the issue (UNODC, 2023).

A significant step forward in understanding the phenomenon had already been taken by the Italian National Anti-Corruption Authority (ANAC), which provides the public with seventy indicators for measuring corruption risk across different territories. These are organized into three dashboards: public procurement, municipalities, and context³.

2.1. Procurement and municipal risk indicators

One of the key dimensions concerns public procurement, which includes seventeen risk indicators providing information related to the purchasing activities of administrations located in the Italian provinces (Sbicca, 2024b). An example of a corruption risk indicator in public procurement is the use of discretionary procedures or tenders with very few bidders, as well as delays and cost overruns. The literature highlights that low competition in tenders, combined with a high degree of discretion, is typically a signal of corruption risk.

It is important to emphasize the central role of risk indicators as tools for preventing and combating irregularities in public procurement markets, including fraud, corruption, conflicts of interest, and collusive practices. The increasing availability of large datasets has also drawn growing attention to the potential of developing advanced algorithms, using big data analytics and artificial intelligence alongside traditional statistical analyses. In particular, machine learning can help identify more targeted red flags, both at the level of individual transactions and in the overall purchasing behavior of a specific administration or a group of administrations within a given territorial area (Sbicca, 2024a).

The five municipal indicators are calculated at the level of individual administrations, in this case, the 745 Italian municipalities with a population equal to or greater than 15,000 inhabitants. These indicators were derived from a statistical analysis of the relationships between variables potentially related to corruption (including per capita taxable income, which reflects the level of socioeconomic well-being) and corruption episodes that occurred at the level of individual administrations.

³ <https://www.anticorruzione.it/il-progetto>.

2.2. Context indicators

A section of ANAC's corruption risk indicator system, consisting of forty-eight "context indicators," draws clear intellectual inspiration from *The Report on Equitable and Sustainable Well-being (Bes)* and the *SDGs Report: Statistical Information for the 2030 Agenda in Italy* (Istat, 2024a, 2024b).

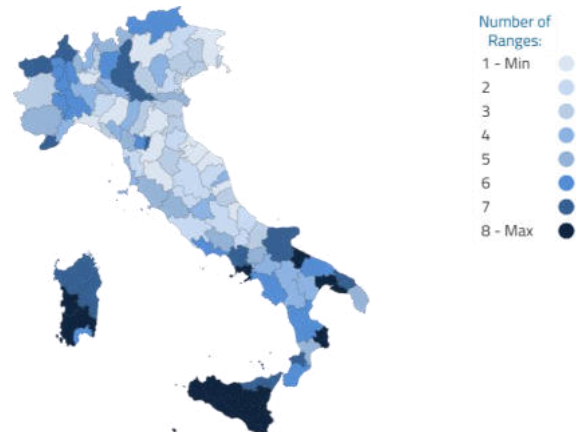
ANAC's context indicators share with the Bes and SDGs reports a well-established methodology that has been used for years to measure complex, multidimensional phenomena - such as well-being and corruption - at both national and international levels. This methodology specifically involves organizing indicators into domains (or pillars) and using composite indicators to simplify the interpretation of complexity arising from multiple dimensions by reducing it to a single summary measure.

In particular, the context indicators support corruption risk analysis across territories by considering 18 provincial-level indicators grouped into four thematic domains: education, economy, crime, and social capital. The selection of these domains and their associated indicators was guided by the relationships between corruption and a range of cultural, legal, economic, social, and political-institutional factors that can influence its spread and persistence, as identified primarily in the economic literature.

For each domain, a composite index is calculated. These four thematic indices are then further synthesized into an additional "composite of composites" index. A composite index is a one-dimensional measure of a multidimensional phenomenon that cannot be directly observed, making it particularly useful for analyzing the complexity of latent factors that shape the context in which corruption occurs, a phenomenon that is inherently elusive and not easily reducible to direct, unidirectional cause-effect relationships.

The methodology used to construct these composite indices is called AMPI (Mazziotta and Pareto, 2024; 2025), which has been implemented and adopted by Istat for the Bes report, and more recently for the construction of the Municipal Fragility Index and the Educational Poverty Index. The territorial level considered by context indicators is the province, with data sourced from various institutions (Istat, Invalsi, Ministry of the Interior, Ministry of Economy, Agcom, Avis).

Below are maps illustrating the composite indicators for each pillar, summarising the corruption risk at provincial level. The indicators can range from 70 to 130, and in the base year 2014 are worth 100 for Italy as a whole. In the maps, 8 equal ranges were used, and higher levels are associated with a higher corruption risk, as indicated by the colour scale.

Figure 1 - Composite indice for Education.

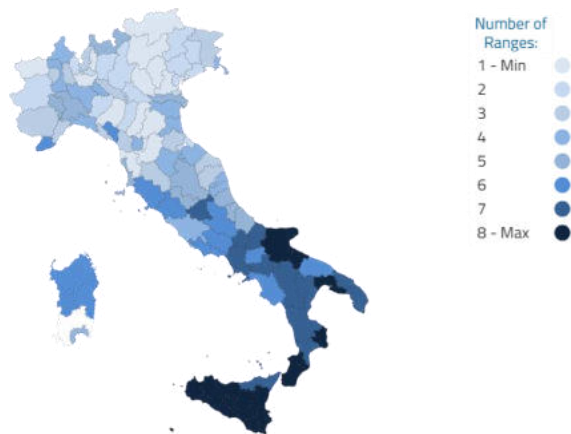
Source: ANAC - elaborations based on Istat data

The Education pillar includes three indicators:

1. High School Graduates Indicator: number of registered people ranging from 25-64 years old who have completed at least upper secondary school per 100 people of the same age group;
2. University Graduates Indicator: number of 30-34 years old with a university degree per 100 persons aged 30-34 registered in the population register;
3. NEET Indicator: number of registered 15-29 years old not engaged in employment, education or training per 100 registered 15-29 years old.

Higher levels of corruption are associated with lower levels of education in the population. One possible explanation is that individuals with higher levels of education possess skills and knowledge that make them more aware of the value of civil liberties and less tolerant of corruption. For the same reasons, higher corruption levels are generally associated with lower levels of human capital. Moreover, in contexts where corruption is higher, the emigration of skilled individuals tends to be significantly greater, leading to brain drain issues.

In the map, the lowest values of the composite education indicator are recorded in the provinces of Bologna (80.2), Trento (84.9), and Ancona (85.1), representing the areas with the highest levels of human capital and the lowest corruption risk. Conversely, the highest values - and therefore the lowest levels of human capital and the highest corruption risk - are found in Palermo (121.7), Sud Sardegna (120.2), and Catania (118.7).

Figure 2 - Composite indice for Economy.

Source: ANAC - elaborations based on Istat and Agcom data

The Economy pillar includes six indicators:

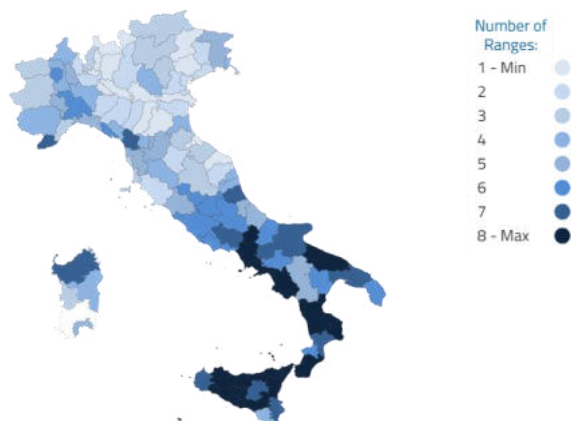
4. Income Indicator: per capita gross income;
5. Employment Indicator: number of labour force participants per 100 registrations in the population register of the age group 20-64;
6. Entrepreneurship Rate Indicator: number of enterprises per 1,000 inhabitants;
7. Attractiveness index: ratio of incoming flows of individuals in employment or study to the total number of active individuals (incoming, outgoing, and resident) in the province of residence;
8. Broadband diffusion Indicator: percentage of buildings reached by broadband;
9. Differentiated waste collection Indicator: percentage of municipal waste separately collected for recycling.

A high level of income and a fair distribution of wealth, employment, the ability to attract both domestic and foreign investment, and support for the creation and growth of entrepreneurial activities - as well as strong market competition and economic freedom - are all factors associated with lower levels of corruption. Furthermore, higher levels of Internet usage are linked to lower corruption levels, as the web facilitates the spread of information and serves as a tool for monitoring the exercise of public power. Finally, efficient management of urban waste - a sector often vulnerable to corruption due to potential capture by economic operators and organized crime - is also associated with lower levels of corruption.

The lowest values of the composite economy indicator are found in the provinces of Milan (79.5), Bologna (84.2), and Florence (85.8), identifying them as areas with the most favorable economic conditions and the lowest corruption risk. At the

opposite end, the highest values - indicating the least favorable economic contexts - are observed in Crotone (119.2), Agrigento (118.6), and Enna (118.3).

Figure 3 - Composite index for Social Capital.



Source: ANAC - elaborations based on Invalsi, Avis and Ministry of the Interior data

The Social Capital pillar includes five indicators:

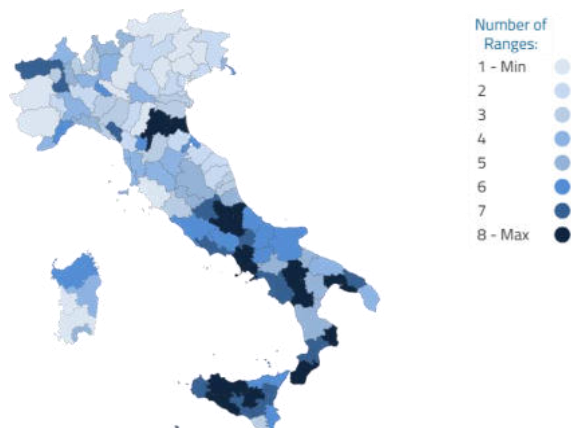
10. Invalsi Segregation Indicator: “Economic, Social and Cultural Status” (ESCS) gap indicator (provides a measure of the difference between the average socio-economic-cultural status of the families of students in a class, compared to the average ESCS of the school);
11. Invalsi Mathematics Test Cheating Indicator: likelihood that the class in which the student is placed has engaged in opportunistic behaviour when completing the Invalsi tests;
12. Invalsi Mathematics Test Between-Class Variability Indicator: percentage of schools in which the variance in Invalsi mathematics test scores between classes is higher than the national figure;
13. Blood Donation Indicator: percentage ratio between the number of donations and the resident population;
14. Women’s Participation in Politics Indicator: percentage of elected women out of the total number of mayors.

Community cohesion - along with reliability, loyalty, and mutual trust among social actors - forms the foundation for the effective development of economic transactions and the relationship between citizens and institutions. Greater trust in institutions and the political system (vertical trust), and in interpersonal social relations (horizontal trust), is associated with lower levels of corruption.

There is strong empirical evidence, based on social learning models, showing that pro-social behavior at the individual level is significantly influenced by the conduct of fellow citizens and political leaders. Conversely, corrupt politicians generate (and legitimize) corrupt citizens. There is also a risk that adults involved in corruption internalize these antisocial behavioral norms and pass them on to their children - either directly or through peer interactions - leading the younger generation to adopt dishonest behavior, such as cheating.

The lowest values of the composite social capital indicator are recorded in Lecco (91.5), Sondrio (92.3) and Modena (92.1), highlighting areas with strong social cohesion and civic engagement, typically associated with lower corruption risk. Conversely, the highest values are found in Reggio Calabria (116.4), Isernia (116.2), and Caserta (115.6), indicating weaker social capital and greater potential vulnerability to corruption.

Figure 4 - Composite indice for Crime.



Source: ANAC - elaborations based on Istat data

The Crime pillar includes four indicators:

15. Corruption, Extortion, and Embezzlement Crimes Indicator: ratio between the criminal proceedings initiated because of crimes of corruption, extortion and embezzlement, and the resident population;
16. Crimes Against Public Order and Environmental Crimes Indicator: ratio of criminal proceedings initiated because of crimes against public order and the environment to the resident population;

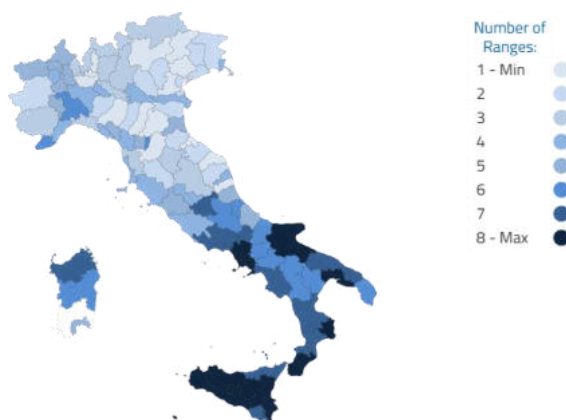
17. Crimes Against Property and the Public Economy Indicator: ratio of criminal proceedings initiated for crimes against the public heritage and economy to the resident population;
18. Other Crimes Against the Public Administration Indicator: ratio between criminal proceedings initiated for other crimes against the Public Administration and the resident population.

The spread of corruption can be significantly influenced by overall crime levels, the effectiveness of the judicial system in combating them, and the degree of protection offered to those harmed by corrupt activities. The higher the number of criminal proceedings initiated for these offenses, the higher the associated corruption risk.

The provinces with the lowest values of the composite criminality indicator are Vicenza (93.9), Monza and Brianza (94.7), and Sud Sardegna (94.8), which show lower levels of criminal activity and reduced corruption risk. On the contrary, the highest values - signaling more critical situations - are recorded in Pescara (122.6), Enna (122.5), and Reggio Calabria (119.8).

The map that follow depict the “composite of composites” index.

Figure 5 - Composite of Composites index.



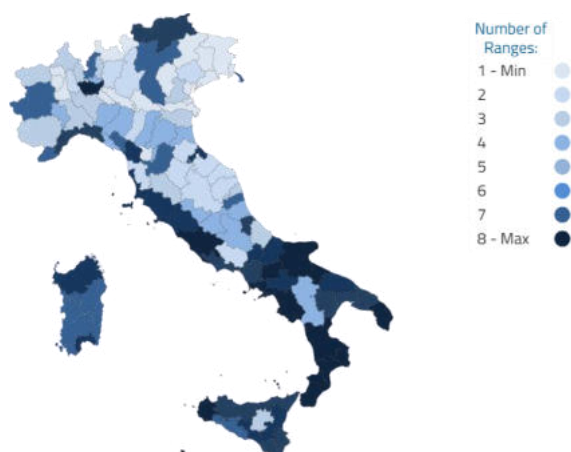
Source: ANAC - elaborations based on Istat, Agcom, Invalsi, Avis and Ministry of the Interior data

The overall composite indicator, which summarizes all the dimensions considered, records its lowest values in the provinces of Milan (90.6), Bologna (91.9), and Modena (92.1). These areas represent the most virtuous provinces in terms of socio-economic and institutional performance and therefore show a lower corruption risk. Conversely, the highest values - and thus the greatest overall

vulnerability and higher corruption risk - are observed in Enna (115.8), Crotone (115.1), and Palermo (114.6).

The map that follow depict one of the 25 additional simple indicators not included in the thematic domains: the Gini Inequality Index.

Figure 6 - Gini index.



Source: ANAC - elaborations based on Ministry of Economy and Finance data

The Gini Inequality Index is of particular interest due to the complex socio-economic implications arising from the phenomenon it measures, namely, economic inequality. The reasons for considering this indicator are primarily related to the social sphere. Greater economic inequality is associated with a higher likelihood of criminal behavior; moreover, when individuals perceive that they are being treated unfairly, their tendency to seek shortcuts to achieve economic well-being may increase. As previously mentioned, there exists a dangerous vicious cycle. Only the rich or well-connected have access to opportunities and can use their wealth to influence laws. The result is fewer investments in healthcare, education, and infrastructure. The poorest segments of the population suffer the most, as they depend more heavily on public services. Citizens may lose trust in institutions and come to believe that corruption is the only path to success. For these reasons - as already noted - inequality is listed among the factors identified by the UN 2030 Agenda as contributing to violence, insecurity, and injustice (preceding corruption, government inefficiency, and the illicit flows of arms and money).

In the map, the lowest values of the Gini Index (2018) - expressed as actual Gini coefficients and not normalized through the composite indicator methodology, since this index does not belong to any pillar - are observed in Belluno (36), Pordenone

(37), and Lodi (37). Conversely, the highest levels of inequality are recorded in Milan (48), Crotone (47), and Reggio Calabria (46), where income disparities are more pronounced, suggesting higher socio-economic polarization and greater potential vulnerability to corruption.

2.3. The importance of social capital.

Regarding the four domains, it is interesting to note that two of the analyzed dimensions - human capital (here expressed in terms of education) and social capital - are considered by modern economic literature as key determinants of both economic growth and social well-being. Specifically, social capital can be understood through concepts such as community cohesion, reliability, loyalty, and mutual trust among social actors. These factors form the foundation for the effective development of economic transactions and relationships between citizens and institutions (Banfield, 1958; Putnam, 1993). Greater trust in institutions, the political system, and interpersonal relationships is consistently associated with lower levels of corruption.

The five social capital indicators can be described as reflecting behaviors such as opportunistic attitudes in school tests, socio-economic segregation in schools, and, conversely, altruism and gender equality. Notably, the last two indicators are both included in the Bes framework (respectively, in the social relations domain and cross-cutting across other domains), while one is a specific target of the UN 2030 Agenda under Goal 5 “*Achieve gender equality and empower all women and girls*”.

Social capital is therefore a useful indicator for representing the context in which the phenomenon of corruption manifests. However, the relationship is also bidirectional, as the harm caused by corruption likely exceeds the immediate monetary waste it generates. Corruption brings with it numerous distortions that affect both the public and private spheres, including the erosion of trust it causes among citizens. For this reason, corruption undermines the very fabric of civil life and can consequently reduce social capital, thereby also hindering growth and well-being.

3. Conclusion

In conclusion, the corruption risk indicator system developed and made publicly available by ANAC - through an interactive dashboard accessible to the entire community - represents a significant national contribution to the achievement of Goal 16.5 of the UN 2030 Agenda: “*Substantially reduce corruption and bribery in all their forms*”.

In particular, the indicator system designed by ANAC was intentionally conceived to be clear and user-friendly, with a strong focus on transparency, dissemination, and sharing of results. Behind this platform lies a complex structure of IT infrastructures, datasets, and algorithms; yet the dashboards remain intuitive and visually engaging, especially for younger generations, encouraging reflection, participation, and civic awareness. The underlying perspective of the indicator portal is to strengthen ethical awareness and collective understanding of the serious social damage caused by corruption. While prevention and enforcement are necessary conditions to address this phenomenon, they are not sufficient on their own. In the long term, the most effective lever remains the growth of social capital.

References

- BANFIELD E. C. 1958. *The Moral Basis of a Backward Society*. Free Press
- CHANDLER D. 2023. *Free and Equal: What Would a Fair Society Look Like?*. London: Allen Lane.
- GNALDI M., PONTI B. 2018. *Misurare la corruzione oggi: obiettivi. metodi. Esperienze*. Milano: Franco Angeli.
- ISTAT 2024a. *Rapporto Bes 2023*. Roma
- ISTAT 2024b. *Rapporto SDGs 2024. Informazioni statistiche per l'Agenda 2030 in Italia*. Roma
- MAZZIOTTA M, PARETO A. 2024. *Statistica per gli indici composti*. Torino: Giappichelli.
- MAZZIOTTA M, PARETO A. 2025. *Statistics for Composite Indicators*. Berlin: Springer.
- PICCI, L. 2024. *Rethinking Corruption*. London, Routledge.
- PUTNAM R. D. 1993. *Making democracy work: Civic traditions in modern Italy*. Princeton N.J.: Princeton University Press.
- SBICCA F. 2024a. Intelligenza artificiale e anticorruzione, *Rassegna Trimestrale Osservatorio AIR*, XV, 4, 39-46.
- SBICCA F. 2024b. La misurazione del rischio di corruzione negli appalti, *Rivista economica del Mezzogiorno*, 3-4/2023, 549-600.
- UNODC 2023. *Statistical framework to measure corruption*. Vienna: UNODC.

Fabrizio SBICCA, Autorità Nazionale Anticorruzione, f.sbicca@anticorruzione.it, fsbicca1@gmail.com. The opinions expressed in this paper are the author's own and do not reflect the view of ANAC.

MULTIDIMENSIONAL WELL-BEING DEPRIVATION AMONG ITALIAN YOUTH

Elisabetta Segre, Alessandra Tinto, Miria Savioli,
Anna Villa, Romina Fraboni¹

Abstract. The aim of this work is to examine the deprivation of young people (18-34) living in Italy along several dimensions of well-being. We use the Alkire-Foster (A-F) methodology, which relies on a dual-cut off method of identification to calculate a multidimensional deprivation indicator with several desirable characteristics, including decomposability. The identification of dimensions and indicators is grounded on the framework implemented by Istat to measure Equitable and sustainable well-being (BES framework, from the Italian acronym). Since the A-F methodology requires data for all indicators at the individual level, we use the multipurpose households' survey on Aspects of Daily Life yearly conducted by Istat, covering a wide range of BES dimensions and indicators. We identify five dimensions (Health, Work and education, Subjective well-being, Social cohesion, and Living context). From the results, we can draw conclusions on the trend, the dimensions and the population groups contributing the most to well-being deprivation. Those living in the south show the highest levels of deprivation, especially in the Work and education dimension. The dimension contributing the most to youth well-being deprivation is Social cohesion. Special attention should be devoted to the Health dimension: its contribution to the overall level of multidimensional deprivation is relatively higher in the northern regions, and this dimension is the only one that shows a steady worsening over time.

1 Methodological approaches to multidimensional poverty measurement

Over the last few decades, the conceptualisation of poverty has undergone a significant transformation, shifting from a predominantly income-based approach to a broader, multidimensional framework. This evolution reflects growing recognition that income alone is not sufficient to capture the complex and interrelated aspects of deprivation that individuals experience. Early theoretical contributions by Anand and Sen (1997, 2009), Atkinson (2003), Bourguignon and Chakravarty (2003), were instrumental in challenging the prevailing unidimensional paradigm. These scholars emphasized the need to account for various dimensions of well-being—including

¹ Authors contributions: Romina Fraboni and Anna Villa paragraphs 1 and 2; Elisabetta Segre paragraph 3; Miria Savioli and Alessandra Tinto paragraph 4; Elisabetta Segre and Alessandra Tinto paragraph 5 and Conclusions.

health, education, housing, and social participation—which together provide a more comprehensive assessment of human development and deprivation.

Despite its normative appeal, the multidimensional approach remained a relatively novel and emerging research stream until the early 2000s. According to Aaberge and Brandolini (2014), the literature on multidimensional poverty and inequality was still developing at that time. A recent systematic review by D’Attoma and Matteucci (2024) confirms this trend, showing that over 60% of the academic publications on multidimensional poverty between 1999 and 2019 appeared only after 2015.

Among the various approaches developed to elaborate a measure of multidimensional poverty at the individual level, the Alkire-Foster (AF) method (Alkire and Foster, 2011) emerges as the most widely applied. This method, which requires the availability of data on a wide set of dimensions for the same individuals, operationalises multidimensional poverty using a dual cutoff strategy. Individuals are first identified as deprived within each selected dimension, and then classified as poor if the weighted sum of their deprivations exceeds a chosen threshold. The method yields several poverty measures, including the headcount ratio, the intensity of deprivation, and an adjusted headcount that captures both prevalence and breadth. The flexibility of the AF method—allowing for context-specific choices of dimensions, indicators, weights, and poverty thresholds—has made it particularly suitable for national adaptation, while remaining comparable across contexts. One of the most prominent applications of the AF method is the Multidimensional Poverty Index (MPI), first introduced by Alkire and Santos (2010) and included in the Human Development Reports published by the United Nations Development Programme (UNDP, 2010). The MPI focuses on three core dimensions—health, education and standard of living—using ten indicators to assess deprivations at the household level.

Although the AF method dominates empirical applications, it is not the sole methodology employed in multidimensional poverty research. Alternatives are based on fuzzy set approach, pioneered by Cheli and Lemmi (1995) and later developed by Betti, Cheli, and Lemmi (2006), or on multivariate statistical techniques, like principal component analysis (PCA) and factor analysis (see D’Attoma and Matteucci 2024 for a review). These are particularly helpful for large datasets with numerous variables but limited theoretical guidance on weighting. However, the reliance on statistically derived weights may lead to measures that lack normative clarity or interpretability for policy purposes (Aaberge and Brandolini, 2014).

The AF method has been applied predominantly in the global south. Yet, in recent years, the application of these methods has expanded to high-income countries. The AF method has been applied by Suppa (2016, 2018) for Germany, by Glassman

(2024) and Dhongde and Haveman (2017) for the United States. Whelan *et al.* (2014) and Alkire and Apablaza (2016) have used the AF to assess poverty and social exclusion across EU countries, while Billi and Scotti (2018) and De Rosa (2022) applied it in the Italian context.

The paper is structured as follows. In the next paragraph we state the aim of this study, in paragraph 3 we briefly present the AF method, in paragraph 4 we present indicators and thresholds and in paragraph 5 we analyse the results obtained by applying the AF method to the survey data to get insights on the youth condition in Italy from a multidimensional point of view. We devote the last paragraph to the conclusions.

2 Aim

In this paper, we apply the AF method to the Italian context, focusing on the youth condition and grounding the measurement of multidimensional poverty on the concept of well-being deprivation. Young people are a very complex and heterogeneous group. In recent decades, it has become increasingly challenging for young people in Italy to reach their full potential and take advantage of opportunities. This has led to discouragement in participation at various levels (political, social and cultural) and a postponement of the transition to adulthood. For these reasons, the population of interest ranges between 18 to 34 years. As the method requires the availability, on the same individuals, of multi-dimensional information from a unique data source, we use the households' survey on Aspects of Daily Life conducted yearly by Istat. Specifically, here we focus on the 2019-2023 time period, to check whether the Covid-19 pandemic has influenced young adults' deprivation. We rely on the ISTAT framework for measuring well-being (BES) to identify relevant dimensions and indicators.

3 The Alkire and Foster methodology

The AF methodology is a counting-based approach used to identify and aggregate multidimensional poverty (Alkire and Foster, 2011). It involves two key steps: identification and aggregation.

In the identification step, a person is considered deprived in a given dimension if their achievement falls below a defined cutoff. Then, a weighted sum of deprivations is calculated for each person. A person is identified as multidimensionally poor if their total deprivation exceeds a poverty threshold k .

Formally, let y_{ij} be the achievement of individual i in indicator j , and let z_j be the deprivation cutoff for dimension j . Define:

$$g_{ij} = \begin{cases} 1 & \text{if } y_{ij} < z_j \\ 0 & \text{otherwise} \end{cases}$$

Let w_j be the weight of indicator j . Then the weighted deprivation score for person i is:

$$c_i = \sum_{j=1}^d w_j g_{ij}$$

The person is identified as poor if $c_i \geq k$, where k is the poverty threshold. We set the threshold at 0.33: to be classified as poor, an individual must be deprived in at least 1 out of 3 indicators of each dimension.

The Adjusted Headcount Ratio M_0 is the mean of the censored deprivation score $c_i(k)$, which is the deprivation score censored of all deprivations, lower than k :

$$M_0 = \frac{1}{n} \times \sum_{i=1}^n c_i(k)$$

The M_0 can also be written as the product of H (incidence of poverty) and A (intensity of poverty):

$$M_0 = H \times A = \frac{q}{n} \times \frac{1}{q} \sum_{i=1}^q c_i(k)$$

where q is the number of persons identified as poor in the dual-cutoff approach.

The MPI is decomposable by population subgroup and by dimension, making it highly informative for policy targeting. It captures both the prevalence and breadth of poverty and allows for nuanced poverty tracking across time and space.

The decomposability property allows to assess which subgroups contribute most to overall multidimensional poverty. Additionally, the M_0 can be broken down into dimensions or indicators, allowing to assess the contribution of each to overall poverty. For the purpose of this study, we will refer to M_0 as multidimensional well-being deprivation index.

4 Dimensions, indicators, data

We rely on the framework to measure equitable and sustainable well-being, BES from the Italian acronym (Bacchini *et al.*, 2021; Istat, 2024), to identify relevant dimensions and indicators taking into account the specificity of the youth population. Yet, while the BES framework is measured through a dashboard of multisource

indicators, the AF method requires data to be taken from a unique data source. We use the multipurpose households' survey on Aspects of Daily Life conducted yearly by Istat, since 1993, which allows us to calculate individual indicators for a wide range of relevant dimensions within the conceptual framework of the BES (such as subjective well-being, social relations, cultural participation, etc.) and allows comparability over time. Where feasible and appropriate, we replicate indicators included in the BES dashboard using similar definitions and classifications. For example, we computed an indicator of employment and school enrolment using Aspects of Daily Life data, which proxies the NEET indicator included in the BES dashboard and computed using Labour Force Survey data. Five relevant dimensions are identified and described by three indicators each. We obtain a framework of fifteen indicators to which we assign the same weight (1/15).

Different criteria were used to define the deprivation cutoffs depending on the indicator in question. In some cases, the indicator itself identified distress (e.g. the alcohol consumption indicator); in other cases, a theoretical threshold was defined based on the score (e.g. a life satisfaction score below 6, in a 0-10 scale); and for other indicators, the cutoff was defined based on the distribution (e.g. the trust in parliament cutoff was identified as the average young person's score). The indicators and their respective deprivation cutoffs are shown in Table 1.

Table 1 – *Dimensions, indicators and cutoffs.*

Dimension	Indicator*	Cutoff
HEALTH	Perceived health	Do not report "good" or "very good" health conditions
	Alcohol use	Report at least one risky behaviour in alcohol consumption (overconsumption or binge drinking)
	Mental health	Mental Health Index below the first quintile of the distribution calculated for the 18-34 year old population (mh=56)
WORK, EDUCATION AND TRAINING	Employment and school enrolment	Neither employed nor education or training
	Cultural participation	During the past year, did not engage in any of the nine cultural activities considered: 1. at least four times to the cinema; 2. at least once to the theater; 3. at least once to museums and/or exhibitions; 4. at least once to archaeological sites; 5. at least once to monuments; 6. at least once to classical music/opera concerts; 7. at least once to concerts of other music; 8. reading the daily newspaper at least three times a week; 9. reading at least four books;

Table 1 (cont.) – Dimensions, indicators and cutoffs.

Dimension	Indicator*	Cutoff
WORK, EDUCATION AND TRAINING	Educational achievement	20-34 years old with at most a high school degree; 18-19 years old with at most a middle school degree and are not enrolled in school, courses or institutes
SUBJECTIVE WELL-BEING	Life satisfaction	0 to 5 on a scale 0 to 10
	Future perspectives	They think that in the next 5 years their situation will get worse
	Leisure time satisfaction	They are little or not at all satisfied with leisure time
SOCIAL COHESION	Social relation satisfaction	They are little or not at all satisfied with relationships with friends
	Civic and political participation	They do not engage in any of the activities considered: 1. talking about politics at least once a week; 2. getting informed about the facts of Italian politics at least once a week; 3. expressing opinions on social or political issues through websites (e.g. blogs, social networks, etc.) in the last 3 months
	Trust in parliament	On a scale of 0-10 they rated below the average for young people=3.6 (<4)
LIVING CONTEXT	Satisfaction with landscape	They say that the landscape of the place where they live is affected by degradation (dilapidated buildings, degraded environment, deteriorated landscape)
	Satisfaction with environmental quality	They say they are little or not at all satisfied with the environmental situation (air, water, noise, etc.) of the area where they live
	Difficulty in accessing services	They declare great difficulty in accessing 3 or more essential services out of the 11 considered: 1. pharmacies 2. emergency room 3. post office 4. police, carabinieri 5. municipal offices 6. nursery school 7. kindergarten 8. primary school 9. junior high school 10. grocery shops, markets 11. supermarkets

* The same weight is assigned to each indicator (1/15).

5 Results

In 2023 the 22% of the population aged 18-34 years living in Italy was multidimensionally deprived (H) (Figure 1). Those identified as deprived are above the deprivation threshold, on average, in 41% of the indicators (A).

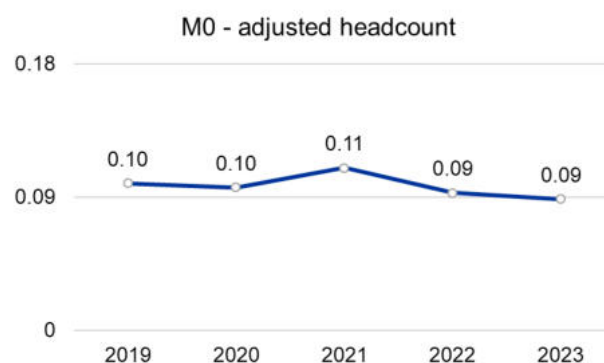
Figure 1 – Incidence (H) and intensity (A) of well-being deprivation among the youth. Italy 2019-2023.



Source: Elaboration on Aspects of Daily Life data.

Combining incidence and intensity of deprivation, in the same year, the value of the adjusted multidimensional well-being deprivation index M_0 is 0.09, the lowest level in the time series (Figure 2). Looking at the evolution over the 5-year period of the M_0 , we observe a peak during the pandemic in 2021, due to a sharp increase of H (27%), while the intensity shows a rather stable pattern.

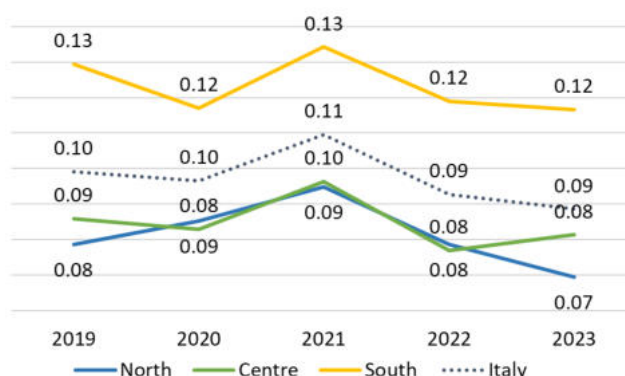
Figure 2 – Adjusted multidimensional well-being deprivation index (M_0). Italy 2019-2023.



Source: Elaboration on Aspects of Daily Life data.

In the Italian context it is relevant to consider territorial inequalities. The M_0 score, which can be calculated by macro regions (Nuts1), shows a higher index in the southern regions (including the main islands Sicily and Sardinia) throughout the entire period under consideration. Figure 3 also shows that the M_0 score in 2023 is lower than in 2019 in all macro territorial areas, indicating an improvement in the well-being of young people.

Figure 3 – M_0 for macro-regions. Italy 2019-2023,

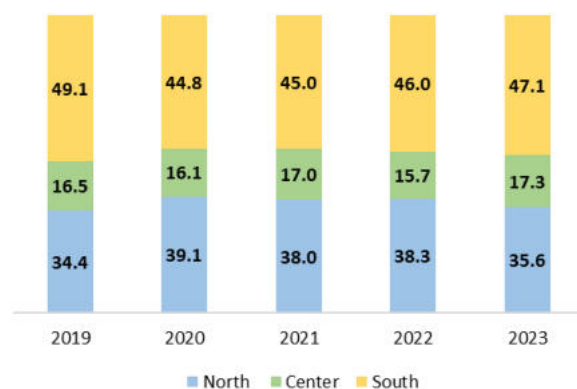


Source: Elaboration on Aspects of Daily Life data.

The previous analysis suggests that in the southern regions, the youth suffer more from multidimensional well-being deprivation. The additive nature of M_0 allows us to compute the percentage contribution of each population subgroup to overall multidimensional well-being deprivation when relative population size is accounted for. This analysis confirms that the highest contribution comes from those living in southern regions, although, during the pandemic crisis, we witnessed a temporary increase in the contribution coming from youths living in northern regions (Figure 4).

The M_0 can also be decomposed to look at the contribution of each dimension to the overall level of deprivation: the dimension contributing the most is Social cohesion (26.3% in 2023), followed by Work, education and training (22.1% in 2023) (Figure 5).

Figure 4 – Percentage contribution of population subgroups to the overall level of M_0 . Italy 2019-2023.



Source: Elaboration on Aspects of Daily Life data.

Monitoring the evolution over time shows how this latter dimension has been the most affected by the pandemic crisis, in fact its contribution peaked to 25.3% in 2021, but in 2023 it decreased to a lower level than what was observed in 2019. Special attention should be devoted to the Health dimension, for which it emerges a steadily increasing contribution over time, from 14.9% in 2019 to 16.8% in 2023.

Figure 5 – Contribution of each dimension to the overall level of M_0 . Italy 2019; 2021; 2023



Source: Elaboration on Aspects of Daily Life data.

The underlying structure of youth well-being deprivation differs markedly across macro-regions. The Social cohesion dimension shows the highest contribution for each population subgroup in the North and Centre (over 27%), but slightly lower in the South (25.2%). Instead, in the southern regions, the highest contribution is given by the Work, education and training dimension (26.1%, compared to 18% in the North and 19.7% in the Centre).

In the North, the second highest contribution comes from the Health dimension (20.3%, compared to 16% in the Centre and 14.4% in the South), which follows Social cohesion and overcomes the Work education and training dimension.

Figure 6 – Contribution of each dimension to the overall level of M_0 by macro regions. Italy, 2023.



Source: Elaboration on Aspects of Daily Life data.

6 Conclusion

In 2023, 22% of people aged 18-34 living in Italy were multidimensionally well-being deprived, on average across the 41% of the 15 considered indicators. The impact of the pandemic on youth well-being deprivation is evident, particularly in terms of a higher incidence. However, in 2023, Italian youth were in better conditions in terms of well-being deprivation compared to 2019 (the pre-pandemic benchmark).

When looking at territorial inequalities in youth deprivation, the Adjusted multidimensional well-being deprivation index M_0 is consistently higher in the southern regions (including the main islands) throughout the period under consideration.

The dimension contributing the most to youth well-being deprivation is Social cohesion. Those living in the South show the highest levels of deprivation, and special attention should be devoted to the Work, education and training dimension. Another critical issue arises the Health dimension: its contribution is relatively higher in the northern regions. Moreover, this dimension is the only one that shows a steady worsening over time.

Despite its many advantages, the multidimensional approach is not without limitations. Methodological choices such as the selection of dimensions, indicators, weights, and poverty thresholds are often contested as arbitrary. As future developments of our work, we aim at assessing sensitivity of results using different deprivation and poverty cutoffs.

References

- AABERGE R., BRANDOLINI A. Multidimensional poverty and inequality. *Discussion Papers*, No. 792, Statistic Norway Research Department.
- ALKIRE S., APABLAZA M. 2016. Multidimensional Poverty in Europe 2006–2012: Illustrating a Methodology. *OPHI Working Paper 74*, University of Oxford, Oxford.
- ALKIRE S., FOSTER J. 2011. Understandings and misunderstandings of multidimensional poverty measurement. *Journal of Economic Inequality*, Vol. 9, pp.289-314.
- ALKIRE S., SANTOS M.E.. 2010. Acute Multidimensional Poverty: A New Index for Developing Countries. *Human Development Research Paper 2010/11*, United Nations Development Programme.
- ANAND S., SEN A.K. 1997. Concepts of Human Development and Poverty: A Multi-dimensional Perspective. *Background Paper*, United Nations Development Programme, Human Development Report 1997.
- ATKINSON A.B. 2003. Multidimensional Deprivation: Contrasting Social Welfare and Counting Approaches. *Journal of Economic Inequality*, Vol. 1, pp. 51-65.
- BACCHINI F., BALDAZZI B., DE CARLI R., DI BIAGIO L., SAVIOLI M., SORVILLO M. P., TINTO A. 2021. The Evolution of the Italian Framework to Measure Well-Being. *Journal of Official Statistics*, Vol. 37, No. 2, pp. 317-339. <https://doi.org/10.2478/jos-2021-0014>
- BETTI G., CHELI B., LEMMI A., VERMA V. 2008. The Fuzzy Set Approach to Multidimensional Poverty: the Case of Italy in the 1990s. In: KAKWANI N.

- and SILBER J. (Eds.), *Quantitative Approaches to Multidimensional Poverty Measurement*, Palgrave Macmillan, pp. 30-48.
- BILLI A., SCOTTI M. 2018. La povertà multidimensionale: sperimentare l'MPI in Italia. *LaborEst*, Vol. 16, pp. 20-24.
- BOURGUIGNON F., CHAKRAVARTY S. R. 2003. The measurement of multidimensional poverty. *Journal of economic inequality*, Vol. 1, pp. 25-49.
- CHELI B, LEMMI A. 1995. A "Totally" Fuzzy and Relative Approach to the Multidimensional Analysis of Poverty. *Economic Notes*, Vol. 24, No. 1, pp. 115-134.
- DE ROSA D. 2021. Are Italians Getting Multidimensionally Poorer? Evidence on the Lack of Equitable and Sustainable Well-Being. *Italian Economic Journal* Vol. 8, pp. 145-174.
- DHONGDE S., HAVEMAN R. 2017. Multi-Dimensional Deprivation in the U.S. *Social Indicators Research*, Vol. 133, No. 2, pp. 477-500.
- D'ATTOMA I., MATTEUCCI M. 2024. Multidimensional poverty: an analysis of definitions, measurement tools, applications and their evolution over time through a systematic review of the literature up to 2019. *Quality and Quantity*, Vol. 58, pp. 3171-3213
- GLASSMAN B. 2024. The Composition of the Population Deprived in Multiple Dimensions. *Social, Economic, and Housing Statistics Division Working Papers* No. FY-2024-30, United States Census Bureau.
- ISTAT. 2024. *Bes 2023. Equitable and sustainable well-being in Italy*. Istituto nazionale di statistica, Rome.
- SEN A. K. 2009. *The Idea of Justice*. London: Penguin.
- SUPPA N. 2016. Comparing monetary and multidimensional poverty in Germany. *OPHI Working Paper 103*, University of Oxford, Oxford.
- SUPPA N. 2018. Towards a multidimensional poverty index for Germany. *Empirica*, Vol. 45, pp. 655-683.
- WHELAN, C.T., NOLAN, B., MAÎTRE, B. 2014. Multidimensional Poverty Measurement in Europe: An Application of the Adjusted Headcount Approach. *Journal of European Social Policy* Vol. 24, pp. 183-197.

Elisabetta SEGRE, Istat, elisabetta.segre@istat.it
Alessandra TINTO, Istat, alessandra.tinto@istat.it
Romina FRABONI, Istat, romina.fraboni@istat.it
Miria SAVIOLI, Istat, miria.savioli@istat.it
Anna VILLA, Istat, anna.villa@istat.it

PROJECTING ITALY'S LABOUR MARKET: ASSESSING THE SUSTAINABILITY OF THE WORKFORCE BY 2050¹

Marco Marsili, Martina Lo Conte, Marco Rizzo,
Cristina Ocello, Andrea Spizzichino

Abstract. Istat produces annual projections on population and households to describe future demographic trends, providing both overall values and detailed age and sex breakdowns. In a context of rapid population ageing, Italy stands out as one of the oldest countries in the world, with a mean age of the population close to 47 years. This demographic evolution draws attention to the sustainability of the future of the labour market, in terms of both size and age pattern of the active population. On 1 January 2025, the working-age population (15–64 years) represents 63.4% of the total, marking a slight decrease compared to 2024. In contrast, the share of those aged 65+ reaches 24.7%, up by 0.4 percentage points from the previous year. Ageing, longer education and low fertility are expected to reshape labour supply in the coming decades, with major implications for economic growth, welfare systems, and policy planning. In this work we present a secondary level projection model to evaluate labour market trends in Italy up to 2050. The analysis focuses on activity rates by sex and five-year age group. The model is based on a static approach where predicted activity rates are applied to population forecasts. Key factors influencing labour participation are explicitly considered, including increasing life expectancy, delayed entry into the labour market due to higher education attainment, and the progressive rise in retirement age. However, the aim of this work is not to estimate future employment or unemployment rates, given the many economic implications that would require consideration in a medium-long term perspective. The main goal is to assess the long-term sustainability of the labour market and to explore how demographic dynamics may affect the availability of the workforce in the future.

1. Introduction

The progressive aging of the population is one of the most significant demographic transformations currently affecting Italy and many other developed countries. This phenomenon is not limited to an increase in the average age but also entails a profound shift in the population structure, with older age groups making up an increasingly larger share compared to those of working age.

¹ Although this paper is the outcome of the authors' joint reflections, paragraph 1 was drafted by Andrea Spizzichino, paragraphs 3,4 by Cristina Ocello, paragraphs 2,5,6 by Marco Rizzo, paragraph 7 by Martina Lo Conte and paragraph 8 by Marco Marsili.

This change has direct and substantial implications for the labour market. On one hand, the shrinking proportion of people between the ages of 15 and 64 - traditionally considered the population in active age - implies a potential decline in the labour supply. Fewer people of working age may result in fewer available workers, which could impact overall productivity, economic growth and sustainability of pension and welfare systems.

On the other hand, the fact that life expectancy has been rising, and retirement age has been gradually increasing, leads to a longer stay in the labour force. More and more individuals remain in an active status beyond the age of 65, whether by personal choice, financial necessity, or because of pension reforms.

Furthermore, population aging interacts with other demographic trends, such as declining birth rates and growing numbers of young people pursuing higher education, who tend to enter the labour market later than in the past. The result is a shrinking of the so-called "core" segment of the labour force - the age group that has traditionally borne the greatest economic and productive burden in the country.

This paper fits within this context by integrating official population projections and labour market statistics produced by Istat. Specifically, a derived projection model has been developed to estimate the evolution of the Italian labour market up to 2050. The model focuses on labour force participation rates, broken down by sex and five-year age group, using a static approach that applies the estimated participation rates to demographic projections.

2. Literature Review

Given the relevance of the issue, many national statistical offices and international organizations develop their own projection models. Among all, the U.S. Bureau of Labor Statistics stands out for producing forecasts that extend well beyond labour force participation, covering even employment, industry output, and final demand (Dubina, 2004). Projection horizons generally range from ten to fifty-five years (EPC, 2024).

The literature identifies four main approaches to projecting participation rates: (1) Judgmental (qualitative) methods: based on scenarios or targets established by experts. (2) Time extrapolation models or growth curves: describe the historical evolution of a variable as a function of time and extend the trend into the future, in particular, sigmoid curves (such as logistic curves), being well suited to processes tending toward stabilization, are widely used. (3) Regression models: estimate the relationship between participation rates and economic, demographic, or cultural factors. (4) Cohort-based approach: estimates participation rates based on the probability of entering or exiting the labour force for each cohort; these probabilities are kept constant or extrapolated over time to generate projections. See Houriet-Segard (2011) for a review of methodologies.

The main European reference in this field is the projection model developed by Carone in 2005 for the European Commission, within the Ageing Working Group. This model is based on a cohort-based approach projecting age- and sex-specific participation rates up to 2050. This methodology follows the OECD approach, with one relevant modification: the use of single years of age instead of five-year age groups. The method allows capturing generational differences in participation profiles, such as the increase in female participation. Projections are formulated under a “no policy change” scenario. Key results from this model highlight a projected decline in the active population and its ageing, because of the approaching retirement of the baby-boom generations and the lower birth rates in younger generations entering the working-age population (Carone, 2005).

A further international reference for active population projections is provided by the International Labour Organization (ILO). Their projections are developed using econometric methods, which, due to their flexibility, ensure international applicability and comparability. Specifically, the ILO develops three scenarios: (1) Constant scenario: participation rates are kept constant over the projection period, with only population changing. (2) Imputation scenario: participation rates are obtained using an imputation procedure for five-year age groups. (3) Logistic trend scenario: participation rates are extrapolated using various logistic trend variants for each time series (ILO, 2015).

3. Objectives

Considering the projected decline in the working-age population by 2050 (Istat, 2024), this project aims to estimate the evolution of labour force participation and assess its implications for labour market sustainability. The research question is: “*Will the active population be able to meet labour market demand over the next 25 years?*”.

Population aging, declining birth rates, and migratory flows will significantly affect the availability and composition of the workforce. Analyzing these elements allows for the anticipation of potential imbalances between labour supply, demand and the definition of targeted strategies to support labour market resilience. The main objective is to project activity rates disaggregated by structural variables such as sex, age, and territory. According to the ILO, labour market indicators should be calculated not only in aggregate but also disaggregated by relevant characteristics (ILO, 2023), as aggregate stability may conceal significant underlying variations. This is the case in Italy, where differences by sex and region are particularly marked.

The analysis extends to 2050, with five-year age groups from 15 to 74. Extending the activity rate beyond the canonical 65 reflects projected pension eligibility requirements. The predicted number of potential workers will be derived from

projections accounting for trends in life expectancy, the pension system, and educational participation.

This projection is part of Istat's broader forecasting system, which since 1989 has been producing demographic projections at national and regional level. In 2021, the system was extended to municipalities and to households by type. Its main feature is an integrated approach, where demographic, household, and labour force components are analysed in mutual interaction.

4. Data

Building a model that can be capable of predicting the future evolution of the potential pool of workers requires putting together a considerable database. In particular, the data used in this study are as follows:

- 1) Base population: we use the Istat median-scenario probabilistic population projections by sex, age, and region (base 1.1.2024), covering the forecast period from 2025 to 2050 (Istat, 2024).
- 2) Labour market participation: data used to construct participation indicators come from the Labour Force Survey (LFS). We use the active population and the corresponding activity rate, disaggregated by sex, region, and five-year age groups from 15 to 74. The time series covers the period 2004–2024.
- 3) Education enrolment: to account for the postponement of labour market entry due to longer educational pathways, we use enrolment rates derived from the Istat Labour Force Survey.
- 4) Retirement age: to capture the evolution of the pension system, we include the projected minimum legal age for retirement, calculated annually by the State General Accounting Department in the report "Medium- and long-term trends of the pension and welfare system – 2024". These projections are based on previous Istat median-scenario population projections (base 1.1.2022) (MEF, 2024).

5. Model

The model is based on the static method known as the Propensity Model. This approach relies on *propensity rates*, which in this case of study are equivalent to activity rates. In fact, they are defined as the proportion of individuals in age group x who are in the labour force at time t :

$$Propensity Rate_{x,t} = \frac{P_{LF,x,t}}{P_{x,t}} \quad (1)$$

The labour force is defined as the sum of employed individuals and those actively seeking employment (i.e., unemployed).

The proposed method offers several advantages: it aligns well with official population projections, produces widely used labour market indicators such as the number of active/inactive individuals and activity rates, is easily replicable and provides a good level of detail in the outputs.

The model consists of six main steps, each of which is discussed in detail below.

5.1 Estimating the Household Population

To ensure consistency with the definition of the population used in the LFS, we first estimate the population living in private households. Individuals residing in institutional households (e.g., hospitals, military barracks, prisons, care homes, religious communities) are then excluded from the projected population.

We calculated average incidence rates of the institutionalised population by sex, five-year age group, and region. Given the relative stability of this population over observed time, we assumed a constant trend in these incidence rates throughout the forecast horizon.

By applying the complement to 100 of these percentages to the total projected population from 2025 to 2050, we obtain the population living in private households by region, sex, and age group.

5.2 Calculating the Total Activity Index (TAI)

The projection of the future evolution of the active population is based on a synthetic indicator that summarises activity behaviours over time. This indicator, referred to as the Total Activity Index (TAI), is calculated as the weighted sum of age-specific activity rates, with weights given by the person-years lived in each age group:

$$TAI_t = \sum_{x=15-19}^{70-74} Activity\ Rate_{x,t} \cdot L_{x,t} \quad (2)$$

Where x = five-year age group, t = year.²

The L_x values, which represent the person-years lived in each five-year age group x , by sex s , in year t , are derived from official Istat life tables. Under the assumption of independence between mortality and labour force participation, the TAI represents the average number of years a cohort of individuals would be expected to spend as part of the labour force (i.e., employed or actively seeking work) under the age-specific conditions observed in a given year.

² For clarity, the subscripts for disaggregation by sex (s = male, female) and geographical area (i = North-West, North-East, Centre, and South) have been omitted from the formula.

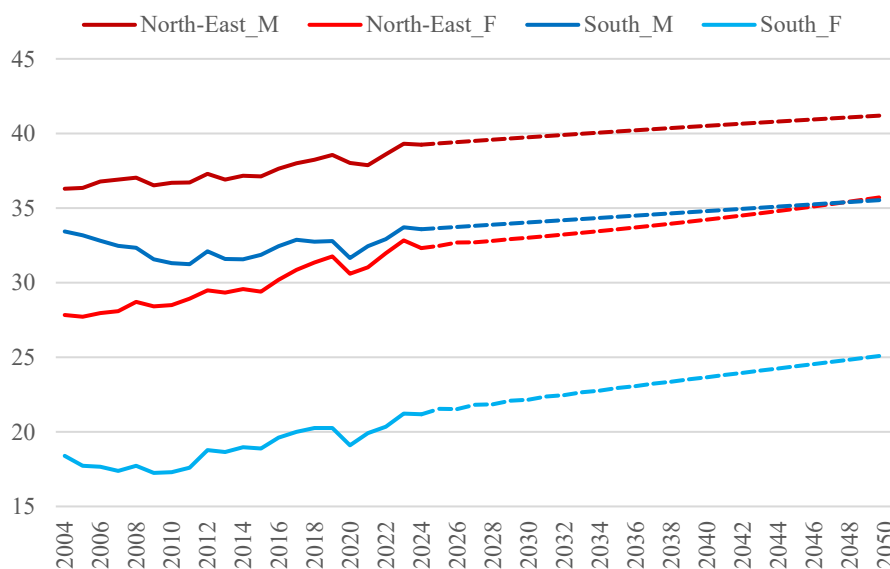
For reference, in Italy in 2024, the TAI was 36.9 years for men and 28.1 years for women. This means that, on average, a man could expect to spend nearly 37 years as part of the labour force, a woman about 28 years. TAI values are calculated at the NUTS-1 level: North-West, North-East, Centre and South. This choice was made to allow for more stable extrapolations, as the results are less affected by small and volatile values such as those observed at the regional level.

5.3 Projecting the TAI

To produce projections of the Total Activity Index up to 2050, we applied forecasting techniques that ensure both statistical robustness and plausibility of the results over time. The projections are based on the historical time series data and make use of the most reliable models for temporal extrapolation, selected according to goodness-of-fit criteria coherence with observed trends.

The TAI was disaggregated by sex and geographical area to reflect heterogeneous labour market dynamics across population. Separate models were estimated for each subgroup, allowing the projections to capture differentiated trends by gender and territory. The final output consists of a set of harmonised projections that preserve internal consistency and ensure analytical detail at subnational level.

Figure 1 – Observed and extrapolated TAI by sex. North-East and South Italy - 2004-2050.



5.4 Adjusting the age distribution of Activity Rates

Once the TAI has been projected for each forecast year, age-specific activity rates (by sex and age group) for 2025–2050 are obtained by redistributing the TAI on the average distribution observed in 2022–2024.

Instead of assuming a static age distribution, the model incorporates changes driven by two key demographic and institutional dynamics: the evolution of the pension system and the increasing educational attainment among youth.

The rise in the minimum legal retirement age - driven by Law no. 122/2010 - is expected to delay exit from the labour market for older individuals. This results in a wider area under the right tail of the age-activity curve.

At the same time, prolonged education among young people delays entry into the labour market (Carone, 2005), thus reducing the area under the left tail of the curve - although with a lesser effect than that driven by the pension system.

The impact of later retirement is handled by incorporating the projected retirement age as estimated by the State General Accounting Office (MEF, 2024) in its annual report "Medium- and Long-Term Trends of the Pension and Healthcare System". First, we calculate the elasticity of activity rates (AR) for older age groups with respect to changes in the retirement age over 2004–2024, separately by sex and geographical area:

$$e = \frac{\Delta AR / AR}{\Delta age_r / age_r} \quad (3)$$

Using the average elasticity values by sex, age group, and region, and the projected retirement age from MEF, we adjust the 2022–2024 age distribution of activity rates accordingly:

$$AR_{t,x,s} = \left(AR_{22-24,x,s} \cdot e \cdot \frac{age_{r_t} - age_{r_{24}}}{age_{r_{24}}} \right) + AR_{22-24,x,s} \quad (4)$$

To model delayed entry into the labour force, we use enrolment rates from Istat Labour Force Survey. For each sex and age group, we estimate the probability of exiting the education system over the 2012–2022 period:

$$P_{x,s,t} = \frac{School\_Rate_{x,s,t} - School\_Rate_{x+1,s,t+1}}{School\_Rate_{x,s,t}} \quad (5)$$

We then compute the average trend in these probabilities for younger cohorts and adjust the 2022–2024 activity rate distributions to account for the share of

individuals likely to remain in education each year, assuming future trends follow the pattern observed over 2012–2022.

5.5 From TAI to age-specific activity rates

Once the age distribution of activity rates - corrected for retirement and education effects - is calculated for each forecast year, sex, and geographical area, final activity rates are obtained through:

$$AR_{x,s,t} = AR_{x,s,22-24} \cdot \frac{TAI_{s,t}}{TAI_{s,22-24}} \cdot \frac{L_{x,s,22-24}}{L_{x,s,t}} \quad (6)$$

Where the second and the third factors adjust the distribution to match the projected TAI and the changes in mortality (person-years lived) over time:

5.6 Deriving the projected active and inactive population

Finally, applying these projected activity rates to the projected household population (from step 1), we obtain the active population by sex, age group, and geographical area up to 2050. The inactive population is derived by subtracting the active population from the household population. National-level estimates are produced in bottom-up approach by aggregating single geographical areas.

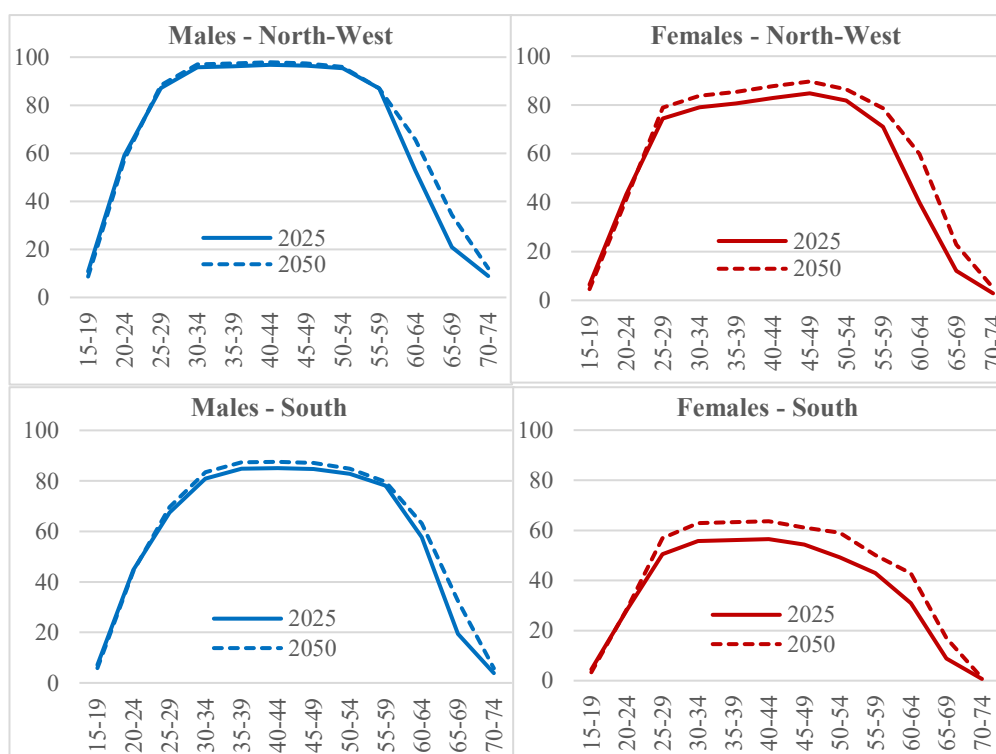
6. Results

The activity rate for the age group 15-74 in Italy is expected to increase over the entire period, rising from 57.9% in 2024 to 61.9% in 2050 (+4 percentage points). Significant gender differences persist. The male activity rate will grow from 66.5% in 2024 to 68.3% in 2050, while the female rate, starting from a considerably lower level of 49.4%, is expected to reach 55.0% by 2050. This trend reflects a gradual but meaningful convergence in labour force participation between men and women. One underlying reason for this trend is the higher rate of female education. It is already evident that labour force participation is higher among female graduates. Given the expected further growth in the number of women with tertiary education.

Nevertheless, the distribution of activity rates shows a lower labour market participation for females than males at all ages. Moreover, territorial differences are evident. Figure 2 shows the projected activity rates by age group and sex in the North-West and South Italy - the geographical areas with the highest and lowest levels. In the North-West the activity rate for men in the 30-49 age group will reach over 96% in 2050, while in the South it will just exceed 87%, almost 10 percentage points less. Females' rates are much lower but in North-West they will overcome 80%. An increase for the female rate in the South is expected by 2050. In the core

working age groups (30-54) the activity rate in 2050 is expected to reach almost 64%, up from just over 50% in 2024.

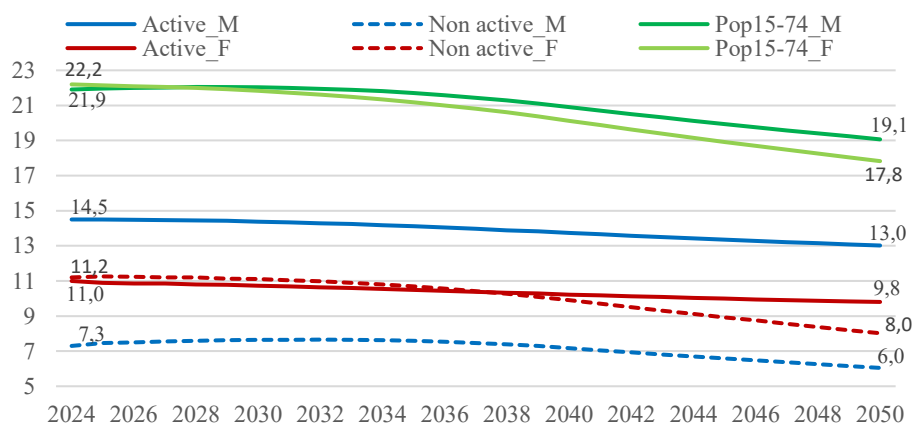
Figure 2 – Activity rates by gender and age class. North-West and South Italy – Years 2024 and 2050. Percentage values.



Despite the increase in activity rates, the size of the active population is expected to decrease for both sexes. Figure 3 shows a gradual but marked change in the labour market, driven mainly by an ageing and decreasing population. The overall working-age population is expected to decline steadily: from around 22.2 million in 2024 to 19.1 million in 2050 for men, from 21.9 to 17.8 million for women. Within this shrinking population, the number of active individuals also declines: active males fall from 14.6 to 13.0 million, while active females decrease from 11.0 to 9.8 million. In this scenario, the non-active population declines notably, particularly among women, from 11.2 to 8.0 million. Although female participation remains significantly lower than male participation throughout the period, it is interesting to note that among women the chance of an active population overtaking the inactive one is expected around 2038, equalling what has always been observed among men.

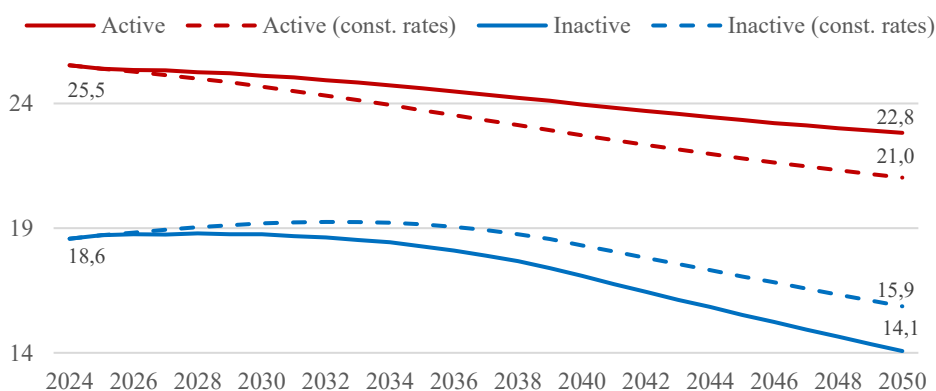
Our labour force projections underscore the dual challenge Italy has to face in the coming decades: a declining working-age population and persistent but narrowing gender disparities in labour market participation.

Figure 3 – Population by activity status and gender. Italy – Years 2024 - 2050. Millions.



To evaluate how future labour market dynamics are shaped by changes in participation behaviour rather than by demographic trends, a forecasting exercise of the active and inactive population was carried out assuming constant rates. Activity rates observed in 2024 were applied to the median scenario of the population projection throughout the projection horizon.

Figure 4 – Population by activity status projected with constant and variable rates. Italy – Years 2024 - 2050. Millions.



The results show that assuming unchanging participation rates has significant effects: if labour market participation remained fixed at the most recent observed levels, by 2050 the number of active individuals would be almost two million lower (22.8 million in the variable-rate scenario versus 21 million in the constant-rate scenario). Conversely, the inactive population would increase, expanding the share of people who are neither employed nor actively seeking work to 15.9 million individuals.

7. Conclusions

The experiment appears to yield robust results and could strengthen the set of projections carried out by Istat, by adding to core demographic indicators and family structure valuable insights into the potential labour force.

The resulting information may hold significant socio-demographic value, helping policymakers gain a clearer understanding of potential changes in the share of the labour force and of the broader social dimensions connected to this issue.

The preliminary results highlight that, in a context of a projected population decline (–16.4% of residents aged 15-74 between 2024 and 2050 according to the medium scenario), the working-age population may experience a less pronounced decrease (–10%), particularly if progress continues to be encouraged among women. This also involves a continued increase in participation at older adult ages under current legislation.

Regarding women and South Italy, there is significant potential for growth in the active segment of the population. Currently, these groups show much lower values compared to men and other geographical areas. Investing in these areas could help slow down the decline of the Italian working-age population, thereby supporting the labour market. However, much like other well-known future demographic trends (especially births and deaths), the structural effects of population dynamics have a significant - and in some respects irreversible - impact on the overall levels of the future labour force, even under assumptions of rising activity rates.

The future evolution of the job offer in Italy will be influenced by various structural factors, not only demographic, especially technological. The main trends that will probably characterize the next decades consist of a progressive digital transformation and automation of society, with growing sectors such as ICT and artificial intelligence. The effect on the job offer will involve the growth of roles linked to technology, but also the need to retrain workers in traditional sectors, which many companies already struggle to find today. On a purely demographic level, this requires proactive policies towards international migratory processes, considering the overall modest contribution that could come from future births, in the search for

the human capital that the country will need to face the future socio-economic challenges.

The decline in the working-age population is therefore one of the most critical challenges for Italy in the next decades. Unless structural interventions are made, the real risk is to have not an adequate number of workers to support all the growing sectors. An increase in female participation alone should be seen as an opportunity, as it would mean millions more female potential workers. Likewise, targeted interventions in disadvantaged areas, particularly in the South, lead to the conclusion that success is possible, with clear economic and demographic benefits for the country.

References

- CARONE G. 2005. *Long-term labour force projections for the 25 EU Member States*. European Commission – Directorate General for Economic and Financial Affairs.
- EPC. 2024. *2024 Ageing Report: Underlying Assumptions & Projection Methodologies*. November 2023.
- HOURIET-SEGARD G., PASTEELS J. 2011. *Projections of economically active population: a review of national and international methodologies*. International Labour Office - Geneva: ILO, 2011.
- DUBINA K. S. 2024. Labor force and macroeconomic projections overview and highlights, 2023–33, *Monthly Labor Review*, U.S. Bureau of Labor Statistics, August 2024.
- ILO. 2015. *Labour Force Estimates and Projections, 1990-2050*, 2015 edition, Geneva.
- ILO. 2023. *Resolution concerning statistics of work, employment and labour underutilization*. 19th International Conference of Labour Statisticians. Geneva: International Labour Organisation.
- ISTAT. 2024. *Previsioni della popolazione residente e delle famiglie. Base 1/1/2023*. Rome: Istituto Nazionale di Statistica, July 2024.
- MEF. 2024. Le tendenze di medio-lungo periodo del sistema pensionistico e socio-sanitario. Previsioni elaborate con i modelli della Ragioneria Generale dello Stato. Rome: Ministero dell'Economia e delle Finanze, June 2024.

Marco MARSILI, Istat, marsili@istat.it
Martina LO CONTE, Istat, loconte@istat.it
Marco RIZZO, Istat, marco.rizzo@istat.it
Cristina OCELLO, Istat, cristina.ocello@istat.it
Andrea SPIZZICHINO, Istat, spizzich@istat.it

POVERTY RISK AND TERRITORIAL DISPARITIES IN EUROPE: A CLUSTERWISE LASSO REGRESSION APPROACH

Simona Cafieri, Gianmarco Borrata

Abstract. In 2024, more than 93 million people in the EU were at risk of poverty or social exclusion, highlighting persistent territorial disparities and the urgent need for accurate and robust measurement. This article proposes an innovative two-stage methodology to improve the estimation of poverty risk across European territories by leveraging high-dimensional socio-economic data. The approach combines a clustering phase, which captures territorial heterogeneity, with Lasso regression for variable selection and model simplification, ensuring parsimony and interpretability. The application to different degrees of urbanisation reveals that the determinants of poverty vary spatially, with significant differences both in the composition of clusters and in the relevance of explanatory variables. The results provide new insights for the design of effective, territorially targeted anti-poverty policies and contribute to the European debate on regional inequalities through a comparative and statistically sound approach.

1. Introduction

Over the past decades, poverty risk has remained a core topic in socio-economic research, involving diverse disciplines such as economics, sociology, and statistics. A widely used metric is the at-risk-of-poverty rate, defined as the share of individuals with equivalised disposable income below 60% of the national median (Eurostat, 2024). This relative measure captures income distribution within countries and serves as a proxy for broader dimensions such as inequality and social exclusion.

Another measure widely used in the European policy context is the At Risk of Poverty or Social Exclusion (AROPE) indicator, which corresponds to the sum of persons who are either at risk of poverty, or severely materially and socially deprived or living in a household with a very low work intensity. It is one of the main indicators to monitor the EU 2030 target on poverty and social exclusion and was the headline indicator to monitor the EU 2020 Strategy poverty target. As one of the main indicators of the EU 2030 Agenda, AROPE provides insight into socioeconomic vulnerability and highlights the multidimensional nature of poverty and exclusion in Europe (Eurostat, 2021).

Poverty risk is shaped by a complex interplay of socio-economic determinants, including welfare policies (Chircop *et al.*, 2022), labour market conditions (Reluga

et al., 2025), and access to quality education (Eurostat, 2025) and healthcare services (Renahy, 2018). Empirical evidence shows that regions with higher educational attainment and stronger social infrastructure tend to report lower poverty risks (Copus *et al.*, 2015). Conversely, structural unemployment and limited public services increase vulnerability (Serban, 2021).

Poverty, inequality, and exclusion often overlap conceptually and empirically, this overlap makes measurement and policy formulation more complex. Moreover, shared drivers such as long-term unemployment affect these dimensions simultaneously, further blurring analytical boundaries.

A spatial perspective adds another layer of complexity. Urban, suburban, and rural areas differ significantly in terms of opportunities, costs of living, and access to services. While urban centres offer broader access to education and employment, they are often associated with higher housing costs and income disparities. Rural areas, by contrast, may face chronic limitations in infrastructure and labour market integration, leading to persistently higher poverty rates. Suburban contexts show intermediate characteristics but can also experience uneven development.

This study investigates how the relationship between socio-economic variables and poverty risk varies across degrees of urbanisation in Europe. By applying an innovative two-stage methodology—clustering followed by sparse regression—we aim to uncover latent spatial structures and identify the most relevant predictors in each context. The goal is to provide actionable insights for developing differentiated, evidence-based policies tailored to the specific challenges of cities, towns, and rural areas. The next section explores how poverty risk differs across degrees of urbanisation and identifies the multi-dimensional vulnerabilities specific to each context.

2. Poverty Risk and Urbanisation in Europe

Poverty risk in Europe displays marked territorial disparities, closely linked to the degree of urbanisation—typically classified into cities, towns and suburbs, and rural areas. According to Eurostat data, in 2024, about 93.3 million people in the EU were at risk of poverty or social exclusion. Of these, 5.6 million lived in households experiencing all three dimensions of severe disadvantage: monetary poverty, severe material and social deprivation, and very low work intensity.

Additional combinations also reveal multi-dimensional vulnerability: 11.4 million experienced both income poverty and low work intensity, while 8.4 million combined poverty with severe deprivation. These patterns are shaped by structural features specific to different territorial settings.

Urban centres often provide broader access to employment and education but face challenges such as high living costs and greater income inequality, which may offset these advantages for lower-income groups. Rural areas, by contrast, are often

characterised by limited access to services, lower educational attainment, and fewer job opportunities—conditions that contribute to persistently high poverty risks. Towns and suburbs tend to fall between these two extremes, showing more heterogeneous profiles depending on national and regional contexts.

These spatial dynamics highlight the importance of incorporating territorial dimensions into anti-poverty strategies. Effective policies must be adapted to the unique constraints and opportunities of each area type, with a focus on balancing accessibility, affordability, and service provision across the urban–rural spectrum. In light of these spatial disparities, we apply a novel statistical framework to disentangle the role of socio-economic factors in explaining poverty risk across urban, suburban, and rural areas.

3. Methodology

Clusterwise Regression Model (CRM) (Spath, 1979; 1982) is an effective framework to model the relationship between a dependent variable and a set of explanatory variables in the presence of unobserved heterogeneity among observations. CRM assumes an underlying clustering structure within the data, which enables a more nuanced interpretation of regression results, especially in high-dimensional and heterogeneous socio-economic data; CRM has been widely applied in domains such as market segmentation, manufacturing, process modelling (Ganjigatti *et al.*, 2007), infrastructure management (Khadka *et al.*, 2017), spatial analysis (Openshaw, 1977), meteorological forecasting (Bagirov *et al.*, 2017), air quality prediction (Poggi *et al.*, 2011), and machine learning (Karmitsa *et al.*, 2020). Its flexibility in capturing data-driven clusters makes it a valuable tool for exploring complex, multi-faceted relationships.

In this study, we extend the CRM approach by integrating it with the Least Absolute Shrinkage and Selection Operator (Lasso) regression. The resulting method—Clusterwise Regression with Lasso—combines unsupervised clustering with regularised regression, allowing for both identification of latent subgroups and simultaneous variable selection within each cluster. Specifically, the dataset is partitioned into clusters based on an optimal number determined empirically, and a separate Lasso regression model is estimated for each subgroup. This combined approach handles heterogeneity and multicollinearity, while improving model clarity and prediction accuracy.

The general formulation of Clusterwise Lasso regression can be described as follows:

$$\min_{\beta} \sum_{k=1}^K \left[\sum_{l \in C_k} (y_l - \beta_{k0} - \sum_{j=1}^J \beta_{kj} x_{lj})^2 + \lambda \sum_{j=1}^J |\beta_{kj}| \right] \quad (1)$$

where:

K is the number of clusters,

C_k represents the set of indices of data points in cluster k ,

β_{k0} and β_{kj} are the intercept and coefficients for the k -th cluster,

λ is the regularization parameter controlling the sparsity of the solution.

Cross-validation is a widely used method for selecting the optimal regularization parameter λ in Lasso regression (Roberts, 2014).

This method proceeds by splitting the data into “folds”. Then over a sequence of tuning parameter values, penalized models are fitted to all but one of the folds and the predictive performance of each model is gauged over the “left-out” fold. This process is repeated until each fold has been left out. The value of the tuning parameter is then chosen to be the value in the sequence that has the smallest aggregated prediction error (or cross-validation error). By selecting the optimal λ , cross-validation helps identify the most relevant predictors, simplifying the model while retaining essential information (Hastie, 2009).

The CRM algorithm is executed alternating between the following two steps until convergence to a stationary value:

Step1 – Representation phase (best fitting):

The local Lasso regression models are estimated by minimizing the objective function (Equation 1).

Step 2 – Assignment phase (partition P_k):

The optimal clusters that minimize the objective function are obtained according to the following assignment rule:

$$C_k = \{e_i \in E: |\widehat{e}_{i(k)}}|^2 < |\widehat{e}_{i(h)}}|^2\}, \text{ for all } h \neq k$$

where:

- $\hat{e}_i$ is the i -th residual from the regression model.

Therefore, observation $\hat{e}_i$ is assigned to cluster C_k if the sum of squared errors is minimal for that cluster's regression model¹.

4. Evaluating Poverty Risk in Europe through Clusterwise Lasso Regression

The application of Clusterwise Lasso Regression allows for a nuanced assessment of poverty risk determinants across different levels of urbanisation in Europe. By combining clustering with penalised regression, the approach captures latent heterogeneity and enhances interpretability through context-specific variable selection.

¹ The statistical analysis was carried out by using the software R-studio and package used for Lasso regression is `glmnet` in R programming environment available on the CRAN (<https://CRAN.R-project.org/package=glmnet>).

The analysis is based on Eurostat data², drawing on harmonised indicators from the Sustainable Development Indicators (SDI) and the Degree of Urbanisation classification. A set of 20 socio-economic variables (see Table 1), covering education, employment, income, and housing, was selected based on theoretical relevance and data availability for 2023.

This integrated method identifies homogeneous territorial clusters and estimates separate regression models for each group. The resulting framework accommodates multicollinearity and structural differences between urban, suburban, and rural areas, offering insight into the most influential poverty risk predictors across spatial contexts.

Figure 1 illustrates the spatial distribution of poverty risk by urbanisation level across European countries, while Figure 2 reports the optimal number of clusters identified via the elbow method. Three clusters were selected in each context to balance model fit and parsimony. Figure 3 displays the clustering results obtained through Clusterwise Lasso Regression algorithm, illustrating the classification of European countries according to their respective degrees of urbanisation. The analysis was conducted separately for cities, towns and suburbs, and rural areas.

The spatial distribution of the at-risk-of-poverty rate across European countries shows that, in Western and Northern Europe, urban areas generally display lower poverty rates, reflecting higher levels of economic development and more comprehensive social protection systems. In contrast, urban centres in certain Southern and Eastern European countries exhibit comparatively higher poverty risks, likely due to structural economic disparities and varying levels of service accessibility.

Rural areas reveal the most pronounced geographical inequalities, with consistently elevated poverty rates observed in Central and Eastern Europe. These regions are often characterised by limited labour market opportunities, infrastructural deficits, and reduced access to public services. Towns and suburban areas show more heterogeneous patterns: while some align closely with national averages, others diverge significantly, particularly in Southern European countries where regional imbalances remain substantial.

Table 2 reports the estimated coefficients from Clusterwise Lasso Regression model applied to cities, with the dataset segmented into three clusters, as determined by the elbow method. Each cluster includes countries sharing similar socio-economic profiles that influence poverty risk in urban settings.

² <https://ec.europa.eu/eurostat/web/database>

Table 1 - *Socio-economic Indicators used in the analysis.*

Variable	Indicator	Definition
Y	At- Poverty Risk Percentage	Percentage of people at risk of poverty on the total population
X1	Low Education	People aged 18-24 who have completed at lower secondary education and have not attended further education or training courses
X2	Education Rate	Rate of participation in education or training - Age 18-64
X3	Low-Level Education Population	Population by education level: "Less than primary, primary and lower secondary education (Level 0-2) - Age 15-64"
X4	Medium-Level Education Population	Population by education level: "Upper secondary and post-secondary non-tertiary education (Level 3 and 4) - Age 15-64"
X5	High-Level Education Population	Population by education level: "Tertiary education (Level 5-8) - Age 15-64"
X6	Employment Rate	Employment rates - Age 15-64
X7	NEETs 15-24	Young people not in employment, education, or training - Age 15-24
X8	NEETs 25-34	Young people not in employment, education, or training - Age 25-34
X9	Youth Employment (Level 3-4)	Employment rate of young people not in education or training: "Upper secondary and post-secondary non-tertiary education (Level 3 and 4)"
X10	Youth Employment (Level 5-8)	Employment rate of young people not in education or training: "Tertiary education (Level 5-8)"
X11	Housing Cost Overburden	Housing cost overburden rate
X12	Median Income	Median income
X13	Severe Material Deprivation	Severe material deprivation rate
X14	High Income Share	Share of people with income at or above 130% of median income
X15	Under-occupied Housing	Percentage of people living in under-occupied dwellings
X16	Part-Time Employment (Level 0-2)	Part-time employment rate by job type: "Less than primary, primary and lower secondary education (Level 0-2)"
X17	Part-Time Employment (Level 3-4)	Part-time employment rate by job type: "Upper secondary and post-secondary non-tertiary education (Level 3 and 4)"
X18	Part-Time Employment (Level 5-8)	Part-time employment rate by job type: "Tertiary education (Level 5-8)"
X19	Self-Employed Percentage	Percentage of self-employed workers
X20	Unemployment Rate 15-64	Unemployment rate of people aged 15-64

In Cluster 1, participation in education and youth employment are positive variables for reducing the risk of poverty, while the presence of NEET young adults

significantly increases the risk of poverty. In Cluster 2, low education and material deprivation are negative determinants, while a higher share of high incomes helps to reduce poverty. In Cluster 3, widespread secondary education has a positive effect in reducing poverty, but the risk remains high in the presence of material deprivation and disadvantaged housing conditions.

While urban areas show some commonalities in educational and employment-related determinants of poverty, suburban regions reveal more heterogeneous and context-dependent patterns.

Figure 1 Maps of Poverty Risk Rate in Europe for different degree of urbanisation.

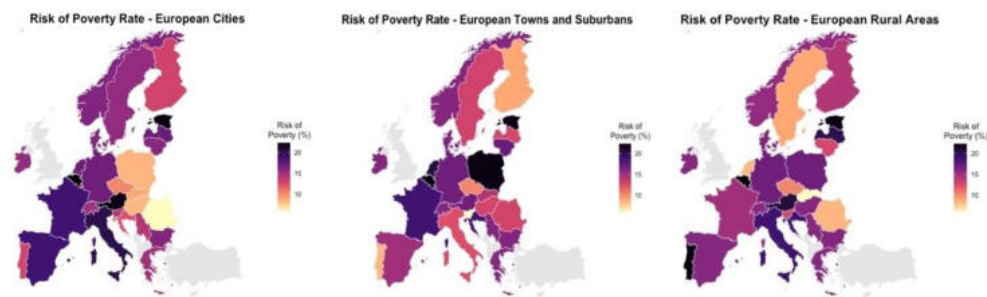


Figure 2 - Elbow plot.

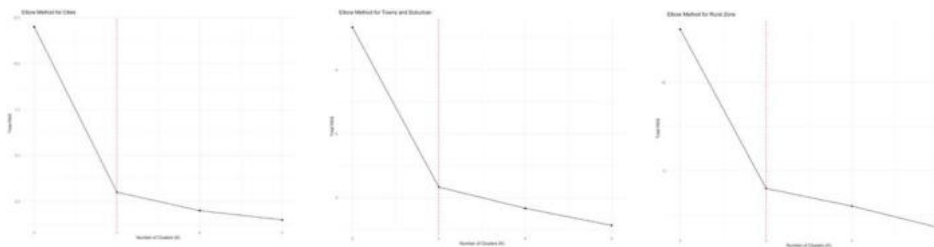


Figure 3 - Classification of European Regions for different urbanisation degree.

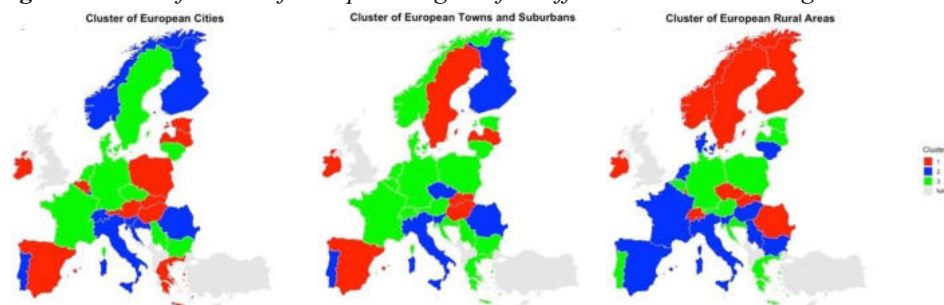


Table 2 – Coefficients for European Cities.

Variable	Cluster 1	Cluster 2	Cluster 3
Low Education	0.11	0.50	0
Education Rate	-0.23	0	-0.16
Low-Level Education Population	0	-0.11	-0.31
Medium-Level Education Population	0	0	-0.79
High-Level Education Population	0	0	0
Employment Rate	0	0	0
NEETs 15-24	0	0	0
NEETs 25-34	0.44	0	0.01
Youth Employment (Level 3-4)	-0.67	0	-0.05
Youth Employment (Level 5-8)	0	-0.06	0
Housing Cost Overburden	0	0	0
Median Income	0	0	0
Severe Material Deprivation	0	0.28	0.29
High Income Share	0	-0.05	0
Under-occupied Housing	0	0	0.05
Part-Time Employment (Level 0-2)	0	0	0
Part-Time Employment (Level 3-4)	0	0	0
Part-Time Employment (Level 5-8)	-0.39	-0.05	0
Self-Employed Percentage	-0.47	-0.19	0
Unemployment Rate 15-64	0.08	0	0

Table 3 shows the coefficients from the Clusterwise Lasso model for European towns and suburbs, grouped into three clusters by socio-economic traits.

In Cluster 1, the risk of poverty increases in the presence of young NEETs, high housing costs, and under-occupation of the home, while youth employment acts as a positive factor in reducing poverty. In Cluster 2, vulnerability is associated with low education, NEETs, and unemployment, while higher levels of education and higher employment contribute to reducing the risk. In Cluster 3, there is a high level of vulnerability linked to NEETs, housing costs, and labor market fragility, which is only partially offset by positive factors such as tertiary education, self-employment, and a higher proportion of high incomes.

Compared to urban and suburban areas, rural regions tend to exhibit more structural constraints, including lower service availability and more persistent unemployment. Table 4 reports coefficients from the Clusterwise Lasso model for rural areas, divided into three clusters.

Table 3 – *Coefficients for European Towns and Suburbs.*

Variable	Cluster 1	Cluster 2	Cluster 3
Low Education	0	0.22	0
Education Rate	-0.18	0	0
Low-Level Education Population	0	0	0
Medium-Level Education Population	0	0	0
High-Level Education Population	0	-0.28	-0.10
Employment Rate	0	-0.10	-0.07
NEETs 15-24	0.21	0	0.35
NEETs 25-34	0	0.15	0.28
Youth Employment (Level 3-4)	0	0	0
Youth Employment (Level 5-8)	-0.06	0	-0.15
Housing Cost Overburden	0.23	0	0.35
Median Income	0	0	0
Severe Material Deprivation	0	0	0
High Income Share	0	0	-0.09
Under-occupied Housing	0.20	0	0
Part-Time Employment (Level 0-2)	0	0	0
Part-Time Employment (Level 3-4)	0	0	0
Part-Time Employment (Level 5-8)	0	0	0
Self-Employed Percentage	0	-0.15	-0.22
Unemployment Rate 15-64	0	0.22	0

In Cluster 1, the presence of young NEETs and under-occupation of housing increase the risk of poverty, while higher average incomes, education, and youth employment play a positive role in reducing poverty. In Cluster 2, the risk increases in the presence of low education and adult NEETs, but is mitigated by youth employment, higher education, and a higher share of high incomes. In Cluster 3, the main negative determinants are material deprivation, housing costs, and unemployment, while education and overall employment remain positive variables.

In some clusters, the coefficient associated with the variable “Under-occupied Housing” shows a positive sign, which may appear counterintuitive. Rather than indicating improved living standards, this association can reflect structural inefficiencies in the housing stock or demographic imbalances.

As highlighted by Eurofound, in several post-communist and Southern European countries many households occupy relatively large dwellings that are energy-inefficient and costly to maintain, which can generate financial strain despite the apparent availability of space (Eurofound, 2023). Other studies further suggest that housing deprivation contributes to poverty even among households that appear well-off in terms of space but lack adequate quality or affordability (Hick *et al.*, 2022). These findings indicate that the positive sign of under-occupation in our results should be interpreted as a signal of latent housing-related vulnerabilities.

Nevertheless, we acknowledge that European indicators may not fully reflect local housing conditions.

Table 4 – Coefficients for European Rural Areas.

Variable	Cluster 1	Cluster 2	Cluster 3
Low Education	0	0.20	0
Education Rate	-0.19	0	-0.33
Low-Level Education Population	-0.07	0	0
Medium-Level Education Population	0	0	-0.07
High-Level Education Population	0	-0.04	0
Employment Rate	0	0	-0.14
NEETs 15-24	0.19	0	0
NEETs 25-34	0	0.20	0
Youth Employment (Level 3-4)	0	0	0
Youth Employment (Level 5-8)	-0.11	-0.44	0
Housing Cost Overburden	0.04	0	0.09
Median Income	-0.37	0	0
Severe Material Deprivation	0	0	0.32
High Income Share	0	-0.22	0
Under-occupied Housing	0.65	0	0
Part-Time Employment (Level 0-2)	0	0	0
Part-Time Employment (Level 3-4)	0	-0.18	0
Part-Time Employment (Level 5-8)	0	0	0
Self-Employed Percentage	0	0	0
Unemployment Rate 15-64	0.18	0	0.30

5. Limitations and Future Research

While the proposed methodology captures spatial heterogeneity and improves model interpretability, it has some limitations. The cross-sectional nature for 2023 data limits temporal inference; future work could explore dynamic clustering or longitudinal extensions. In addition, supplementing the statistical analysis with case studies or qualitative data may offer additional insights.

Another limitation is the potential endogeneity of some explanatory variables, which may generate reverse causality; addressing this issue would require causal inference or instrumental variable approaches in future research.

6. Conclusion

This work demonstrates the effectiveness of Clusterwise Lasso Regression in analyzing spatial inequalities in poverty risk across urban, suburban, and rural areas in Europe. The results reveal significant spatial heterogeneity: different area types show distinct socio-economic profiles and sensitivities to key variables such as education, youth employment, NEET rates, and housing conditions. By combining clustering and regularized regression, the method captures latent structures and

enables the identification of context-specific predictors, highlighting the limits of uniform modelling approaches to poverty analysis.

The findings support the design of differentiated, evidence-based policies aligned with the principles of the European Pillar of Social Rights³ and the EU's cohesion policy framework⁴. For instance, urban areas may benefit from actions supported by the European Social Fund Plus⁵ (ESF+) aimed at improving access to education, promoting youth employment, and enhancing social inclusion. In contrast, rural and peripheral regions—where infrastructure gaps and material deprivation are more pronounced—could be targeted through place-based interventions financed by instruments like the Just Transition Fund⁶ or the European Regional Development Fund (ERDF), including investments in mobility, broadband access, and support for sustainable local economies. The proposed analytical framework can support policymakers in designing tailored interventions. These should account for the structural characteristics of each territory.

Future developments may include the adoption of non-linear modelling approaches, the temporal extension of the analysis to capture trends and dynamics, and the integration of spatial methods to account for geographical interdependencies and regional spillover effects.

References

- BAGIROV A. M., MAHMOOD A., BARTON A. 2017. Prediction of monthly rainfall in Victoria, Australia: Clusterwise linear regression approach. *Atmospheric research*, Vol. 188, pp. 20-29.
- COPUS A., MELO P. C., KAUP S., TAGAI G., ARTELARIS P. 2015. Regional poverty mapping in Europe—Challenges, advances, benefits and limitations. *Local Economy*, Vol.30, No. 7, pp. 742-764.
- CHIRCOP D., MÜLLER K., NAVARRA C., PASIKOWSKA-SCHNASS M. 2022. *EU welfare systems and the challenges of poverty and inequality*.
- EUROFOUND. 2023. *Unaffordable and inadequate housing in Europe*, Publications Office of the European Union, Luxembourg.
- EUROSTAT. 2021. Glossary: At risk of poverty or social exclusion (AROPE).
- EUROSTAT. 2024. Latest developments in income dynamics and poverty.
- EUROSTAT. 2025. Living conditions in Europe - poverty and social exclusion.

³ https://ec.europa.eu/regional_policy/funding/erdf_en

⁴ <https://www.eib.org/en/projects/topics/regionaldevelopment/index#:~:text=The%20European%20Union's%20Cohesion%20Policy,and%20finance%20cohesion%20throughout%20Europe.>

⁵ <https://commission.europa.eu/funding-tenders/find-funding/eu-funding-programmes/european-social-funden>

⁶ https://commission.europa.eu/funding-tenders/find-funding/eu-funding-programmes/just-transition-fund_en

- GANJIGATTI J. P., PRATIHAR D. K., 2007. Global versus cluster-wise regression analyses *Journal of materials processing technology*, Vol. 189, No.1-3, pp. 352-366.
- HASTIE T. 2009. *The elements of statistical learning: data mining, inference, and prediction*.
- HICK R., POMATI M., STEPHENS M. 2022. Severe housing deprivation in the European Union: A joint analysis of measurement and theory. *Social Indicators Research*, Vol. 164, No. 3, pp. 1271-1295.
- KARMITSA N., TAHERI S., BAGIROV A., MAKINEN P. 2020. Missing value imputation via clusterwise linear regression. *IEEE Transactions on Knowledge and Data Engineering*, Vol. 34, No. 4, pp. 1889-1901.
- KHADKA M., PAZ A. 2017. Comprehensive clusterwise linear regression for pavement management systems. *Journal of Transportation Engineering, Part B: Pavements*, Vol. 143, No. 4.
- OPENSHAW S. 1977. A geographical solution to scale and aggregation problems in region-building, partitioning and spatial modelling. *Transactions of the institute of british geographers*, pp. 459-472.
- POGGI J. M., PORTIER B. 2011. PM10 forecasting using clusterwise regression. *Atmospheric Environment*, Vol. 45, No. 38, pp. 7005-7014.
- RELUGA K., KONG D., RANJBAR S., SALVATI N., VAN DER LAAN M. 2025. The impact of job stability on monetary poverty in Italy: causal small area estimation.
- RENAHY E., MITCHELL C., MOLNAR A., MUNTANER C., NG E., ALI F., O'CAMPO P. 2018. Connections between unemployment insurance, poverty and health: a systematic review. *The European Journal of Public Health*.
- ROBERTS S., NOWAK G. 2014. Stabilizing the lasso against cross-validation variability. *Computational Statistics & Data Analysis*, Vol. 70, pp.198-211.
- SERBAN A. M., BRAZIENÈ R. 2021. *Young People in Rural Areas: Diverse, Ignored and Unfulfilled*.
- SPATH H. 1979. Algorithm 39 Clusterwise linear regression. *Computing*. Vol. 22.
- SPATH H. 1982. A fast algorithm for clusterwise linear regression. *Computing*. Vol. 29.

Simona CAFIERI, Istat, cafieri@istat.it

Gianmarco BORRATA, Università Federico II, gianmarco.borrata@unina.it

A MACHINE LEARNING APPROACH FOR THE ANALYSIS OF DEMOGRAPHIC FEATURES OF THE SOCIO-ECONOMIC DEPRIVATION AT SUB-MUNICIPAL LEVEL

Matilde Bonelli, Giancarlo Carbonetti, Elena Grimaccia, Debora Tronu

Abstract. This study provides a machine learning analysis of the social and demographic features of territories, associated with different levels of deprivation, measured by the Socio-Economic Deprivation Index (SED-I). The SED-I has been developed by the Italian National Institute of Statistics (Istat) and is aimed at measuring socio-economic and educational deprivation at sub-municipal level. In this paper, we exploit the availability of socio-economic indicators and demographic context variables at Sub-Municipal Areas (SMAs) level to provide useful information for policies aimed at contrasting the economic, social, and educational deprivation as measured by the SED-I. In the context of socio-economic deprivation, territories may be characterised by a variety of interrelated variables: indicators related to the level of education in the area, employment, household structure, demographic composition referring to population density, foreign subpopulations, and age, and finally, social conditions, are employed in the analysis. Principal Component Analysis (PCA) is employed to summarise the information contained in this large number of correlated indicators. This unsupervised learning method allows us to analyse the relationships among these variables and the SED-I, pointing out the differences between two different socio-economic environments such as Trieste and Cagliari. Furthermore, a K-means cluster analysis is employed to identify population groups with similar composition in relation to deprivation and demographic features. In the K-means cluster analysis, Elbow and Silhouette methods are used to choose the optimal number of clusters. The analysis is carried out focusing on Trieste and Cagliari data, to provide a robust application on different socio-economic contexts.

1. Introduction

The measurement of socio-economic deprivation at a detailed spatial level is increasingly recognised in the literature as essential for the design of effective and equitable public policies. Spatial analyses conducted on very fine territorial levels allow the identification of localised areas of deprivation that are often hidden by larger aggregates (Allik *et al.*, 2016). High levels of detail enable targeted interventions that address the specific needs of the most vulnerable populations, improving resource allocation and reducing social inequalities. Moreover, granular data increases the ability to monitor policy impacts over time and adjust strategies

dynamically. The approach is in line with the growing emphasis on evidence-based and place-based policy making.

This study analyses Sub-Municipal Areas (SMA): areas defined by municipalities for functional, administrative, or statistical purposes. Principal Component Analysis (PCA) is employed to summarise the information contained in many correlated indicators. In the context of socio-economic deprivation, SMAs may be characterised by a variety of interrelated features such as the level of education in the area, employment, households' composition, population's citizenship and age and access to services. This unsupervised learning method allows us to analyse the relationships among these variables and between territorial features and deprivation, measured by the Socio-Economic Deprivation Index (SED-I). The SED-I has been developed by the Italian National Institute of Statistics (Istat) to provide a measure of socio-economic and educational deprivation at sub-municipal level (Carbonetti *et al.*, 2025a; Carbonetti *et al.*, 2025b). Results obtained applying the methodology to Trieste and Cagliari have been compared.

This paper aims at answering the following research questions: first, we aim at identifying how social deprivation, measured by the SED-I, is associated to the main demographic, social and economic features of SMAs; furthermore, we classify SMAs according to these features; and finally, we can identify the most vulnerable areas, where to target policies.

To identify groups of territorial units that share similar socio-economic profiles, a K-means cluster analysis is applied. This unsupervised learning method provides homogeneous but mutually distinct clusters based on their values on the SED-I and related variables. Identifying sub-municipal areas with similar deprivation's patterns can be grouped for tailored policy design, thus improving the efficiency of resource allocation.

Together, these ML techniques allow for a comprehensive, flexible, and evidence-based analysis of socio-economic features of deprived areas. Their combined use enhances the interpretability of complex data structures and provides a solid foundation for informed decision-making at different territorial scales.

Following this brief introduction, the second chapter presents the data used in the study, and more specifically the indicators used and the correlations among demographic features available at local level. In the third chapter, we will detail the statistical and machine learning methods employed to address our research objectives. Chapter four presents and interprets the results, explaining how these findings can inform the development of effective policies that consider the fragmentation of the Italian territory and its diverse needs. Finally, some conclusions are drawn.

2. Data

This study analyses the demographic features of the territories, associated with different levels of deprivation, with a focus on the most vulnerable areas of two municipalities, Trieste, and Cagliari. As part of the project, launched by the Italian National Institute of Statistics (Istat) and aimed at measuring the socio-economic deprivation of individuals and households at the sub-municipal level, the most critical areas are identified using the Socio-Economic Deprivation Index (SED-I), a composite index which measures household and individual deprivation as a tangible condition of hardship, as distinct from simple exposure to risk¹. The definition of deprivation used is: *“a condition in which households and individuals experience difficulties in adequately meeting their basic needs due to insufficient economic, employment, educational and social resources and opportunities”*.

After a careful experimental phase (Carbonetti *et al.*, 2025a; Carbonetti *et al.*, 2025b), the following nine individual indicators were identified as manifest variables composing the SED-I, using census, administrative sources, and thematic registers, to measure – with accurate, integrated, and geocoded data – the different components of deprivation at the sub-municipal level:

- Economic deprivation: % of individuals aged 70 and over living alone and not owning a home; % of individuals in households in which no member is employed or receiving a pension from work; % of individuals in low equivalised income households.
- Occupational deprivation: Employment rate 25-64 years old (with negative polarity); % of individuals aged 0-64 living in households with very low work intensity; % of employed persons aged 25-64 “not stable” during the year.
- Educational deprivation: % of individuals aged 25-64 without upper secondary school education; % of individuals aged 15-29 who are not employed and are not enrolled in any regular course of study; % of students dropping out or repeating the year.

These indicators are normalised and aggregated with equal weight using the Adjusted Mazziotta-Pareto Index (AMPI) methodology, which produces a non-compensatory composite index based on not fully substitutable of individual indicators and on non-linear function (Mazziotta and Pareto, 2016; Mazziotta and Pareto, 2017). Here are the main conceptual aspects: the normalization method (Constrained Min-Max Method) of individual indicators allows the comparison of values of statistical units, both in space and time, against a common reference that

¹ Istat already produces an indicator which measures social and material vulnerability of the population. The Social and Material Vulnerability Index measures the exposure of some population groups to situations of risk, such as uncertainty of their social and economic condition (Istat, 2020).

does not change over time; the aggregation function is an average penalised by a variance function that avoids the “compensation effect” typical of linear functions.

Data normalisation is based on a transformation of the individual indicators with respect to two values, referred to as goalposts, sets a statistical unit of reference equal to 100 at a base year. The values obtained fall roughly in the range (70:130), where 100 represents the reference figure.

In this study, SED-I is calculated for Sub-Municipal Areas (SMAs). As the baseline used in the calculation is the value of the individual indicators calculated at municipal level (set equal to 100), the values of SED-I are not comparable between different municipalities.

To study the socio-demographic characteristics of the population living in the most deprived areas, a specific set of indicators has been employed, deriving data mainly from census results (Table 1).

Table 1 – *Socio-demographic indicators used in the analysis.*

Individual indicator	Sources
4 Population Density (population/area)	PPHC
5 Size of households (population/households)	PPHC
6 Foreigners (% as a share of total population)	PPHC
7 Employment rate (15+ years old)	PPHC
8 Young people (0-24) (% as a share of the total population)	PPHC
9 Elderly (65+) (% as a share of the total population)	PPHC
10 Students (% as a share of the total population)	PPHC
11 M/F ratio	PPHC
12 Youth (0-24)/Elderly (65+) ratio	PPHC
14 Foreigners 65+ years old (% as a share of the total foreigners)	PPHC
15 One-person households (% out of total households)	PPHC
16 Households with 5 or more members (% out of total households)	PPHC
17 University graduates aged 25-64 (% of the population aged 25-64)	PPHC
18 Replacement rate (pop. 20-24/pop. 60-64 ratio)	PPHC
19 Individuals in households benefiting from social exclusion transfers (% as a share of the total population)	PPHC Income Register

Sources: Istat, *Permanent Population and Housing Census (PPHC)* and *Income Register*. Reference year: 2021.

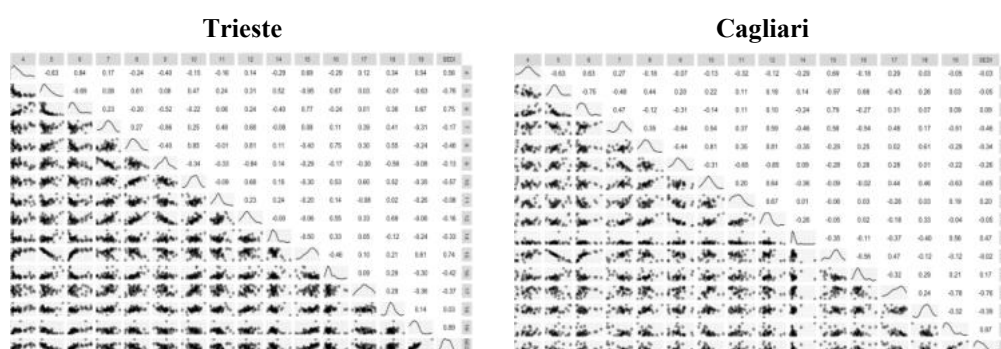
The analysis presented in this paper is focused on Trieste and Cagliari, two municipalities with very different socio-economic conditions and, therefore, needing distinct policies, adapted to their specific context. Both municipalities have a population characterised by a high share of elderly people and one-person households. However, Trieste stands out for its higher number of foreign residents and a more solid employment structure, accompanied by better household economic conditions. In contrast, Cagliari has a lower employment rate and greater economic vulnerability, while its adult population is more educated than that of Trieste.

These differences are confirmed also by the correlation analysis of the indicators used in this study (Figure 1). The correlation matrices of the two municipalities show

greater differences in the interrelationships between the employment rate and other socio-demographic variables. In both contexts, employment rates are negatively correlated with the share of elderly population and, to a lesser extent and positive correlated with the proportion of graduates. More marked differences emerge about citizenship and household size. Specifically, in Cagliari, the employment rate shows negative correlations with both the share of families with 5 or more members and the share of foreign residents and positive correlation with a one-person households (as % of total households), whereas such relationships are not observed in Trieste. This suggests that, in Cagliari, lower employment levels are associated with the presence of foreign citizens and larger households, while in Trieste employment levels appear to be mainly influenced by the age structure and the educational attainment of the population. with the proportion of graduates. More marked differences emerge regarding citizenship and household size. Specifically, in Cagliari, the employment rate shows negative correlations with both the share of families with 5 or more members and the share of foreign residents, whereas such relationships are not observed in Trieste. This suggests that, in Cagliari, lower employment levels are associated with the presence of foreign citizens and larger households, while in Trieste employment levels appear to be mainly influenced by the age structure and the educational level of the population.

The analysis of the correlation among SED-I and the other indicators highlights, for both municipalities, a higher positive correlation with individuals in households benefiting from social exclusion transfers. For Trieste, SED-I also shows a strong positive relationship with the share of foreigners and one-person households. For Cagliari, there is a strong negative correlation between SED-I and the share of students (as a percentage of the total population) as well as university graduates aged 25–64 (as a percentage of the population aged 25–64).

Figure 1 – Correlation of indicators (Istat, 2021).



3. Methods

To achieve the goals of our analysis we have adopted two unsupervised machine learning approaches. The first unsupervised machine learning technique we have employed is the Principal Component Analysis (PCA), which is able to identify a smaller number of representative variables that explain most of the variability of the original dataset, composed of a set of correlated variables (James *et al.*, 2021). We have used this technique to make an unsupervised exploration of the dataset, which includes the SED-I and the set of socio-demographic variables shown in table 1, for the two municipalities under study. The basic idea of performing PCA is that each of our n observations lies in a p -dimensional space, and we are seeking a smaller number of dimensions to represent them, which are the principal components. We are now interested in knowing the *cumulative proportion of variance explained* (PVE) by the first M principal components (PC), determined by the procedure. For the purpose of PCA we use this quantity to decide how many principal components to retain among all those resulting from the totals, which in general are the $\min(n-1, p)$ considering our matrix X with dimension $(n \times p)$. A direct tool that we have used is the analysis of the scree plot, where we look for the point at which the curve connecting the PVE across each subsequent PC creates an elbow.

The K-Means cluster method is framed among the unsupervised machine learning techniques and has the aim of finding partitions of the dataset under study with similar values, which are called clusters. Silhouette and Elbow methods have been used to find the optimal number of clusters. The K-means method involves the computation of the within-cluster variation, which summed over all K-clusters must be as small as possible (James *et al.*, 2021). In this paper, we employ the K-Means R-Function, using the Hartigan-Wong algorithm (1979), with squared Euclidean distance to measure similarity between observations. By default, it starts by randomly selecting a set of observations as the initial cluster centres and then iteratively reassigns points and updates centres to minimize the within-cluster sum of squares. This process continues until no further improvement is possible, producing the final cluster assignments and centroids.

4. Results

To predict the Socio-Economic Deprivation Index (SED-I) in the municipality of Trieste and Cagliari, based on our set of demographic contextual features, we have applied machine learning techniques, as presented in the previous Section. Here, we illustrate which demographic characteristics are most related to the SED-I according

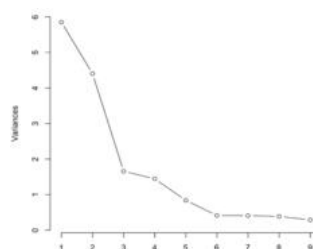
to our study. For both municipalities, the SED-I and the set of demographic contextual variables have been included in the computation, after being standardized.

Results of the PCA show that the “Individuals in households benefiting from social exclusion transfers (as a share of the total population)” feature plays a key role in the level of deprivation. Despite this important common feature, Trieste and Cagliari display different characteristics in their principal components.

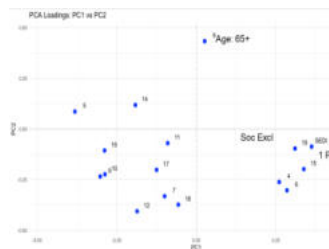
For Trieste, the first three principal components (PCs) are analysed (Figure 2), as they together explain 74.5% of the total variance. The first PC is determined by the SED-I, the households’ size feature (one-person households as a % out of total households) and by the share of individuals in households benefiting from social exclusion transfers (as a percentage of the total population). The second PC is defined by the age composition of the population: the variable representing the highest loading is the share of elderly population (65+ years old) as a % of the total population. The third PC is mainly explained by the employment rate (15+ years old) and by the sex composition of the population (M/F ratio).

Figure 2– PCA results for Trieste (Istat, 2021).

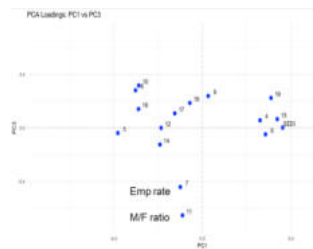
A. PCA scree plot



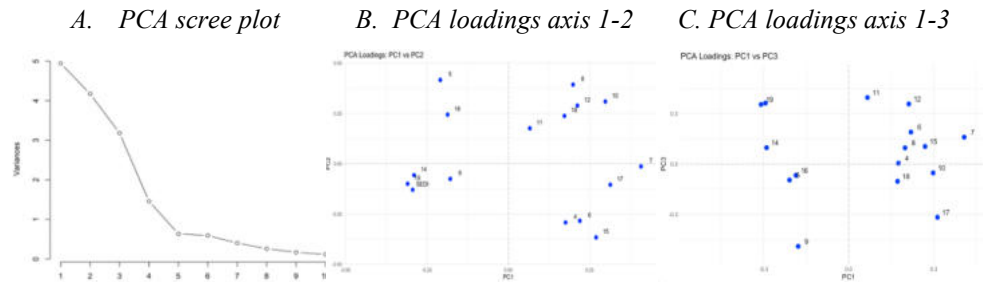
B. PCA loadings axis 1-2



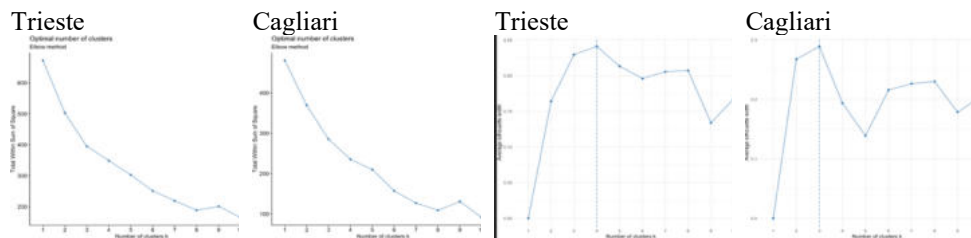
C. PCA loadings axis 1-3



For Cagliari, the first three principal components (PCs) are presented as well since they together explain 76.8% of the total variance (Figure 3). The first PC is determined by the employment rate (15+ years old) and by university graduates aged 25-64 (% of the population aged 25-64), therefore both variables refer to the socio-economic condition. The second PC is defined by household and age compositions: size of households (population/households) and young people (0-24 years old) as a % of the total population. The third PC is characterized by sex and age compositions: M/F ratio and elderly (65+ years old) as a % of the total population.

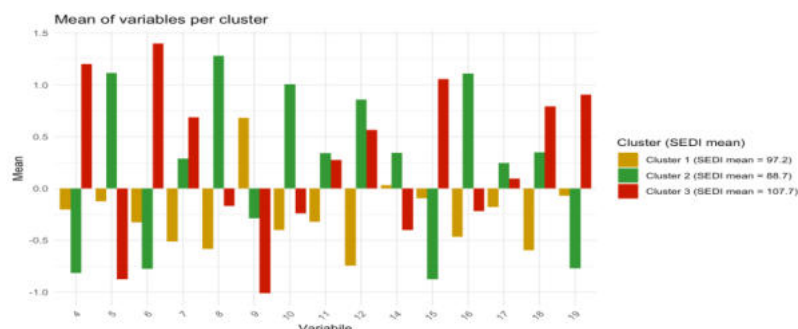
Figure 3 – PCA results for Cagliari (Istat, 2021).

These differences in PCA structures between Trieste and Cagliari reflect structural socio-economic divergences in the two municipalities, as described in Section 2. In this regard, the following K-Means cluster analysis shows similarities and differences among SMAs, separately for Trieste e Cagliari. For both municipalities, the number of optimal clusters have been selected equal to three using the Silhouette and the Elbow Method (James *et al.*, 2021) as shown in Figure 4.

Figure 4 - Elbow and Silhouette methods for Trieste and Cagliari.

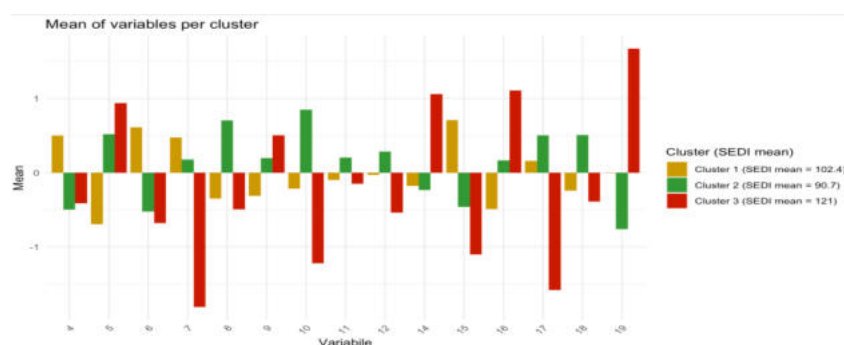
For both municipalities the SED-I and the set of contextual demographic variables have been included in the computation, after being standardized. The results of the K-Means cluster analysis for the municipality of Trieste have identified cluster number 3 as the most vulnerable cluster as it is characterised by districts with a higher average value of the SED-I.

Figure 5 shows the averages values for each variable in the different clusters. The variables are standardized to make meaningful comparison of the differences between cluster 1, 2 and 3 (the most vulnerable one). The latter is characterized by higher values of population density (population/area), foreigners (% as a share of the total population), one-person households and individuals in households benefiting from social exclusion transfers; on the other hand, is also characterised by a lower value of elderly (65+ years old) as a % of the total population.

Figure 5 – *K-Means cluster analysis of Trieste (Istat, 2021).*

The results of the K-Means cluster analysis for the municipality of Cagliari have also identified cluster number 3 as the most vulnerable cluster as it is characterised by SMAs with a higher average value of the SED-I. In fact, the characterisation of this cluster is different, compared to the first and the second cluster (Figure 6), because it is characterised by lower values of employment rate (15+ years old), student % as a share of population, university graduates aged 25-64 (% of the population aged 25-64), one-person households and foreigners (% as a share of the total population).

On the other hand, the third and more deprived cluster is characterized by higher values of households with 5 or more members (% out of total households) and foreigners 65+ years old (% as a share of the total foreigners). Finally, this cluster, like what observed for Trieste, has a higher value of individuals in households benefiting from social exclusion transfers (% as a share of the total population).

Figure 6 – *K-means cluster analysis of Cagliari (Istat, 2021).*

Figures 7 and 8 show the maps of the two municipalities under analysis, in which the SMA are categorised on the left with the SED-I and on the right with the assignment to the clusters we obtained in our analysis. We notice that the classification of socio-economic deprivation by SMA is quite similar with both methods, except for one SMA of Cagliari (“Mulinu Becciu”) which has very different socio-demographic characteristics from the others. This SMA is in fact characterized by the higher share of elderly people (65+ years old), lower employment and education levels, but it also shows good economic conditions.

Figure 7 – Comparison of the level of deprivation of Trieste (Istat, 2021).

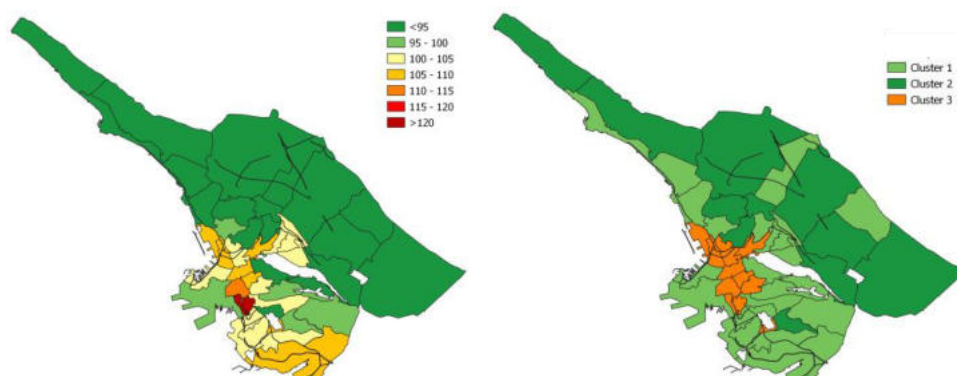
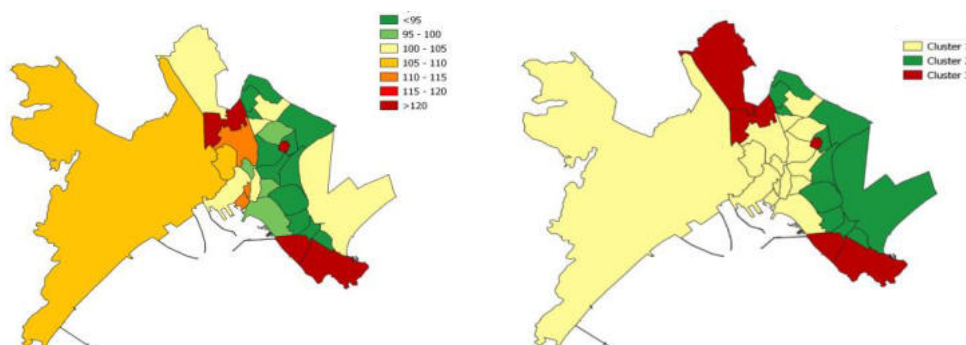


Figure 8 – Comparison of the level of deprivation of Cagliari (Istat, 2021).



This paper presents the first attempt to classify different sub-municipal areas with the same methodology. However, some previous information is available for Cagliari (Istat, 2024), and our results align and extend them.

5. Conclusions

This analysis offers a detailed characterization of deprived areas across the two municipalities of Trieste and Cagliari, highlighting distinct socio-demographic patterns. In Trieste, deprivation – as measured by the Social and Economic Deprivation Index (SED-I) – is primarily social in nature. It is closely linked to a significant share of people living alone and the presence of foreign populations. In contrast, deprivation in Cagliari is more strongly associated with economic hardship and lower educational attainment, indicating structural challenges related to employment and human capital development. These differences underscore the importance of tailoring local interventions to the specific profiles of vulnerability within each area.

The analysis was enhanced through the application of two machine learning methodologies: Principal Component analysis and K-means cluster analysis. The first enabled the identification of the most influential variables associated with the SED-I, highlighting the central role of social exclusion transfers, education, and demographic characteristics in shaping vulnerability. K-means clustering allowed us to group municipalities into internally homogeneous clusters, uncovering latent patterns in the data and enabling a differentiated interpretation of local vulnerability dynamics. The findings are robust across different methodologies and geographic contexts and offer useful evidence to support targeted policy interventions. In particular, the consistent association between high deprivation and social exclusion transfers, as well as the protective effects of employment, education, and youth presence, provide actionable insights for designing effective, place-based social and economic strategies.

References

- ALLIK M., BROWN D., DUNDAS R., LEYLAND A. H. 2016. Developing a new small area measure of deprivation using 2001 and 2011 census data from Scotland. *Health & Place*, Vol. 39, pp. 122–130.
- CARBONETTI G., BIASCIUCCI F., CUTILLO A., MAZZIOTTA M., QUONDAMSTEFANO V., TAMBURRANO M.T., TRONU D. 2025a. Measuring socio-economic deprivation at sub-municipal level through the integration of census and administrative data. *Italian Journal of Economic, Demographic and Statistical Studies – RIEDS*, Vol. LXXIX No.1 Gennaio-Marzo 2025.
- CARBONETTI G., BIASCIUCCI F., CUTILLO A., MAZZIOTTA M., QUONDAMSTEFANO V., TRONU D. 2025b. An innovative approach for the analysis of socio-economic phenomena at sub-municipal level: the household

- deprivation study project. Data, Statistics and AI for Well-Being of People and Organizations. *Book of Short Papers of the ASA Rome Conference*, pp. 121-126. Padua: Cleup. <https://doi.org/10.26398/asaproc.0090>
- HARTIGAN J. A., WONG M. A. 1979. A K-Means Clustering Algorithm, *Journal of the Royal Statistical Society Series C: Applied Statistics*, Vol. 28, Issue 1, March 1979, pp. 100–108.
- ISTITUTO NAZIONALE DI STATISTICA 2024. *Sicurezza e stato di degrado delle città e delle loro periferie, Audizione presso la Commissione parlamentare di inchiesta sulle condizioni di sicurezza e sullo stato di degrado delle città e delle loro periferie*, 26 giugno 2024, Istat, Roma, 2024.
- ISTITUTO NAZIONALE DI STATISTICA 2020. *Le misure della vulnerabilità: un'applicazione a diversi ambiti territoriali*, Istat, Roma, 2020.
- JAMES, G., WITTEN, D., HASTIE, T., TIBSHIRANI, R. 2021. Unsupervised Learning. In: *An Introduction to Statistical Learning*. Springer Texts in Statistics. Springer, New York, NY.
- MAZZIOTTA M., PARETO A. 2017. Synthesis of indicators: the composite indicators approach. In Maggino F. (Ed.) *Complexity in Society: From Indicators Construction to their Synthesis. Social Indicators Research Series.*, Springer, pp.159-191.
- MAZZIOTTA M., PARETO A. 2016. On a Generalized Non-compensatory Composite Index for Measuring Socio-economic Phenomena. *Social Indicators Research*, Vol. 127, No. 3, pp. 983-1003.

Matilde BONELLI, University of Bologna, matilde.bonelli@studio.unibo.it
Giancarlo CARBONETTI, Istat, carbonet@istat.it
Elena GRIMACCIA, Istat, elgrimac@istat.it
Debora TRONU, Istat, tronu@istat.it

EMPLOYMENT PATTERNS BEFORE AND AFTER CHILDBIRTH IN ITALY: A COUNTERFACTUAL STUDY USING ADMINISTRATIVE DATA¹

Gianni Corsetti, Sara Gigante, Anita Guelfi, Valentina Talucci

Abstract. This paper investigates the labour market dynamics of parents in Italy, focusing on the impact of motherhood on employment conditions before and after childbirth. Using linked administrative data from the Basic Registry of Individuals (RBI) and the Annual register on earnings, working hours and labour cost for persons and enterprises (RACLI), we analyse a population of parents with children born in 2019 who were employed in the private, non-agricultural sector.

Adopting a longitudinal and counterfactual approach, we track employment trajectories one year before and three years after childbirth, comparing parents with non-parents to isolate the effect of motherhood on labour market participation.

Preliminary results reveal a process of "selection into parenthood," whereby women who become mothers tend to already have a more stable and advantageously compensated work profile before the child's birth.

The study also examines wage differentials and access to support measures such as parental leave. In summary, the research offers a detailed perspective on how job stability influences reproductive decisions and how labor market inequalities impact women's careers during a critical life transition in contemporary Italy.

1. Research objectives

This study adopts a counterfactual approach to examine the impact of motherhood on women's occupational trajectories and conditions, using integrated population-based administrative data. Rather than addressing demographic decline broadly, the research focuses on a specific question: how childbirth affects employment patterns across different family structures, nationalities, and labour market positions.

The main objective is to profile individuals—Italian and foreign nationals—who entered parenthood, analysing their employment conditions before and after childbirth. Key labour market indicators include wage differentials, access to income

¹ Gianni Corsetti (Section 3.1); Sara Gigante (Section 4); Gianni Corsetti e Sara Gigante (Section 3.2); Anita Guelfi (Section 1); Valentina Talucci (Section 2); tutti gli autori? (Section 5)

support measures (such as the Wage Guarantee Fund, Cassa Integrazione Guadagni), parental leave uptake, and other relevant variables.

The analysis is anchored in 2019, chosen as the baseline year to assess the interplay between fertility, labour market participation, and external shocks. The study relies on the Basic Registry of Individuals (RBI) to identify parents of children born in 2019, who are then linked to the Annual register on earnings, working hours and labour cost for persons and enterprises (RACLI). This defines the analytical universe: "parents of children born in 2019, employed in the private non-agricultural sector during that year."

2. Background and Context

Italy faces a persistent demographic challenge characterized by low fertility rates and aging population. The total fertility rate (TFR) has steadily declined since the post-war baby boom, reaching a provisional low of 1.18 children per woman in 2024 (Istat, 2024). This decline, combined with increased life expectancy, is reshaping the age structure, increasing the old-age dependency ratio and reducing the working-age population.

Female labour market participation remains low and uneven, influenced strongly by family responsibilities. In 2024, only 53.3% of women were employed compared to 71.1% of men, with a particularly low employment rate among women aged 25–34, where caring for young children often limits workforce engagement (Istat, 2025). This dynamic is central to understanding fertility decisions and labour market outcomes.

Overall, the intersection of low fertility and constrained female employment underscores the demographic and socioeconomic challenges Italy faces, setting the stage for this study's focused investigation.

Projections suggest a modest rise in fertility to 1.38 children per woman by 2050, with births peaking around 404,000 in 2038. Nevertheless, the number of women of childbearing age will continue to decline, while the population aged 65 and over is expected to grow significantly, reaching 34.5% by 2050. These trends will likely intensify demographic and labour market challenges, particularly concerning the balance between dependent and working-age populations.

3. Empirical Strategy

3.1. Data

As already mentioned in the introductory section, our data are derived from the Basic Registry of Individuals (RBI) and encompasses "parents of children born in 2019" as recorded in the Anvis system. This dataset has been integrated with the Annual register on earnings, working hours and labour cost for persons and enterprises (RACLI), thereby defining the population under study as "parents of children born in 2019, who were employed in the private, non-agricultural sector during the reference year."

The Basic Registry of Individuals, Families, and Cohabitations represents the unique reference for official statistics concerning permanent resident population, first of all for the permanent census and the demographic statistics. This registry is compiled annually through the integration of multiple administrative and statistical sources, including:

- the administrative archives within the Integrated Microdata System (SIM);
- the National Registry of Resident Population (ANPR);
- the Virtual Statistical Registry (ANVIS), which is continuously updated with microdata on demographic flows originating from the 2011 Census population;
- the Permanent Census, to identify over- and under-coverage within the registry.

To compute the annual demographic balance, the final RBI archive ensures internal consistency between the stock of permanent residents recorded at the beginning and end of the year and the demographic flow data documented in Anvis over the same period.

Variables within the RBI include demographic and socio-economic characteristics such as sex, date of birth, municipality of residence (usual and/or registered), place of birth, citizenship status, marital status, family and/or cohabitation arrangements, and educational attainment.

The Annual Registry on Earnings, Working Hours and Labour costs for persons and enterprises (RACLI) constitutes the employed workers' module of the Thematic Labour Registry, specifically covering the non-agricultural private sector. RACLI currently incorporates administrative sources related to the labour market and serves as an input for integrated statistical production.

Upon full implementation, the Thematic Labour Registry will encompass all job positions—both dependent and non-dependent—across public and private sectors, constituting a comprehensive microdata repository on employment and labour income. This database will facilitate statistical analyses at both individual and economic unit levels and serve as a source for producing additional registers.

The statistical unit of RACLI is the job position, defined as the contractual relationship between a worker and an employer that began on a starting date and is characterized, if the position has ended, by a termination date. The scope of observation includes dependent job positions within companies classified under the ASIA register and belonging to the non-agricultural private sector.

3.2. *Methods*

Our data integration relies on deterministic record linkage, employing a unique pseudonymized individual identifier to merge information from multiple administrative sources. Specifically, from approximately 420,000 births recorded in 2019 within Anvis, about 390,000 mothers and 358,000 fathers were successfully matched in the Basic Registry of Individuals (RBI). The unmatched subset—around 30,000 mothers—is primarily due to incomplete or missing parental data during integration into the Integrated Microdata System (SIM), as well as the recent implementation of municipal registry transfers to the National Registry of Resident Population (ANPR). Additionally, some parents were non-residents as of December 31, 2019, which affected linkage completeness.

By leveraging these linked administrative data and applying the counterfactual framework, this study aims to provide a refined and precise analysis of the impact of motherhood on women's employment trajectories, overcoming limitations of traditional survey-based approaches.

This study employs a counterfactual approach, a fundamental technique in causal inference within social sciences. The core idea is to compare observed outcomes—such as women's employment trajectories after childbirth—with hypothetical scenarios in which the “treatment,” namely motherhood, did not occur. This allows us to estimate the causal effect of motherhood on occupational trajectories and employment conditions by isolating its impact from other confounding factors. Since the counterfactual scenario is by definition unobservable, we approximate it using a combination of deterministic record linkage, longitudinal data, and comparative analyses between groups with different exposure statuses.

4. Results

This integrated database allows us to longitudinally track individuals' demographic and employment trajectories both before and after childbirth (see Section 3.1). For instance, in 2018, the year preceding childbirth, 43.9% of women who gave birth in 2019 held an active dependent employment position in the private, non-agricultural sector, which we define as having performed at least one hour of

paid work. We found that employment rates varied by household composition: 36.7% for mothers living in households with at least one minor child, versus a notably higher 51.7% for those in households without minors. Among women who did not have children in 2019, overall employment incidence was 38.2%, with a rate of 34.4% for those living with minors and 42.2% for those without.

This initial descriptive analysis, while subject to potential compositional effects and selection bias, highlights key distinctions between groups. It is crucial to acknowledge that, to ensure valid causal inference, these descriptive statistics must account for selection bias, as the two groups may not be inherently comparable, and confounding from spontaneous dynamics, where the outcome variable might change independently of the maternity event.

Women who became mothers in 2019 and were employed in the private sector showed a higher concentration in Italy's Center-North (74.3% vs. 63.9% of the total mother population) (Table 1).

Table 1 - Summary of the linkage outcome. Percentage values. Year 2018.

Characteristics	Total		Women with a position in the non-agricultural private sector	
	No child in 2019	At least one child in 2019	No child in 2019	At least one child in 2019
Geographic Area				
Center- North	65	63.9	77.3	74.3
South	35	36.1	22.7	25.7
Household Composition				
No minor	75	47.6	80.5	57.2
At least one minor	25	52.4	19.5	42.8
Age Group				
15-25 years old	17.1	7.8	14.3	9
25-35 years old	33.9	54.1	43.5	61.7
35-45 years old	36.8	36.9	36.2	28.8
45-55 years old	11.2	1.1	5.9	0.5
Education Level				
No degree	79.6	79.3	77.2	72.2
Degree	20.4	20.7	22.8	27.8
Position Type				
Non-full time, full-year position	-	-	79.3	73.1
At least one full-time, full-year position	-	-	20.7	26.9

Source: Authors' own calculations based on RBI/Anvis-RACLI data.

Furthermore, among employed mothers, the proportion with at least one minor child (42.8%) is significantly lower compared to the overall group of mothers (52.4%). This may indicate that stable dependent employment is more common for women having their first child, as the presence of multiple children could complicate

labor market participation. The age distribution is similar across both groups, though the 25-35 age bracket is more predominant among employed mothers. This suggests that the combination of work and motherhood is more frequent at younger, central reproductive ages.

Finally, our findings indicate that employed mothers exhibit a higher incidence of holding a university degree compared to the general population of mothers. This result underscores a strong correlation between higher educational attainment and a greater likelihood of having a stable, dependent employment position before childbirth.

In summary, the women who became mothers in 2019 and were employed in the private sector in 2018 present a more "advantageous" or "structured" profile. They are more concentrated in Italy's Centre-North, have a higher propensity to hold a university degree, and tend to have fewer children in the family unit compared to the general population of mothers.

To effectively isolate the causal effect of parenthood on women's labor market trajectories and attribute observed differences in employment outcomes to the parenthood event, we employed a robust methodological approach: counterfactual analysis. This approach minimizes confounding bias by comparing observed outcomes with a hypothetical scenario where the "treatment"—in this case, motherhood—did not occur (see Section 3.2.).

Specifically, we utilized a non-experimental design combined with a non-parametric matching technique (Marchesi et al., 2011; Morgan et al., 2007). This method, applied to our longitudinal data, allows us to approximate the unobservable counterfactual outcome and conduct comparative analyses between groups with different exposure statuses. To ensure methodological rigor and the robustness of our results, the analysis was structured into four distinct phases:

1. Identification of outcome variables: the initial phase involved defining key labour market indicators to capture dimensions of job quality and employment stability. Specifically, three sets of outcome measures were considered: (a) Differences in job quality indicators preceding the parenthood event, including employment termination rates, hourly wages, labour costs per paid hour, and the prevalence of fixed-term and part-time contracts; (b) Employment continuity, measured by the persistence of job positions throughout the five-year period, essential for understanding medium-term labour market stability; (c) Medium-term effects assessed by examining the same job quality indicators used in (1a) over a five-year observation window post-parenthood, providing insights into sustained employment impacts.
2. Identification of treatment group: this phase involved isolating the "treatment" cohort, defined as women who gave birth in 2019.

3. Selection of covariates for counterfactual construction: to construct an appropriate control group (counterfactual), pre-treatment covariates (X) were selected based on their relevance to labour market outcomes and worker characteristics. These variables were used to generate strata for matching, ensuring comparability between treated and control units. The variables included: (X1) Geographic region, capturing local labour market heterogeneity; (X2) Age categorized in ten-year intervals, to control for age-related labour market effects; (X3) Educational attainment (graduates versus no graduates), reflecting differences in employment prospects; (X4) Family status (presence of minors), representing the pre-parenthood household context; (X5) Country of birth (Italy versus abroad), accounting for origin-related labour market disparities; (X6) Presence of a full-time, full-year (*ffy*) dependent employment position in the year preceding childbirth, as a proxy for job stability and intensity before the parenthood event.
4. Matching Procedure: The final phase of our analysis implemented a rigorous 1:1 matching protocol. This process was designed to ensure the control group closely mirrored the treatment group across a set of selected, pre-defined characteristics. The matching was specifically applied to the population of women who held at least one dependent employment position in the non-agricultural private sector in 2018 and subsequently gave birth in 2019.

Thanks to these comprehensive data sources, we were able to select a control group that almost perfectly mirrors the treatment group across all pre-event characteristics. The differences in percentage points for key socio-demographic characteristics between the women who had a child in 2019 and the counterfactual group are all negligible (equal to zero).

The high quality of this outcome is directly attributable to the availability of administrative records and microdata on the entire population. This level of detail and coverage allows for a highly precise matching process. The minimal difference confirms that potential confounding factors present before motherhood have been successfully balanced between the two groups. This, in turn, allows researchers to confidently attribute any subsequent differences in labor market trajectories to the causal effect of motherhood.

After controlling for key socio-demographic characteristics—including age, educational attainment, geographic region, country of birth, and the presence of minors in the household—our analysis reveals that employed women who became mothers in 2019 had a distinctive profile in 2018, the year before they gave birth.

This pattern suggests a process of "selection into parenthood" or "sorting" within the labor market. These prospective mothers were already in a more stable position than their peers: they were more likely to hold permanent employment positions

(+4.6 percentage points) and experienced fewer instances of job activation (-5.2 percentage points) or termination (-0.6 percentage points) (Figure 1).

Furthermore, these women tended to work more hours (+14.3%) and consequently earned a higher annual remuneration (+13.7%) even before the childbirth event (Figure 2). This suggests that the women most likely to enter motherhood were those already in a stronger, more secure labor market position.

This pattern strongly confirms that job stability acts as a key determinant, facilitating reproductive choices among working women. These findings align with the hypothesis that employment security is a crucial factor in fertility decisions, corroborating prior literature emphasizing a positive association between job stability, improved economic conditions, and parenthood (Anderson & Pontusson 2007; Esser & Olsen 2012; Alderotti et al., 2021).

The continuity and security provided by a permanent employment relationship, along with a relatively high salary, likely furnish the necessary economic resources and psychological stability to navigate the challenges of motherhood, thereby mitigating both economic and professional uncertainty.

Figure 1 - Differences between incidences between study population and counterfactual in work quality indicators in the proximity of childbirth. Percentage points. Year 2018.

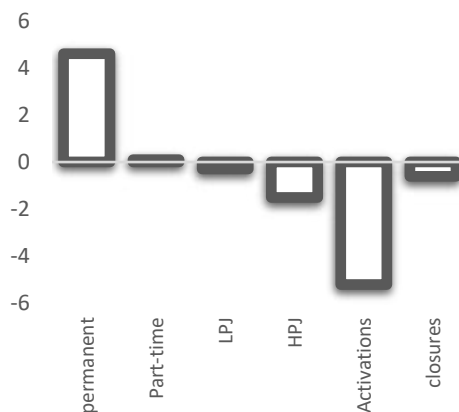
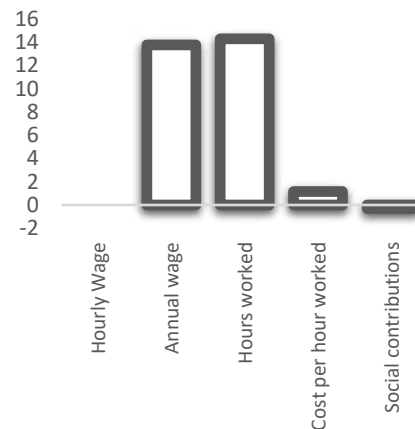


Figure 2 - Differences between median values (right) between study population and counterfactual in work quality indicators in the proximity of childbirth. Percentage values. Year 2018.

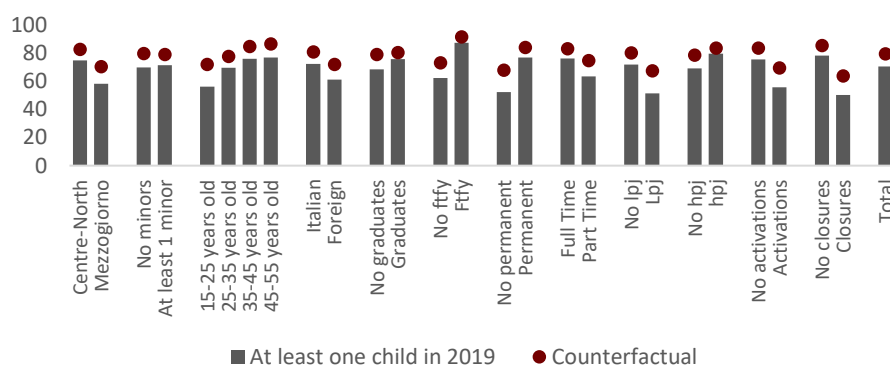


Source: Authors' own calculations based on RBI/Anvis-RACLI data.

Always controlling for initial socio-demographic and professional characteristics, employed women who gave birth in 2019 exhibited lower employment persistence in the non-agricultural private sector through 2022, compared to their childless counterparts. This pattern is particularly pronounced among younger women, those residing in Southern Italy, and individuals who, in 2018, held fixed-term or low pay jobs (Figure 3).

Such evidence aligns with the well-documented concept of the "motherhood penalty," which emphasizes the adverse effects of childbirth on the continuity and stability of maternal employment (Rosina, 2024; Freguja, Romano, Sabbadini, 2025).

Figure 3 - Share of female employees with an active job position in 2018 and 2022 in the non-agricultural private sector by characteristics observed in 2018.



Source: Authors' own calculations based on RBI/Anvis-RACLI data.

Moreover, among women who maintained active employment in the non-agricultural private sector both in 2018 and 2022, those who became mothers in 2019 women experience a lower growth in hourly remuneration (+5.5%) compared to their counterparts. The gap, however, becomes abysmal when considering total annual earnings (inclusive of income-replacement benefits), which grew by only +1.5% for mothers versus a substantial +27.0% for non-mothers. (Table 2). Notably, the diminished growth in annual wages appears largely driven by a reduction in hours worked (+19% vs -6%). This significant discrepancy is a direct consequence of the utilization of maternity and parental leave. While these periods of absence from work are legally protected and provide benefits, the allowances do not fully equate to a regular salary. As a result, the number of hours worked is reduced, leading to a corresponding negative impact on the total annual remuneration received. This highlights how the use of such benefits, while essential for family support, can

contribute to a significant "motherhood penalty" in career progression and lifetime earnings.

Table 2 – *Differences between median values in various indicators calculated on a longitudinal panel for the study and counterfactual populations (2022 vs. 2018). Percentage values. Years 2018 and 2022.*

	Counterfactual	At least one child in 2019
Annual gross earnings	+32.52%	-2.81%
Annual gross earnings (inclusive of allowances)	+26.98%	+1.53%
Hourly Wage	+8.00%	+5.48%
Hours worked	+18.88%	-8.67%
Hourly labor cost	+9.60%	+6.63%

Source: Authors' own calculations based on RBI/Anvis-RACLI data.

These observations corroborate insights from the literature, which consistently highlights the robust penalization of mothers and pregnant women in the labour market across many international experimental studies (El Haj et al., 2024), along with evidence of discrimination in promotions and, though less frequently studied, in dismissals.

5. Conclusions and Discussion

This study provides a detailed analysis of the impact of motherhood on women's labour market trajectories in Italy, leveraging comprehensive administrative data and a robust counterfactual methodology. Our findings confirm the persistent challenges that women face in balancing employment and parenthood, revealing a clear "motherhood penalty" in terms of employment continuity, wage growth, and job stability.

The counterfactual approach highlights that women who gave birth in 2019, despite often entering parenthood from relatively stable and well-paying employment positions, experience a significant decline in labour market participation and slower wage progression compared to childless peers. This penalty is especially acute among younger mothers, those living in Southern Italy, and those holding less stable or lower-paid jobs before childbirth. These results reinforce the notion that employment security and job quality are critical enablers of reproductive decisions and that their absence can intensify economic and professional uncertainties linked to motherhood.

Furthermore, the persistence of wage differentials and slower career advancement for mothers underscores the ongoing structural inequalities within the Italian labour market. These gaps not only affect individual women and their families but also have broader demographic and socioeconomic implications in a context marked by low

fertility and an aging population. Our analysis confirms that labour market disadvantages are a crucial factor contributing to women's reduced employment rates and may indirectly influence fertility decisions.

This study also sheds light on the role of institutional support measures, such as parental leave and the Wage Guarantee Fund (CIG), although further research is needed to assess their effectiveness in mitigating the motherhood penalty and fostering gender-equal labour market outcomes.

Policy implications emerging from these findings include the urgent need to improve employment stability and career progression opportunities for women of childbearing age, particularly in vulnerable regions and job categories. Enhancing access to affordable childcare, promoting flexible work arrangements, and strengthening protections against discrimination can help reduce the economic and professional costs associated with motherhood.

Future research should extend the analysis to more recent birth cohorts and examine the long-term effects of the COVID-19 pandemic on female employment and fertility. Additionally, qualitative investigations into employer practices and workplace cultures could complement our quantitative findings, offering a more holistic understanding of barriers to women's labour market participation post-childbirth.

In conclusion, tackling the motherhood penalty is essential not only for advancing gender equality in the labour market but also for addressing Italy's demographic challenges and supporting sustainable economic growth. Our study provides empirical evidence to inform targeted interventions and contribute to policy debates aimed at fostering inclusive and family-friendly labour market environments

References

- ALDEROTTI G., VIGNOLI D., BACCINI M MATYSIAK A. 2021. Employment Instability and Fertility in Europe: A Meta-Analysis. *Demography*. Vol. 58. Doi: 10.1215/00703370-9164737.
- ANDERSON C.J., PONTUSSON J. 2007. Workers, Worries and Welfare States: Social Protection and Job Insecurity in 15 OECD Countries. *European Journal of Political Research*. Vol. 46, pp. 211 - 235. Doi: 10.1111/j.1475-6765.2007.00692.x.
- CORRELL S. J., BENARD S. 2006. Biased estimators? Comparing status and statistical theories of gender discrimination. In S. R. Thye & E. Lawler (Eds.), *Advances in group processes* (pp. 89–116). [https://doi.org/10.1016/s0882-6145\(06\)230042](https://doi.org/10.1016/s0882-6145(06)230042)

- EL HAJ M., BAERT S., VAN OOTEGEM L., VERHOFSTADT E., LIPPENS L. 2024. Fertility, Pregnancy, and Parenthood Discrimination in the Labour Market: A Systematic Review. *IZA Discussion Paper Series*, No. 17435.
- ESSER I. OLSEN K. 2012, Perceived Job Quality: Autonomy and Job Security within a Multi-Level Framework. *European Sociological Review*. Vol. 28, pp. 443-454. Doi: 10.2307/23272531.
- LEWINS S. 2019. Changing world of work and gender equality: can flexibility in the workplace enable men and women to adapt working time to private time needs throughout their working lives? In Crowley N. & Sansonetti S. *New Vision for Gender Equality*, European Commission, Publications Office of the European Union, pp. 33-36.
- LIVI BACCI M. 2024. *La geodemografia. Il peso dei popoli e rapporti tra gli stati*. Bologna: il Mulino.
- MARCHESII G., TAGLE L., BEFANI B. 2011. *Approaches to the Evaluation of Development Policies' Effects*, Collana Materiali UVAL- Issue 22.
- MORGAN S.L., WINSHIP C. 2007. *Counterfactuals and causal inference: methods and principles of social research*, Cambridge, Eprint.
- ISTAT. 2025. *Rapporto annuale 2025. La situazione del Paese*. Roma: Istituto Nazionale di Statistica.
- ISTAT. 2024. *Indicatori demografici, anno 2024. Statistiche demografiche*. Roma: Istituto Nazionale di Statistica.
- ROSINA A. 2024. *Rapporto demografia e forza lavoro*. Roma: Consiglio Nazionale Economia e Lavoro.
- FREGUJA C., ROMANO M.C., SABBADINI L.L. 2025. *Il lavoro delle donne tra ostacoli e opportunità*. Roma: Istituto Nazionale di Statistica e Consiglio Nazionale Economia e Lavoro.

Gianni CORSETTI, Istat, gianni.corsetti@istat.it

Sara GIGANTE, Istat, gigante@istat.it

Anita GUELFÌ, MEF, anita.guelfi@mef.gov.it

Valentina TALUCCI, MEF, valentina.talucci@mef.gov.it

SOCIAL CAPITAL AT SCHOOL: A TOOL TO MEASURE STUDENTS' ENDOWMENTS

Stefania Badiglio, Luciano Seta

Abstract. This study presents an innovative methodology for measuring social capital among students to detect variations in its distribution across different territorial contexts. The proposed model is based on a multidimensional perspective of social capital, encompassing structural, relational, and cognitive dimensions, and utilizes three tools: a questionnaire, sociometric mapping, and age-appropriate economic games. The work provides a solid methodological framework that is helpful in exploring how social networks, trust relationships, and prosocial preferences develop and differ in relation to the living environment and school. The study aims to contribute to the understanding of social capital as a relational and value-based resource that promotes social cohesion, educational inclusion, and civic participation within school and territorial contexts.

1. Social capital: origins, definitions, and theoretical frameworks

This article will examine the concept of social capital in the educational context, with a focus on the well-being of students and the school community.

Social capital is an intangible concept in social science that attempts to explain collective events and individuals' behaviour through human connections, shared values, and trust. Despite its ambiguity, scholars' reflections shed light on many ideas, particularly relevant when evaluating community-based interventions involving multiple stakeholders, such as in educational contexts (Badiglio, 2025).

The concept of social capital was developed by scholars such as Robert Putnam, James Coleman, Francis Fukuyama, and Pierre Bourdieu, sparking significant interest among sociologists and economists in the 1980s and 1990s. Although the term has existed for over a century, its first appearance was in Lyda Judson Hanifan's work (1916), where he described social capital as social networks in urban areas (Jacobs, 1961).

A first conceptual formulation is attributed to Pierre Bourdieu from the late 1960s, studying France's dominant classes (Bourdieu, 1980). He views social capital as depending on social connections based on accessible resources.

James Coleman (1990) developed a comprehensive social capital theory, emphasizing two key features: the structural aspect, which relates to the connections

between social actors, and the functional aspect, which supports individuals' actions as rational agents. This distinction guides future discussions on social capital.

Building on the work of Granovetter, North, and Coleman, Putnam expands the concept of social capital through fieldwork. His study of Italian society (Putnam *et al.*, 1993) examines the relationships between associations, volunteering, norms, trust, solidarity, tolerance, and civic engagement. While not including altruism in his definition, he notes a strong link between altruism and social connectedness. Fukuyama (1995) claims that social capital is distinct from social networks, primarily comprising shared norms and values. Culture acts as a set of norms that enable collective action, with mechanisms such as norms, values, and ideologies regulating social relations.

A comparison shows problematic features of social capital (Mikiewicz, 2021). Some see it as an individual resource (Bourdieu), while others view it as a collective one (Coleman, Putnam, Fukuyama). Bourdieu, Putnam, and Fukuyama link social capital to the strength of social ties that expand an individual's societal role; Coleman, on the other hand, sees it as an internal endowment, rooted in intimate bonds such as family. Thus, social capital can be a flexible, multidimensional concept (Bourdieu, Coleman), or it can be mainly tied to specific structural or normative aspects (Putnam, Fukuyama).

To bring order, some authors have proposed interpretative suggestions and attempted to establish some common elements. Onyx and Bullen (2000), for example, identify some recurring themes in the literature on social capital:

- **Participation in networks**, which are configured as horizontal associations between individuals or groups and vary in intensity and density.
- **Reciprocity**, understood as the expectation of an exchange of services or favours, both in the short and long term.
- **Trust** involves the willingness to take on social risks based on the expectation that others will act reliably.
- **Social norms**, or the shared values that are often unspoken, regulate daily behaviors and interactions.
- **Proactivity**, characterized by the sense of personal and collective efficacy, is the ability and willingness of citizens to engage actively in the life of their community.

Although these themes are common elements of social capital, their relevance in educational communities varies across subjects and contexts. Research aims to define specific types of social capital, often in response to studies (Woolcock and Narayan, 2000; Mikiewicz, 2021).

From the structural analysis of social networks (Granovetter, 1973; Lin, 2000, 2001), more detailed concepts have been proposed, considering both horizontal and vertical ties between individuals and organizations. Regarding community well-

being, bonding social capital is based on interpersonal solidarity among homogeneous groups working toward shared goals (Wuthnow, 2002; Gittel and Vidal, 1998; Aldridge *et al.*, 2002). Bridging social capital involves weaker ties connecting diverse groups across boundaries (Gittel and Vidal, 1998; Aldridge *et al.*, 2002; Wuthnow, 2002), and linking social capital captures social networks characterised by asymmetrical and mostly vertical social relationships between individuals with different spaces of power (Alguacil Mir and Valdivia-Vizarreta, 2025). resources outside their community (Harrison, Montgomery, & Bliss, 2016).

In a now common tripartition, social capital is examined by differentiating between the structural, normative, and cognitive dimensions. (Uphoff, 1999).

The structural dimension refers to the network of social relationships an individual can activate to access material or symbolic resources. These networks encompass both strong ties, such as family and friendships, and weak ties, which are established in educational, work, or community settings. Networks serve not only as channels for information and support but also as spaces where a sense of belonging, identity, and mutual recognition is built. They can be analysed in terms of density, reciprocity, centrality of actors, and the degree of openness or closure of the network.

The normative dimension encompasses rules, habits, and expectations that govern behaviour within social networks. It operates through norms, practices, moral codes, and cultural models, with trust, reciprocity, and solidarity playing key roles. Trust serves as a cognitive-emotional mechanism that reduces uncertainty and facilitates cooperation.

Finally, the cognitive dimension involves individuals' perceptions of shared norms, values, and social reality within communities. It encompasses beliefs, expectations, and interpretations that influence collective intentionality and the legitimacy of social institutions. Fukuyama (2002) noted that culture, as shared norms and values, is key to communication, meaning negotiation, and cooperation. In education, this includes shared expectations, identification with institutional values, and a sense of belonging to the school community.

The integration of structural, normative, and cognitive dimensions allows us to understand social capital as both a mechanism for social regulation and a resource for development. The primary objective of this work is to develop a set of tools that facilitate the joint analysis of these components, thereby revealing the complexity of social capital and informing the development of effective educational strategies. Schools are ideal environments for observing and promoting social capital, encouraging trust, cooperation, and shared values and meanings.

In these contexts, that aspect of the normative social capital that relates to the characteristics and qualities of personal relationships, such as trust, obligations, respect, and even friendship, has a significant impact on sustaining organizational change and school improvement, with a substantial role of the school leadership

(Bryk & Schneider, 2003; Seta & Badiglio, 2024). In this sense, scholars prefer to speak about relational social capital (Nahapiet and Ghoshal, 1998; Gooderham, 2007).

2. Social capital and social preferences at school

The reflections highlight the complexity of social capital, a multifaceted and challenging phenomenon to investigate (Dasgupta and Serageldin, 1999). While significant in economic and social contexts, effective measurement is needed to make it usable (Onyx and Bullen, 2000; Putnam, 2001; Badiglio, 2025).

The school environment is crucial to students' cognitive development and the cultivation of prosocial values. Social capital serves as both an individual resource and a social regulation mechanism. Relationships among students, teachers, and families form a social fabric where information, support, norms, and values flow (Coleman, 1988; Lin, 2001; Putnam, 2000).

Research on social capital in education mainly focuses on its effects on academic performance, behavioural adaptation, and pathways to success (Parcel & Dufur, 2004; Crosnoe, 2004; Goddard, 2003).

These studies demonstrate that strong peer, teacher, and parent networks, built on trust and reciprocity, predict better academic outcomes and fewer behavioural problems. However, this view risks viewing social capital solely as a tool for educational success, overlooking its role in fostering social preferences and shared values.

This contribution differs from this perspective. Social capital is viewed as a key aspect of students' lives, fostering social preferences such as altruism, trust, and cooperation that extend beyond the school environment and influence interactions outside of it.

This approach requires a greater focus on certain variables that are often overlooked. For example, Van Rossem *et al.* (2015) show that social capital in schools develops through daily, often unconscious interactions that shape norms and classroom climate. Peer networks are not just exchange channels but also foster moral beliefs, collective judgments, shared expectations, and legitimacy of cooperation or exclusion.

Their detection requires considering not only the network structure but also trust, reciprocity, and altruism in supporting peer connections. These social preferences, rooted in and reinforced by a supportive, 'relationally dense' educational environment, express trust, reciprocity, and altruism.

Social preferences develop in schools through interactions and climate, as evident in the practices of helping, collaboration, and the stigmatization of selfishness.

Cohesive classes, where these are common and stable, promote collective well-being and responsibility (Bryk and Schneider, 2002; Badiglio, 2025).

Access to these relational social capital resources is heavily influenced by social position and stratification mechanisms (Bourdieu, 1986; Lin, 2000). School networks are not just places of spontaneous encounter; they follow rules on access, proximity, and recognition that can favour some and marginalize others. Social capital can help integrate and strengthen individuals, especially in open, trust-based networks, but it can also reinforce inequalities, benefiting those with greater cultural, economic, or symbolic resources (Salloum *et al.*, 2017).

In educational settings, social preferences are shaped by personal traits and social processes influenced by the organization of schools. Values and norms are affected by relational climate, friendship networks, teacher leadership, and daily interactions (Salloum *et al.*, 2017; Seta & Badiglio 2024; Badiglio 2025).

This work's methodology provides a comprehensive view of social capital in schools, encompassing not only its functional link to human capital in developing competences, skills, and knowledge, but also its broader implications.

A tool will be created to capture the value-based and relational aspects of social capital, considering interactions with growth, family, friendships, and communities, and their impact on behaviour and choices. Social capital promotes traits such as trust, altruism, and cooperation, influencing students' behaviour.

Individual social capital is shaped not only in school but also by upbringing, family, parental network, and early friendships. A survey conducted across diverse Sicilian regions with varied socio-demographics compared urban and rural schools, examining their differences in cultural, economic, and social capital. It aimed to understand how initial conditions and relationships affect social capital and territorial inequalities.

3. Methodology

The measurement of social capital is a subject of controversy (Putnam, 2001; Onyx and Bullen, 2000; Grootaert, 2004; Claridge, 2018), due to its theoretical complexity and challenges in developing valid tools.

Primarily, one can adopt a community perspective by using international survey tools, such as the World Values Survey (WVS), the European Values Study (EVS), and the General Social Survey (GSS). These instruments are generally too broad and independent of the context. Almost all of them tend to equate social capital with general trust, without considering the context (Thöni *et al.*, 2012).

One can also adopt a group perspective, focusing on certain variables measured at the aggregate level, which capture how the group or organisation holds this capital.

Often in these cases, the focus is on the role and significance of leadership (Seta and Badiglio, 2024).

Finally, one can adopt an ‘egocentric’ perspective. Focusing on this perspective, social capital is characterised as the set of direct relational resources (relationships that the individual has with others) and indirect ones (relationships of the individuals to whom the person is connected).

This study adopts the last perspective to quantify students’ social capital within educational institutions, combining a triangulation approach (Denzin, 2006), which led to the design of three tools: a self-administered questionnaire, a sociometric questionnaire, and three economic games for behavioural experiments (Table 1).

Table 1 - *Social capital measures.*

Tool	Dimension	Variable
Self-administered questionnaire	Relational and cognitive social capital	Trust Safety Responsibility Life satisfaction Altruism Social distance
Sociometric questionnaire	Structural social capital	Degree centrality Harmonic centrality Betweenness centrality, Hub centrality Authority centrality.
Economics games	Social preferences	Reciprocity Trust Cooperation

The self-reported questionnaire aims to assess the subject’s confidence in the strength of his/her social connections, also considering the social distance of these ties, whether they are with family members, peers, school staff, or acquaintances, namely his/her own direct relational resources.

The questionnaire was divided into three sections: general information (age, gender, family composition, parental occupation), indicators of subjective well-being inspired by the structure of the International Survey of Children’s Well-Being (ISCWeB), and assessment of prosocial and altruistic actions (Caprara and Pastorelli, 1993; Pfattheicher *et al.*, 2022).

The central part analysed the main relational contexts (family, school, friends, and neighbourhood), exploring the perceived levels of trust, sense of safety, responsibility, and life satisfaction. The statements proposed included, for example: *I trust my family/classmates; If I have a problem, my family will help me; I feel safe*

at school/at school; I have the opportunity to make decisions about things that are important to me (Rotter, 1971; Betts, Rotenberg, and Trueman, 2009; Imber, 1973). For the assessment of altruism, students were asked to express the frequency of general prosocial behaviors, such as: *I share the things I like with friends, I try to comfort others*.

The sociometric questionnaire reconstructs the social network's structure using a 'name generator' approach (Van der Gaag and Snijders, 2005), where students identify their top three gifted classmates in terms of specific relational resources: reliability, willingness to help, and ability to manage conflicts. This allows for the outlining of the relational networks within the classes, identifying central and peripheral nodes, which is useful for subsequent analysis of the distribution of social capital and inclusion (Ferrin *et al.*, 2007; Rotter, 1980).

Finally, to assess students' social preferences, all students participate in a session of economic games: the Ultimatum Game, the Trust Game, and the Public Good Game, set in 'magical' narrative scenarios with symbolic exchanges of 'gems'. These games were adapted to analyse reciprocity, trust, and cooperation within a playful context.

The variables observed through the utilization of the three tools facilitate the measurement of each student's social capital endowment at an individual level.

The three tools were specifically designed for administration to primary and secondary school students aged between 9 and 12 years. This cohort was chosen because it corresponds to a developmental phase in which the individual gains more independence from the family, and peers begin to play an essential role in the ecological landscape of the individual (Csikszentmihalyi *et al.*, 1977; Bronfenbrenner, 1979; Forbes and Dahl, 2010; Blakemore and Mills, 2014). In this phase of an individual's social capital development, the school plays a significant role.

The construction of a set of tools expressly designed to measure the social capital in children is one of the major novelties of this work.

All the data gathered using the three different tools were analysed within a unique theoretical framework that considers the students' social capital as a multidimensional construct, in which values, social ties, and social preferences play a role and must be measured with specific tools.

4. Conclusions

This contribution proposes an innovative methodology for measuring social capital within the school environment, aiming to explore relational differences across various contexts through the direct involvement of students. The approach

adopted integrates quantitative and qualitative tools, such as questionnaires, sociograms, and economic games, capable of detecting not only the presence of relational networks but also the quality of prosocial preferences that emerge in different educational settings.

This preliminary phase of the work has focused on designing a robust methodological framework capable of capturing the structural, normative, and cognitive dimensions of social capital, without yet proceeding to the analysis of the collected data.

In this sense, the contribution is a theoretical and operational foundation for future empirical investigations, offering a detection model that can be used to compare social capital endowments across territories and to better understand the dynamics of cohesion, inclusion, and participation within schools.

The originality of the proposal lies in recognising the school not only as a place of formal learning but also as a privileged social space for observing social capital. The use of tools suitable for a young audience, such as narrative games and sociometric surveys, has enabled a sensitive and accessible capture of the dimensions of trust, cooperation, and altruism.

Although data analysis is ongoing, the proposed tool allows investigation of how territorial and family conditions affect students' social networks. Focusing on bonding and bridging social capital may be crucial in assessing schools' capacity to include students in culturally diverse or vulnerable settings.

REFERENCE

- ALGUACIL MIR L., VALDIVIA-VIZARRETA P. 2025. Social networks and linkages: A systematic literature review (PRISMA) on the impact of social capital in youth communities. *Pedagogia Social Revista Interuniversitaria*, Vol. 46, pp. 210–227.
- ALDRIDGE S., HALPERN D., FITZPATRICK S. 2002. *Social Capital: A Discussion Paper*. London (UK): Performance and Innovation Unit.
- BADIGLIO S. 2025. *Impatto di un programma psicoeducativo basato sul PBIS (Positive Behavior Intervention and Support) sul benessere e sul capitale sociale degli studenti*. Phd Thesis. Palermo (IT): Libera Università Maria Ss Assunta-LUMSA.
- BETTS L. R., ROTENBERG K. J., TRUEMAN M. 2009. The early childhood generalized trust belief scale. *Early Childhood Research Quarterly*, Vol. 24, No. 2, pp. 175-185.
- BLAKEMORE S-J., MILLS K.L. 2014. Adolescence a Sensitive Period for Sociocultural Processing? *Annual Review of Psychology*, Vol. 65, pp. 187-207.

- BOURDIEU, P. 1980. Le capital social. Notes provisoires. In *Actes de la recherche en sciences sociales*, Vol. 31, p. 248-49.
- BOURDIEU P. 1986. The forms of capital. In Richardson, J. G. (Ed.), *Handbook of theory and research for the sociology of education*. New York, NY: Greenwood Press.
- BRONFENBRENNER U. 1979. *The ecology of human development: Experiments by nature and design*. Harvard University Press.
- BRYK A. S., SCHNEIDERB. 2002. *Trust in schools: A core resource for improvement*. New York, NY: Russell Sage Foundation.
- CAPRARA G. V., PASTORELLI C. 1993. Relazioni tra coetanei. La nomina dei pari come predittore delle forme di adattamento e disadattamento nella prima adolescenza. *Età Evolutiva*, Vol. 44, pp. 86-93.
- CLARIDGE T. 2018. Can social capital be measured? Is any measurement valid? *Social Capital Research*, published online, 30 September 2018.
- COLEMAN J. S. 1988. Social Capital in the Creation of Human Capital. *American Journal of Sociology*, Vol. 9, No. 1, pp. S95-S12.
- COLEMAN R. 1990. *Foundation of Social Theory*. Cambridge: Cambridge University Press.
- CROSNOE R. 2004. Social capital and the interplay of families and schools. *Journal of Marriage and Family*, Vol. 66, No. 2, pp. 267-280
- CSIKSZENTMIHALYI M., LARSON R., PRESCOTT S. 1977. The ecology of adolescent activity and experience. *Journal of youth and adolescence*. Vol. 6, No. 3, pp. 281-294.
- DENZIN N. K. 2006. *Sociological Methods: A Sourcebook* (5th ed.). London: Routledge.
- DASGUPTA P. E SERAGELDIN, I. 1999. *Social Capital. A Multifaceted Perspective*. Washington D.C.: The World Bank.
- FERRIN D. L., BLIGH M. C., KOHLES J. C. 2007. Can I Trust You to Trust Me? A Theory of Trust, Monitoring, and Cooperation in Interpersonal and Intergroup Relationships. *Group & Organization Management*, Vol. 32. No. 4, pp. 465-499.
- FORBES E., DAHL R. E. 2010. Pubertal development and behavior: hormonal activation of social and motivational tendencies. *Brain and cognition*, Vol. 72. No. 1, pp. 66-72.
- FUKUYAMA F. 1995. *Trust. The Social Virtues and the Creation of Prosperity*. New York: Free Press.
- FUKUYAMA F. 2002. Social Capital and Development: The Coming Agenda. *SAIS Review*, Vol. 22, No. 1.
- GITTELL R., VIDAL A. 2000. Community Organizing: Building Social Capital as a Development Strategy. *Contemporary Sociology A. Journal of Reviews*, Vol. 29, No. 2.

- GODDARD R.D. 2003. Relational Networks, Social Trust, and Norms: A Social Capital Perspective on Students' Chances of Academic Success. *Educational Evaluation and Policy Analysis*, Vol. 25, pp. 59-74.
- GOODERHAM P. N. 2007. Enhancing Knowledge Transfer in Multinational Corporations: A Dynamic Capabilities Driven Model. *Knowledge Management Research & Practice*, Vol. 5, No. 1, pp. 34-43.
- GRANOVETTER M. S. 1973. The Strength of Weak Ties. *American Journal of Sociology*, Vol. 78, pp. 1360-1380.
- GROOTAERT C. 2004. *Measuring social capital: An integrated questionnaire*. Danvers: World Bank Publications.
- HANIFAN L. 1916. The Rural School Community Center. *Annals of the American Academy of Political and Social Science*, Vol. 67, pp. 130-138.
- HARRISON J. L., MONTGOMERY C. A., BLISS J. C. 2016. Beyond the Monolith: The Role of Bonding, Bridging, and Linking Social Capital in the Cycle of Adaptive Capacity. *Society & Natural Resources*, Vol. 29, No. 5, pp. 525-539.
- IMBER S. 1973. Relationship of trust to academic performance. *Journal of Personality and Social Psychology*, Vol. 28, No. 1, pp. 145-150.
- JACOBS J. 1961. *The Death and Life of Great American Cities*. New York: Vintage Books.
- LIN N. 2000. Inequality in social capital. *Contemporary Sociology*, Vol. 29, No. 6, pp. 785-795.
- LIN N. 2001. *Social Capital: A Theory of Social Structure and Action*. Cambridge: Cambridge University Press.
- MIKIEWICZ P. 2021. Social capital and education – An attempt to synthesize conceptualization arising from various theoretical origins. *Cogent Education*, Vol. 8, No. 1: 1907956.
- NAHAPIET J., GHOSHAL S. 1998. Social Capital, intellectual capital and the creation of value in firms. *The Academy of Management Review*, Vol. 23, No. 2, pp. 242-266.
- ONYX J., BULLEN P. 2000. Measuring Social Capital in Five Communities. *The Journal of Applied Behavioral Science*, Vol. 36, No. 1, pp. 23-42.
- PARCEL T., DUFUR M. 2004. Capital at Home and at School: Effects on Child Social Adjustment. *Journal of Marriage and Family*. Vol. 63, pp. 32-47.
- PFATTHEICHER S., NIELSEN Y. A., THIELMANN I. 2022. Prosocial behavior and altruism: A review of concepts and definitions. *Current Opinion in Psychology*, Vol. 44, pp. 124-129.
- PUTNAM R. D. 2000. *Bowling Alone: The Collapse and Revival of American Community*. New York: Touchstone Books.
- PUTNAM R. 2001. Social capital: Measurement and consequences. *Canadian Journal of Policy Research*, Vol. 2, No. 1, pp. 41-51.

- PUTNAM R. D., LEONARDI R., NANETTI R. Y. 1993. *Making Democracy Work: Civic Traditions in Modern Italy*. Princeton: Princeton University Press.
- ROTTER J. B. 1971. Generalized expectancies for interpersonal trust. *American Psychologist*, Vol. 26, No. 5, pp. 443-452.
- ROTTER J. B. 1980. Interpersonal Trust, Trustworthiness and Gullibility. *American Psychologist*, Vol. 35, pp. 1-7.
- SALLOUM S., GODDARD R., LARSEN R. 2017. Social Capital in Schools: A Conceptual and Empirical Analysis of the Equity of Its Distribution and Relation to Academic Achievement. *Teachers College Record*, Vol. 119, No. 7, pp. 1-29.
- SETA L., BADIGLIO S. 2024. School Leadership Between Accountability and Values. *Annals of Social Sciences & Management Studies*, Vol. 10, No. 3, ID: 555787
- THÖNI C., TYRAN J.-R., WENGSTRÖM E. 2012. Microfoundations of social capital. *Journal of Public Economics*, Vol. 96, No. 7-8, pp. 635-643.
- UPHOFF N. 1999. Understanding Social Capital: Learning from the Analysis and Experience of Participation. In P. DASGUPTA, & I. SERAGELDIN, (Eds.), *Social Capital. A Multifaceted Perspective*. Washington D.C.: The World Bank.
- VAN DER GAAG M., SNIJDERS T. A. B. 2005. The Resource Generator: Social Capital Quantification with Concrete Items. *Social Networks*, Vol. 27, No. 1, pp. 1-29.
- VAN ROSSEM R., VERMANDE M., VÖLKER B., BAERVELDT C. 2015. Social capital in the classroom: a study of in-class social capital and school adjustment. *British Journal of Sociology of Education*, Vol. 36, No. 5, pp. 669-688.
- WOOLCOCK M., NARAYAN D. 2000. Social Capital: Implications for Development Theory, Research, and Policy, *The World Bank Research Observer*, Vol. 15, No. 2, pp. 225-249 .
- WUTHNOW R. 2002. Religious Involvement and Status-Bridging Social Capital. *Journal for the Scientific Study of Religion*. Vol. 41, pp. 669-684.

Stefania BADIGLIO, Institute for Studies on the Mediterranean, National Research Council of Italy, stefania.badiglio@ismed.cnr.it

Luciano SETA, Institute for Studies on the Mediterranean, National Research Council of Italy luciano.seta@cnr.it

INEQUALITIES BETWEEN MEDITERRANEAN COUNTRIES ON THE NORTH, SOUTH AND EAST SHORES: A MULTIDIMENSIONAL ANALYSIS¹

Francesca Abate, Adriano Cabras, Lucia Martina, Anna Pia M. Mirto,
Adriano Pareto, Francesco P. Rizzo

Abstract. The present study analyzes the inequalities between countries on the North, South and East Mediterranean shores. These geographic areas exhibit different socio-demographic and economic structures, health, and employment status, and unequal access to technological and environmental opportunities. The multidimensional analysis herein presented is carried out along the main key policy areas of the New Agenda for the Mediterranean: a) Human development, b) Economic resilience, prosperity and digital transition, c) Green transition, climate resilience and energy. This research rises under the context of WeMed, a joint project between Istat and CNR that offers an integrated analysis of the social, economic, environmental, and gender dynamics of Mediterranean countries. The WeMed database is the result of a complex process of collection, comparison, and selection of indicators from the most accredited international sources (World Bank, United Nations, ILO, IMF, OECD, Eurostat and Istat). Using Principal Component Analysis (PCA) and Cluster Analysis (CA), the study identifies underlying dimensions and classifies 25 countries into four clusters. The main findings, based on multivariate methods, reveal consistent geographical patterns and atypical national profiles, highlighting the need for diversified, shore-specific policy approaches.

1. Premise

Over the past decade, the Mediterranean basin has undergone a process of convergence, despite persistent inequalities among the countries of its Northern, Southern, and Eastern shores. This convergence has been more evident in socio-demographic dimensions than in economic or environmental ones (Doignon, 2023, Trimarchi, 2008).

Since 2021, the European Commission and the High Representative have presented a joint Communication proposing the launch of a new Agenda for the Mediterranean, aimed at outlining the priorities and framework of the EU's policy towards the Region with a view to a strengthened partnership. The Agenda focuses on five areas of intervention: 1) *rule of law and human development*, supporting

¹ This article is the joint work of the authors, but § 1 and 2 are written by A.P.M. Mirto, § 3 by A. Pareto, § 4 by F. P. Rizzo, § 5 by L. Martina, and § 6 by all the authors. Elaborations by World Bank Development Indicators Database are processed by A. Cabras, elaborations by Orange Data Mining and SAS software are realised by L. Martina and F. P. Rizzo.

democracy and good governance, strengthening the preparedness and resilience of health systems; promoting the empowerment of youth, civil society and gender equality; 2) *resilience, prosperity and digital transition*, restoring confidence in the business environment by encouraging economic diversification, supporting the digital transition in both public and private sectors, and advancing women's economic empowerment; 3) *peace and security*, assisting countries in addressing security challenges and finding solutions to ongoing conflicts; 4) *migration and mobility*, intensifying cooperation on migration through comprehensive, tailor-made partnerships adapted to each country's needs; 5) *green transition, climate resilience, energy and environment*, protecting natural resources and fostering green growth, in line with the objectives of the European Green Deal and climate neutrality by 2050.

This paper focuses on three of these priority areas - Human development (1), Digital transition (2), Green transition (5) - selecting key indicators aligned with the strategic initiatives outlined in the Agenda (see Table 1). A multidimensional analysis was conducted to produce country clusters offering a classification that reflects diverse structural profiles.

The concept of inequality is addressed from a multidimensional perspective. While economic conditions remain a fundamental component, they are not sufficient on their own to ensure the structural reduction of disparities (Capasso and Canitano, 2024). Sustainable development requires simultaneous progress in social, environmental, and cultural dimensions (UNDP, 2024). The living conditions of disadvantaged populations can only improve sustainably through systemic change - particularly in areas that are crucial to individual and collective well-being, such as education and access to essential services. The ambition of the 2030 Agenda is to reduce "all forms of inequality" through an integrated approach guided by its 17 Sustainable Development Goals (SDGs), with Goal 10 being central to this effort (ASviS, 2019).

2. Key indicators and main sources of the Mediterranean New Agenda

The Economic Investment Plan accompanying the Mediterranean Agenda includes flagship initiatives aimed at stimulating long-term socio-economic recovery in the Southern Neighbourhood.

These initiatives are designed to be implemented at both national and local levels, with a strong focus on sustainability, inclusion, and resilience (PCM, 2024). To monitor progress and align with strategic priorities, a set of key indicators has been selected and organized according to the Agenda's main areas of intervention (see Table 1).

These indicators - sourced from official international databases - have been processed for 25 countries across four macro-regions, and along three Mediterranean shores.

Table 1 – Key indicators classified by priority of the New Mediterranean Agenda.

Priority	Flagship Initiatives	Key Indicators	Sources
1.HUMAN DEVELOPMENT	1.1 Promoting youth empowerment and gender equality	1.1.1 Age dependency ratio, young (% of working-age population) - S_DPND_YG	UNPD, Istat
		1.1.2 Share of youth not in education, employment, or training (% of youth population) - S_NEET	ILO, Istat
	1.2 Encouraging culture and education	1.2.1 Average years of schooling (pop. >25 years) - S_AY_SCH	UNDP
	1.3 Strengthening the response of health systems	1.3.1 Life expectancy at birth, total (years) - S_LE00	UNDP, Eurostat, Istat
	1.4 Improving living conditions	1.3.2 Mortality rate, infant (per 1,000 live births) - S_IMRT	UN IGME, Istat
	2.1 Strengthening the business environment	2.1.1 GNI per capita - R_GNP	WB ICP, Eurostat-
	2.2 Increasing private and public sector digitisation	2.2.1 Fixed broadband subscriptions (per 100 people) - R_BBND	OCSE ITU, WBDI
2.RESILIENCE, PROSPERITY AND DIGITAL TRANSITION	2.3 Emancipating female employment	2.3.1 Employment to population ratio, 15+ (%) - R_EMP_TOT	ILO, Istat
	2.4 Encouraging economic diversification	2.4.1 Employment in services (% of total employment) - R_SRV_EMPL	ILO, Istat
		2.4.2 Medium and high-tech manufacturing value added (% manufacturing value added) - R_MNF_TECH	UN IDO
	3.1 Protecting the natural resources of territories	3.1.1 Fertilizer consumption (kilograms per hectare of arable land) - T_CON_FERT	FAO
		3.1.2 Terrestrial protected areas (% of total land area) - T_LND_PTLT	UNEP WCMC
3.GREEN TRANSITION, CLIMATE AND ENERGY	3.2 Promoting sustainable food systems	3.2.1 Water productivity (constant 2015 US\$ GDP per cubic meter of total freshwater withdrawal) - T_GDP_WP	FAO, AQUASTAT data, WB, and OECD GDP estimates
	3.3 Supporting challenges to climate change	3.3.1 PM2.5 air pollution, mean annual exposure (micrograms per cubic meter) - T_PM25	GBDCN
	3.4 Promoting energy from renewable sources	3.4.1 Renewable energy consumption (% of total final energy consumption) - T_RNEW	IEA, IRENA, NSD, WB, WHO

Source: elaborations on European Commission (2023) and WeMed project (2024).

A multidimensional analysis was performed to assess differences and similarities among these countries (see Sections 3, 4, and 5). The selection of indicators was further informed by the 2023 Joint Communication on Renewing the Partnership with the Southern Neighborhood (European Commission, 2023), which outlines several strategic directions:

- Prioritizing poverty reduction through inclusive education strategies and improved access to education for youth and women;
- Ensuring food security by establishing a sustainable framework under the Food and Resilience Facility, supporting less input-intensive, and rooted farming practices;
- Fostering innovation and entrepreneurship, with a focus on start-ups in healthcare, renewable energy, artificial intelligence, and education.

3. The analysis strategy

The analysis strategy followed in the study consists of two steps. In a first stage, Principal Component Analysis (PCA) was used to obtain a rough preliminary overview of the distribution of the 25 countries in the 15-dimensional space of the standardized individual indicators in a lower-dimensional space. As is known, PCA is a multivariate statistical technique for reducing the dimensionality of a dataset by minimizing the loss of information. This result is achieved by replacing a set of correlated variables with a smaller set of uncorrelated variables, called principal components, which are linear combinations of the original variables and retain most of the total variance (the first component has the highest variance, the second has an immediately lower variance, and so on) (Jolliffe, 2002). In the space of the first three principal components, each point has been coloured differently depending on the geographical area (European Union, Western Balkans, Middle East, North Africa) to easily identify the countries that differ significantly from the others in each area. This visualization allows us to detect outliers and assess how similar countries in the same area are in terms of the considered indicators.

In the second stage, the 25 countries were divided into 4 clusters based on the 15 standardized individual indicators, using a hierarchical and a non-hierarchical clustering method, which led to the same result and confirmed the robustness of the clusters.

In the hierarchical approach, we used the Ward method, which builds a hierarchy of clusters, usually represented using a dendrogram, by minimizing the sum of squared errors (SSE)² within the clusters at each step. For this reason, it is considered the most suitable agglomerative method for quantitative variables.

² SSE is the sum of the squared Euclidean distances of each point to its respective clusters centroid.

In the non-hierarchical approach, we used the k -means method, a partition method that divides the countries into k clusters, where $k=4$, to minimize the SSE. Therefore, the two methods minimize the same metric, but the algorithms are very different (Everitt *et al.*, 2011).

The ‘empirical’ classification based on the individual indicators was then compared with the ‘theoretical’ classification based on the geographical area to assess how similar countries in the same territory are in terms of the main key policy areas.

The association between the two classifications (i.e., the two nominal variables with 4 categories forming a two-dimensional contingency table) was assessed using the Cramér’s V , which varies from 0 (corresponding to no association) to 1 (complete association) (Everitt and Skrondal, 2011).

The formula is as follows:

$$V = \sqrt{\frac{\chi^2/n}{k-1}}$$

where χ^2 is the Pearson’s chi-square, n is the number of countries (25) and k is the number of clusters/geographical areas (4).

4. Findings from the Principal Component Analysis

In order to reduce information redundancy, PCA was applied, from which three principal factors emerged, useful to better interpret the data and to highlight possible clusters through their graphical representation.

Prior to proceeding with the PCA, an outlier analysis was conducted, and the suitability of the dataset was checked by the Kaiser-Meyer-Olkin (KMO) test, which returned an overall value of 0.77, indicating an adequate compactness of the data, and the Bartlett’s sphericity test, with a p -value of 2.007×10^{-32} , confirming the presence of significant correlations between the individual variables.

The number of components to be included in the final model was determined using the Kaiser criterion, keeping the components with an eigenvalue greater than 1. The three selected factors together explained just over 80% of the total variability of individual indicators.

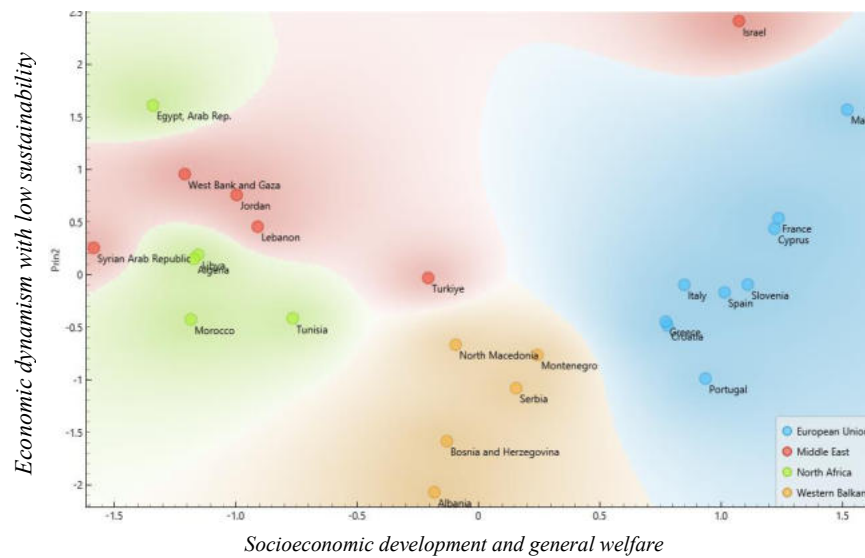
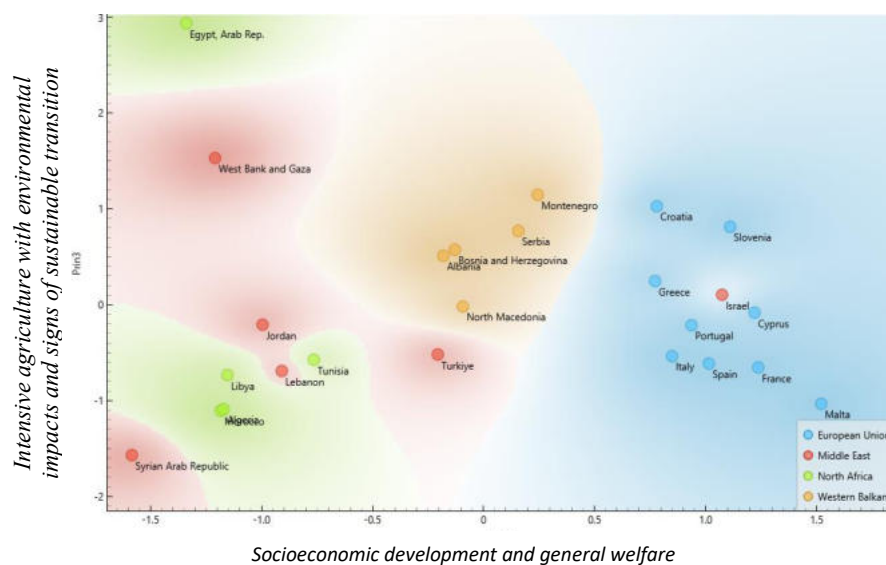
The scatter plot of the first two principal components shows clusters of countries based on the dimensions of socioeconomic progress and low-sustainability economic growth (Figure 1). The clear separation between blocks (EU, North Africa, Middle East, Balkans) indicates a good discriminating capacity of the first two principal components.

Table 2 – Principal Component (PC): label and the highest loadings.

Component	Label	High-loading variables	Interpretation
<i>PC1</i>	<i>Socioeconomic development and general welfare</i>	+ Income, broadband, life expectancy, protected land areas, employment – NEET, Infant mortality	It differentiates more developed and healthy territories, with better environmental and economic conditions, from less developed ones, with higher unemployment, youth distress and mortality rates
<i>PC2</i>	<i>Economic dynamism with low sustainability</i>	+ Water productivity, youth dependency ratio, service employment, fertilizer consumption – Renewable energy consumption	It contrasts growing and dynamic areas, with high water productivity, urbanization, and intensive agriculture, with areas that rely more on green energy and have less intensive agriculture
<i>PC3</i>	<i>Intensive agriculture with environmental impacts and signs of sustainable transition</i>	+ Fertilizer consumption, education, pollution (PM2.5), renewable energy consumption	It highlights territories with high agricultural productivity, but environmental contradictions accompanied by changing social dynamics

The Mediterranean countries are not distributed randomly but reflect consistent patterns: the EU represents advanced development with sustainability challenges; the Middle East and North Africa show low socio-economic development, with North Africa more sustainable and the Middle East more economically dynamic (Audi, 2022). The Balkans are characterized by a lower youth dependency ratio and a less intensive production, but with a greater orientation towards sustainability than the Middle East. Israel, although in the Middle East, is close to the European model in terms of socio-economic development. It is described by high production intensity, but with reduced orientation towards sustainability. Turkey is positioned closer to the Balkans, also reflecting its ambivalent geopolitical and historical position between Europe and Asia. Egypt shows signs of economic and demographic growth, but still depends on unsustainable practices, thus approaching the Middle Eastern profile.

The scatter plot of the first and third principal components clearly shows four distinct groups with different levels of socio-economic development and agricultural approaches (Figure 2). The EU countries have high socioeconomic development and moderate agricultural patterns, some with early signs of sustainable transition.

Figure 1 – Scatter plot of the first and second principal components.**Figure 2** - Scatter plot of the first and third principal components.

An intermediate level of socioeconomic development is observed in the Western Balkan countries, which are associated with medium to high intensity agricultural practices. The North African countries are characterized by a low level of socioeconomic development and low agricultural intensity. A notable exception is

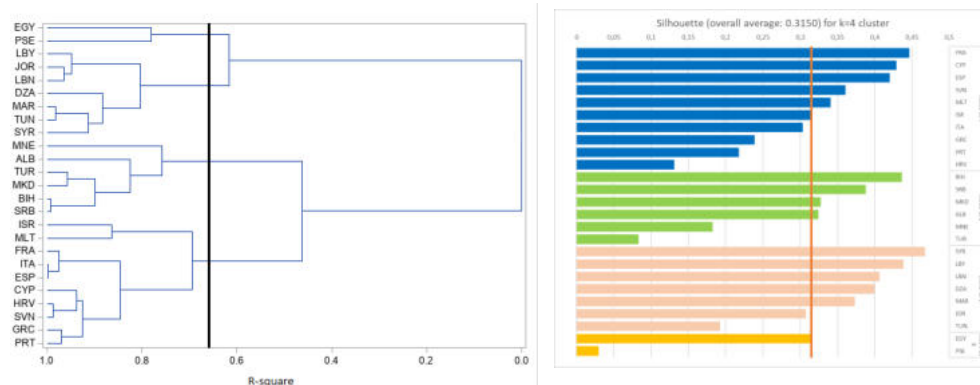
Egypt, which has the highest value on the third principal component. This result suggests a highly intensive agricultural model, associated with significant levels of air pollution, but also with a moderate openness towards education and the use of renewable main energy sources. Finally, the Middle Eastern countries are contrastingly positioned. Their location in the graph shows that structural similarities do not always agree with geographical affiliation. Palestine has intensive and sustainable agriculture but low socioeconomic development; Israel is more aligned with the EU model, both in terms of development and agricultural sustainability. Syria is in a critical position on both axes. Jordan and Lebanon are two countries that share structural characteristics like North African countries more than to their Middle Eastern neighbors. Turkey has socio-economic and structural characteristics that make it close to the Western Balkan countries.

5. Cluster analysis results

Since the variance explained by the first three components is only about 80%, it was decided to use all variables for the CA. The analysis with the hierarchical approach (Ward) on the 15 standardised indicators produced the dendrogram in Figure 3, that suggests a cut with an R^2 equal to 0.695 and a partition into four groups. A non-hierarchical analysis was also performed using the k-means method where $k=4$, that produced the same grouping of territories. The silhouette statistics³ have been computed for each cluster, showing an overall average of 0.315 and values for the first 3 clusters close to the average; only the last group has a very low value (0.1725).

The characteristics of the 4 groups obtained by cluster analysis can be deduced from Table 3, which presents the average values of the indicators in the groups. The first group includes Western European countries with high socio-economic and environmental performance; the second cluster comprises moderately developed countries belonging to Western Balkans with indicators on average compared to other clusters; the third group includes low socio-economic development countries, belonging to North Africa or the Middle East (well defined cluster, Figure 4); the fourth group comprises countries with a very weak socio-economic profile and critical environment (less cohesive cluster composed by two countries).

³ The statistics (Rousseeuw, 1987) is implemented by calculating the silhouette value for each data point and averaging the result over the entire dataset. The silhouette value for a single data point is calculated using the following equation: $Silhouette = (AverageOut - AverageIn) / \max(AverageOut, AverageIn)$. Where *AverageOut* is the minimum average distance between the data point and data within other clusters, and *AverageIn* is the average distance between the data point and other data within the same cluster.

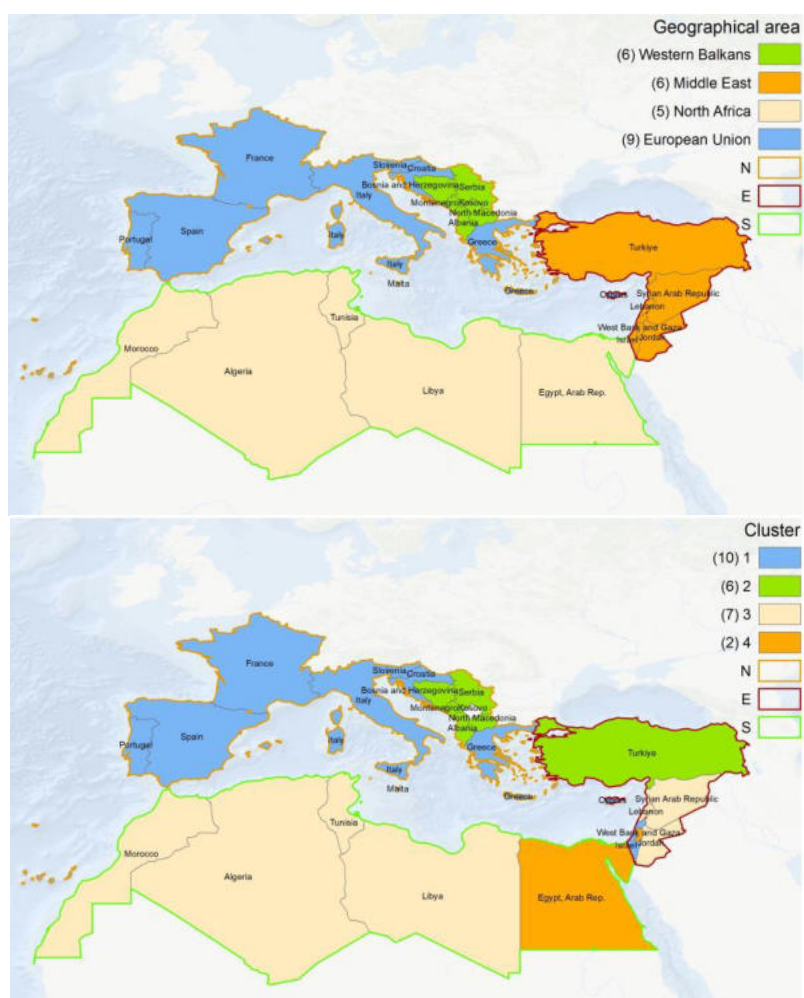
Figure 3 – Dendrogram of hierarchical clustering by Ward's method and Silhouettes plot with $k = 4$.**Table 3** – Silhouette and average values of the individual indicators by clusters.

Statistics/ Individual indicators	Overall	Cluster			
		1	2	3	4
Size	25	10	6	7	2
Silhouette	0.3150	0.3202	0.2904	0.3694	0.1725
S_DPND_YG	33.0	24.3	26.7	43.3	59.1
S_NEET	19.0	10.5	18.9	28.6	27.5
S_LE00	77.4	81.6	76.1	74.2	71.8
S_IMRT	7.5	3.0	5.5	13.9	13.9
S_AY_SCH	10.2	11.7	10.6	7.7	9.9
R_GNP	27,817	45,773	23,742	10,435	11,105
R_BBND	24.9	38.2	26.9	8.4	9.9
R_EMP_TOT	46.5	54.3	47.7	37.2	36.8
R_SRV_EMPL	66.1	74.7	57.4	63.7	56.9
R_MNF_TECH	25.9	36.1	21.8	18.7	13.0
T_CON_FERT	134.9	150.5	98.2	52.6	455.0
T_LND_PTLTD	16.8	30.9	11.2	3.1	10.8
T_GDP_WP	60.0	118.4	24.3	17.2	25.2
T_RNEW	17.5	19.4	29.5	6.4	10.8
T_PM25	20.8	13.1	21.8	25.2	40.6

The comparison between the “theoretical” classification of territories, based on geographical area, and the statistical classification, based on individual indicators (cluster analysis), showing a good but not obvious overlap and interesting anomalies referred to some countries when compared with profiles by geographical area (Figure 4): all EU countries are contained in the first cluster, which also comprises Israel;

the Balkans coincide with the second cluster; the countries of the Middle East and North Africa are divided between the third and fourth clusters. A strong association between the two classifications was observed, as indicated by a Cramér's V of 0.7377.

Figure 4 – *Geographical area and shore classifications compared to statistical clusters.*



6. Final considerations

Based on the results of the multidimensional analysis, this paper proposes a set of policy directions, tailored to the specific profiles of each cluster:

- *Cluster 1* - European Union: consolidate socio-economic performance; address challenges related to ageing, environmental sustainability, and intergenerational equity.
- *Cluster 2* - Balkans and Turkey: support convergence processes with the EU, strengthen education, digitization, and youth inclusion.
- *Cluster 3* - North Africa/Middle East: promote investment in human capital, basic public services, with a focus on sustainability in agriculture and energy use.
- *Cluster 4* - Egypt and Palestine: urgent need for international cooperation and targeted assistance, focusing on health, environment, and demography.

Beyond the specific clusters, the analysis reveals: partial convergence across Mediterranean shores, especially in demography; growing internal diversity within macro-areas, with some countries exhibiting "structurally ambiguous" behavior (e.g., Israel aligns with EU; Albania deviates from the Balkan profile). The statistical classification (via CA) aligns well with the geographical framework.

The next phase of the research will evolve under the ISTAT–CNR partnership within the WeMed project (Abate *et al.*, 2024). It will:

- develop new geo-statistical tools and metadata systems to monitor territorial inequalities across a consolidate set of indicators.
- Inform integrated, multi-level policy actions that reflect complex realities in the Mediterranean region.
- Foster sustainable, equitable, and cooperative development, also aligned with the Sustainable Development Goals.

Finally, this framework reaffirms that reducing Mediterranean disparities requires context-specific, multidimensional strategies and the continuous integration of empirical evidence into policy design.

References

- ABATE F., CANITANO G., CAPASSO S., CAROTENUTO S., CRUCIANI S., DI FILIPPO F., FORTE L., MIRTO A. P. M., RICCI M., ROSSI A. 2024. *WeMed – Società, economia e ambiente nel Mediterraneo*, Edizioni CNR, ISBN: 978-88-8080-702-5 ed. digitale.
- ASVIS 2019. *L'analisi delle diseguaglianze tra i paesi europei rispetto all'Agenda 2030*, Rapporto ASviS.
- AUDI M. 2022. *Income Inequality and Health Across the Mediterranean: A Panel Data Analysis*. Explores how inequality relates to health outcomes (life expectancy

- etc.) across both northern and southern Mediterranean countries. *JBEO*, ISSN 3006-2888.
- CAPASSO S., CANITANO G. 2024. *Mediterranean economies. The new agenda for the Mediterranean: perspectives and challenges*, Bologna, il Mulino, 2024, p. 514, ISBN 978-88-15-39032-5.
- DOIGNON Y., BLÖSS-WIDMER I., AMBROSETTI E., OLIVEAU S. 2023. *Population Dynamics in the Mediterranean: A Demographic Convergence?*. Springer.
- EUROPEAN COMMISSION. 2023. European Parliament recommendation of 14.9.2022 to the Commission and the Commission Vice-President/High Representative of the Union for Foreign Affairs and Security Policy on the renewed partnership with the Southern Neighborhood – a new agenda for the Mediterranean, https://www.europarl.europa.eu/doceo/document/TA-9-2022-0318_EN.pdf.
- EVERITT B., LANDAU S., LEESE M., STAHL D. 2011. *Cluster analysis. (5th edition)*. Chichester: Wiley.
- EVERITT B. S., SKRONDAL A. 2011. *The Cambridge Dictionary of Statistics, (4th edition)*. Cambridge: Cambridge University Press.
- JOLLIFFE I.T. 2002. *Principal component analysis (2nd edition)*. New York: Springer-Verlag.
- PCM – Dipartimento per le politiche di Coesione e per il Sud, *The European House - Ambrosetti 2024. Verso Sud. La strategia europea per una nuova stagione geopolitica, economica e socio-culturale del mediterraneo*, maggio.
- ROUSSEEUW, P. J. 1987. Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics*. Vol.20 pp.53-65.
- TRIMARCHI A. 2008. Di nuovo sulle rive del Mediterraneo, <https://www.neodemos.info/2008/11/05/di-nuovo-sulle-rive-del-mediterraneo/?print=pdf>.
- UNITED NATIONS - UNDP 2024. *Human development report 2023-2024*, <https://hdr.undp.org/content/human-development-report-2023-24>.
- WORLD BANK, DataBank, <https://databank.worldbank.org/>.

Francesca ABATE, Istat, abate@istat.it
 Adriano CABRAS, Istat, cabras@istat.it
 Lucia MARTINA, Istat, martina@istat.it
 Anna Pia M. MIRTO, Istat, mirto@istat.it
 Adriano PARETO, Istat, pareto@istat.it
 Francesco P. RIZZO, Istat, frizzo@istat.it

DEMOGRAPHIC VITALITY IN ITALIAN MUNICIPALITIES: MEASUREMENT AND FEATURES OF THE MOST DYNAMIC AREAS¹

Alessandro Valentini, Francesca Paradisi

Abstract. The population living in Italy has fallen by 1.4 million over the last 10 years. According to the most likely scenario of recent demographic forecasts, the decline will continue in the near future leading to a further decrease of 1.1 million people by 2030. At the same time, the population is ageing: over the last 20 years, the aging index has risen from 136 to 200; the index will exceed 250 in 2030. This trend, however, is not homogeneous in all the territories. The main aim of this work is to identify the most dynamics areas, namely those municipalities where the tendency to population decline and aging is less marked.

At this scope, a synthetic index named as Demographic Vitality Index (DVI), was introduced. DVI measures the degree of "demographic vitality" for each municipality. The index is composed by 8 indicators representing different aspects of demographic vitality: dynamics of population and changes in age structure. DVI represents therefore a new and powerful tool to implement the most appropriate anti-decline and anti-aging policies of the population.

The conceptual framework is the following: i) DVI assumes higher values in municipalities where in the meanwhile the demographic balance tends to be better and the aging process slows down; ii) the national average of DVI is imposed to be equal to 100 for the first year of observation (2019); iii) DVI ranges between 0 and 200. The source of data is the Istat dataset DEMO (demography in figures) for the years 2019-2024 (Permanent census data). Municipality borders are those at 1st January 2025.

According DVI results, demographic vitality tends to reduce during the period of analysis. Differences between the dynamic and the structural components are significant during the years of Covid; in the most recent period they narrow down to almost converge.

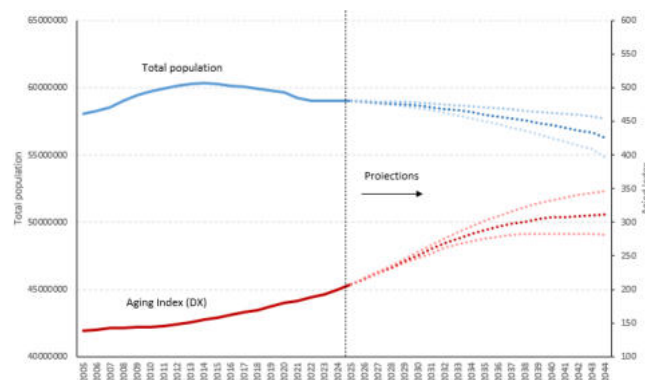
The index is higher in large areas of the northeast (especially in Trentino-Alto Adige, along the Po plain, and the Via Emilia) and in coastal areas, particularly along the Lower Tyrrhenian. Vice-versa DVI is very low in Sardinia, Liguria, and in the Apennine interior areas. In the territories, there are differences depending on the distance to the main services (transport, health, education). Demographic vitality is relatively higher in the Polo areas, followed by the Intermunicipal centre and Belt areas. The worst vitality is accounted in the peripheral and ultra-peripheral municipalities.

¹ The work is the joint result of the two authors that shared the working methodology (Paragraph 2). However, Paragraphs 1, 3 and 4.2 are attributable to Alessandro Valentini; Paragraphs 4.1 is attributable to Francesca Paradisi.

1. Demographic context

The population living in Italy at the beginning of 2005 was around 58 million of inhabitants. In the following ten years, the number of residents increased until the top of 60,345,917 at the 1st January of 2014. From this point, the population started to diminish, and actually (1st January 2025) is less than 59 million. In the meanwhile, the aging process, already in place for several years, accelerates. The Aging index has risen from 131.7 in 2005 to 158.3 in 2015 and to 207.6 in 2025. According to the most recent demographic projections, in the next future (2025-2044) decline and aging will continue in all forecast scenarios (Figure 1).

Figure 1 – Total population (left) and Aging index (right). Observed values and forecasts at 1st January. Italy. Years 2005-2044.



Source: Istat, Resident population by age, gender and civil status (2005-2018); Permanent Census of population (2019-2024); Population projection (2025-2044).

This negative demographic trend has been the subject of many studies for several years in terms of depopulation of rural areas (Macchi Janica, 2016; De Rubentis, 2019), and more in general in terms of demographic alert (Guarracino, 2016) and analysis of territorial resilience (Keck and Sakdapolrak, 2013; Salvia and Quaranta, 2020).

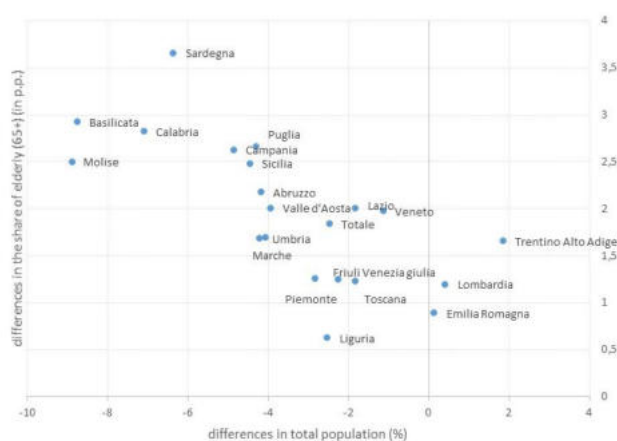
A focus on the different Italian regions has been realised for the most recent period (2019-2025) using results of the permanent census. It should be noted that the change in the total population and in the age structure is not homogeneous between the different regions (Figure 2). These two indicators are inversely correlated: the more the population decline, the more it ages.

The share of elderly (65 years and over) increased in all regions: between 0.62 p.p. in Liguria and 3.65 p.p. in Sardinia (the increase in Italy was of 1.84 p.p.). The total population declined in quite all regions; the drop was particularly significant in Molise (-5.2%), Basilicata (-5.1%) and Calabria (-4.2%). Vice-versa the population

has grown only in South Tyrol (+1.12%), Lombardy (+0.25%) and Emilia-Romagna (+0.09%). Those three regions were the only ones with a demographic trend relatively better in terms of both total population and evolution of demographic structure. On the opposite side Molise, Basilicata, Calabria and Sardinia were the regions with a relatively worst trend both for evolution of the total population and for the increase of elderly.

Peculiar is the case of Liguria: the region with the lowest increase of elderly. This positive figure actually underlies a paradoxical effect linked to the fact that the region has the highest proportion of older people at national level. On the other hand, in this study it is not the level reached by age structure that matters, but how much it changes over time. This approach is useful to understand the level of resilience with regard to aging.

Figure 2 – Differences in total population (%) and in the share of elderly (65+) (in p.p.) between 2019 and 2025 (data at 1st January) by Italian region.



Source: Istat, Permanent Census of population.

2. Method

In recent years, a large bibliography has been devoted to analysing the characteristics of the Italian population and its territories, with particular reference to the relationship between decline and aging. See for example Gesano and Strozza (2011), Blangiardo (2013). Particular attention was deserved to the local consequences of these trends, especially in indoor areas of the country or in rural territories (Rizzo 2015; Cipolloni 2021). A further analysis was focused on the resilience of population in terms of the ability to cope with the shocks caused by the dynamics in progress. The writings of Salone (2017), Colantoni *et al.* (2020) are

interesting at this regard. Bottazzi and Puggioni (2013) introduced a composite *index of demographic malaise* for the municipalities of Sardinia. This index is composed by two parts: the first takes into account episodes of depopulation (for the period 1951-2011), the second refers to some population characteristics, expressive of its structure and its natural movement.

In the present paper, a new composite index is introduced, the index is named Demographic Vitality Index (DVI). The work is inspired by the pioneering study concerning the index of demographic malaise. The proposed methodological advancements of DVI are: i) it is linked to a specific reference year to allow temporal comparisons; ii) the structural and dynamic components are treated separately; iii) the structural component is expressed as annual changes in the age composition.

As in the preliminary studies of Paradisi and Valentini (2024), conceptual framework of DVI is the following: a) the level of demographic vitality is represented by a synthetic figure (Maggino, 2006; OECD, 2008; Mazziotta and Pareto, 2024) measured on a scale between 0 (theoretical minimum) and 200 (theoretical maximum). The value 100 represents the reference point (goalpost). In case of the present paper 100 is DVI for Italy in 2019;

- demographic vitality is a relative concept. Tends to be higher in places where the population increases (or diminishes less in relation to the context) and where age structure is rejuvenated (or gets less older than elsewhere); vice-versa is lower in places where the population declines and the age structure of it is ageing (compared to other territories);
- base indicators are representatives of two aspects of a population (dimensions): dynamic (in terms of rates of birth, death, immigration and emigration) and changes in the age structure (in terms of share of youngers, share of elders, structure of active population, structure of elders).

According to the framework, indicators to calculate DVI, for a specific year and place (for instance at municipality level) are the followings:

- I.1 *birth rate*
- I.2 *death rate*
- I.3 *immigration rate* (from abroad and other Italian municipalities)
- I.4 *emigration rate* (to other Countries and to other Italian municipalities)
- I.5 *changes in the share of Youngers* (0-14 years), between 1st January and 31th December;
- I.6 *changes in the active population index* (15-39 younger working ages; 40-64: older working ages), between 1st January and 31th December;
- I.7 *changes in the share of elderly* (65 years and over), between 1st January and 31th December;
- I.8 *changes in the old population index* (65-84 less old; 85+ very elderly) between 1st January and 31th December-

Table 1 shows in detail the formulas to calculate the different indicators ($I.x$ the generic indicator, where $x = 1$ to 8) for municipality c and year t . More specifically:

Table 1 – Basic indicators of Demographic Vitality Index.

Code	Dimension	Indicator	Formula
I.1	Dynamic	Birth rate	$\frac{B_{c,t}}{0.5(Pop_{c,TOT,t} + Pop_{c,TOT,t+1})}$
I.2	Dynamic	Death rate	$\frac{D_{c,t}}{0.5(Pop_{c,TOT,t} + Pop_{c,TOT,t+1})}$
I.3	Dynamic	Immigration rate	$\frac{IM_{c,t}}{0.5(Pop_{c,TOT,t} + Pop_{c,TOT,t+1})}$
I.4	Dynamic	Emigration rate	$\frac{EM_{c,t}}{0.5(Pop_{c,TOT,t} + Pop_{c,TOT,t+1})}$
I.5	Evolution of structure	Changes in the share of youngsters	$\frac{Pop_{c,0-14,t+1}}{Pop_{c,TOT,t+1}} - \frac{Pop_{c,0-14,t}}{Pop_{c,TOT,t}}$
I.6	Evolution of structure	Changes in active population index	$\frac{Pop_{c,40-64,t+1}}{Pop_{c,15-39,t+1}} - \frac{Pop_{c,40-64,t}}{Pop_{c,15-39,t}}$
I.7	Evolution of structure	Changes in the share of elderly	$\frac{Pop_{c,65+,t+1}}{Pop_{c,TOT,t+1}} - \frac{Pop_{c,65+,t}}{Pop_{c,TOT,t}}$
I.8	Evolution of structure	Changes in the old population index	$\frac{Pop_{c,85+,t+1}}{Pop_{c,65-84,t+1}} - \frac{Pop_{c,85+,t}}{Pop_{c,65-84,t}}$

Notes:

$Pop_{c,GR,t}$ is the population of municipality c on 1 January for age group GR. Where GR is TOT for the total population; 0-14 for ages not yet active (lower than 15 years); 15-39 for the younger group of active population; 40-64 for the older group of active population; 65+ for the no more active population; 85+ for the oldest people.

$B_{c,t}$ and $D_{c,t}$ respectively are the total number of births and the total number of dead in the municipality c year t .

$IM_{c,t}$ and $EM_{c,t}$ respectively are the total number of immigrants (immigration from abroad and immigrations from other Italian municipalities) and the total number of emigrants (emigration to other countries and emigration to other Italian municipalities) in the municipality c during year t .

Each indicator is standardised using the min-max procedure with goalpost. Defining:

- $Rif(I.x)$ as the goalpost (Italy 2019)
 - $Max(I.x)$ and $Min(I.x)$ as, respectively, absolute maximum and minimum of the indicator $I.x$ for all municipalities and years of the time series.
- $$Max(I.x) = Max(I.x, c, t) \forall c, t; Min(I.x) = Min(I.x, c, t) \forall c, t$$

Formulas for the standardization are the followings:

$$Sup(I.x) = Rif(I.x) + [Max(I.x) - Min(I.x)]/2 \quad (1)$$

$$Inf(I.x) = Rif(I.x) - [Max(I.x) - Min(I.x)]/2 \quad (2)$$

$$I.x_{c,t}^{ST} = 200 \frac{I.x_{c,t} - \text{Inf}(I.x)}{\text{Sup}(I.x) - \text{Inf}(I.x)} \quad (3a) \quad \text{or} \quad I.x_{c,t}^{ST} = 200 \frac{-I.x_{c,t} + \text{Sup}(I.x)}{\text{Sup}(I.x) - \text{Inf}(I.x)} \quad (3b)$$

The formula is (3a) if $I.x$ is positively correlated with DVI (indicators I.1, I.3, I.5); (3b) in case of inverse correlation (indicators I.2, I.4, I.6, I.7, I.8).

The dynamic component (DY), the component representing evolution of structure (EV) and DVI are calculated as the arithmetical mean of the standardized indicators, the most intuitive and most used method of synthesis. The average is unweighted in order to attribute the same importance to each indicator.

$$DVI_{c,t}^{DY} = \frac{\sum_{i=1}^4 I.i_{c,t}^{ST}}{4} \quad (4) \quad DVI_{c,t}^{EV} = \frac{\sum_{i=5}^8 I.i_{c,t}^{ST}}{4} \quad (5) \quad DVI_{c,t} = \frac{DVI_{c,t}^{DY} + DVI_{c,t}^{EV}}{2} \quad (6)$$

Indicators (4), (5) and (6) range between 0 and 200.

3 Data

The implementation of the indicators dataset described in Table 1 was a significant part of this work. Indicators are calculated for the period between 2019 and 2025 (1st January) using the permanent census data warehouse. As well known, census data are perfectly aligned with administrative data of demographic registrations. The geographical detail of the dataset is that of municipalities (LAU 2), for the 7,896 actually existing municipalities (boundaries at the 1st January 2025). During the period of analysis, several administrative changes occurred in the borders because of various processes of aggregation and disaggregation. To have an idea, the total number of municipalities was 7,954 at the end of 2018; 7,914 at the end of 2019; 7,903 at the end of 2020; 7,904 at the end of 2021 and 2022; 7,900 at the end of 2023.

Changes in territorial borders have been managed as follows: a) in case of aggregation, adding together the data of extinct municipalities. For instance the municipality of Mornago was established in 2023 thanks to the fusion between Sella Giudicarie, Fondo, Malosco; b) in case of disaggregation by subtracting known data from the total population transferred and applying a proportional statistical model for the other variables. This is the case of separation of Missiliscemi from Trapani.

For each municipality (borders at 1st January 2025) and year, the dataset includes the following variables: births, deaths, immigrations and emigrations (from other Italian municipalities and from abroad); total population and population by age (classes 0-14; 15-39; 40-64; 65-84; 85+) at 1st January and at 31st December.

Each municipality data is then linked to a set of covariates, functional to the analysis of DVI results: region, geographical repartition (North-West, Northeast, Centre, South, and Islands), provincial capital (not capital; capital); typology of

indoor area (Polo, Intermunicipal center, Belt, Intermediate, Peripheral, Ultra-peripheral).

4 Main results

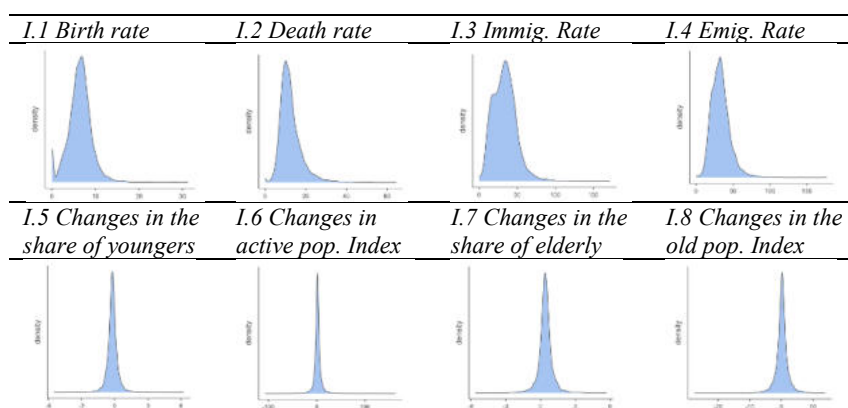
The approach of analysis followed in this paper is twofold. On one side, a preliminary study on the indicators at the basis of DVI was able to identify the main features of the different demographic components. The univariate approach allowed knowing the form of the different distributions and the value of the main representative indexes. Bivariate approach was suitable to evaluate correlations between indicators.

On the other side, the synthetic index DVI was studied in greater detail, in terms of distribution form, historical trend (2019-2024), analysis of the different territorial areas (geographical repartition, type of municipality, typology of indoor area).

4.1. Analysis of base indicators of DVI

Figure 3 shows the frequency distribution of the basic indicators of DVI for the base year 2019; this is the first year for which the results of the permanent census are available at 1st January. Indicators representing components of the structure (I.1, I.2, I.3, I.4) have 0 as the minimum value and have no upper end. The means values are 6.3 and 12.4 for respectively birth and death rate; 33.4 and 33.2 for immigration and emigration rate.

Figure 3 – Frequency distribution of the basic indicators of DVI. Year 2019.



Source: elaboration of authors.

Note that those two distributions (in particular distribution of immigration rate) are bimodal. It depends on the fact that they are the sum of two distinct components

with distinct distributions: domestic and foreign. Indicators representing evolution of the structure (I.5, I.6, I.7, I.8) have no theoretical limits; their means are: -0.2 (I.5), 2.2 (I.6), 0.4 (I.7) and 0.2 (I.8) and are relatively symmetric.

The base indicators are almost uncorrelated. According to the correlation matrix (not reported here), the only two significant exceptions are the strength of the linear relation between I.3 and I.4 ($r=0.628$) and between I.1 and I.5 ($r=0.349$).

The distribution of each indicator and the correlation between indicators do not change significantly over time.

4.2. Analysis of DVI

Application of the method introduced in § 2 to the dataset illustrated in § 3 allows to calculate the composite index DVI for all Italian municipalities in the period 2019-2024. Figure 4 shows the frequency distribution of DVI (year 2019) in the range between 90 and 110 (cases of DVI lower than 90 and upper then 110 are very limited and ignored in this figure).

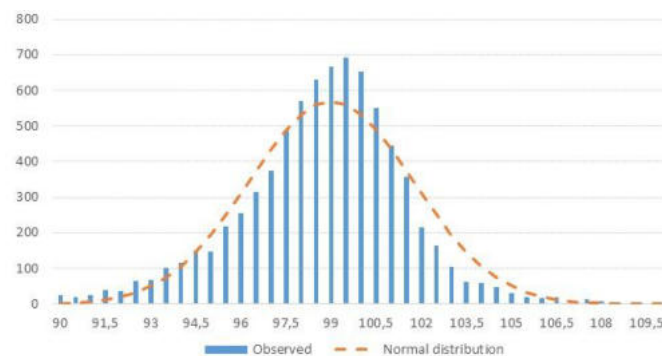
Despite a slightly skewness to the right, the form of the distribution is almost normal. The arithmetic mean of the distribution is 99.40; the median is 99.58. The value for Italy in 2019 (goalpost) is equal to 100; the same for both components: dynamics (DY) and evolution of structure (EV). Figure 5 shows the historical trend of DVI and that of the two components DY and EV for the period 2019-2024. The value of DVI tends to decrease over time. It reaches the value 99.38 in 2024 (-0.62 points). This diminishing depends on distinct effects. In 2020 it was accounted a significant slope, of opposite sign, both on the EV (+0.87 points) and on the DY components (-1.14 points). The reasons are contingents, and mainly related to the Covid consequences, which caused an increase in deaths, particularly for elderly people, with a rejuvenating effect. In the following years, DY grows slightly but always remains below the 2019 initial value; EV decreases according to a linear model falling below 100 in 2023.

The value of DVI is not homogeneous in the different areas of the country. It tends to change according to different territorial characteristics. Table 2 illustrates the value of DVI (years 2019 and 2024) aggregated according to three variables: territorial placement from North to South (in terms of geographical partitions), distance from the main services (type of indoor area) and administrative features (to be or not to be provincial capital). For each variable, differences between the various modalities are statistically significant ($p<0.001$ based on the Anova test). Considering the geographical partitions, DVI assumes higher values in the North, especially in the Northeast, where the highest value is recorded both at the beginning of the period (100.27) and at the end (99.59). The distinction by type of municipality shows for both years a higher demographic vitality in the provincial capitals (100.25

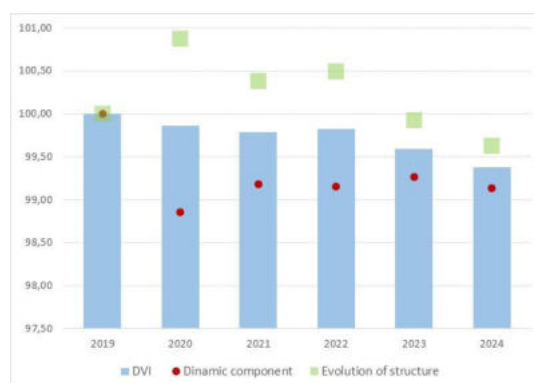
vs 99.89 in 2019; 99.50 vs 99.33 in 2024). Focusing on the different indoor areas, the population is more demographically lively in areas next to the services (of instructions, health and transport), and less lively in more peripheral areas. In any case, in 2024 compared to 2019 there seems to be a recovery of the less central and more peripheral areas. The rate of decrease in Peripheral (-0.11%), Intermediate (-0.28%) and Ultra-peripheral (-0.48%) areas is lower than the rate of decrease in the more central ones (upper than -0.70%).

Figure 6 shows the level of DVI by municipality (quintiles 2019). It is relevant to note that population living in critical municipalities (1st and 2nd quintile, DVI below 98.5) is only 13.7%. In particular, population of the 1st quintile is solely 3.2%. Vice-versa population living in more vitality municipalities (4th and 5th quintile, DVI over 99.7) is 61.6% of the total. Specifically 21.7% of population lives in the municipalities with the highest vitality. Looking at the different territories, the liveliest region is Trentino-Alto Adige with the highest number of municipalities (54.6%) and the highest quota of inhabitants (70.6% of population) that belongs to the 5th quintile. Following Lombardia (28.8% of municipalities; 42.3% of population); Campania and Valle D'Aosta in terms of municipalities (both around 27.0%); Emilia-Romagna in terms of population (32.7%). It is worth to note that Liguria has a very limited quota of inhabitants in the liveliest areas (2.1%). Regions with the worst situation in terms of vivacity (1st quintile) are Molise, Basilicata and Sardinia both in terms of municipalities (respectively 44.1%; 35.9% and 35.5%) and population (17.8%; 12.0% and 9.8%). Worthy of interest the cases of Liguria (33.8% of municipalities and 6.1% of population) and Piemonte (respectively 33.6% and 8.0%).

The comparison between 2019 and 2024 shows a significantly worsening situation: at national level the population living in critical municipalities (1st and 2nd quintiles) reaches a peak of 18.4%, increasing of almost 5 p.p. Similarly, the quota of population of the most demographically lively municipalities (5th quintile) drops by 10 points contracting to 11.9%. The worsening is broadly homogeneous in all regions, with a progressive population shift in the lowest quintiles. Trentino-Alto Adige continues to be the most demographically lively region with over half of the municipalities (51.1%) falling into the 5th quintile. However, the population share in this quintile (40.4%) almost halved compared to the previous five-year period due to the relocation of the two capitals of Trento and Bolzano. A significant loss of population from the 5th quintile is also accounted in Lombardia (-15.8 p.p. because of the outing of Milano), Emilia-Romagna (-14.1) and Veneto (-11.1). Similarly the population of the 1st quintile grows in almost all regions; in particular in Sardegna (+20.5) and in Valle d'Aosta (+10.3).

Figure 4 – Frequency distribution of DVI. Year 2019 (base Italy=100).

Source: elaborations of authors.

Figure 5 – DVI, Dinamic and Evolution of structure. Years 2019-2024 (base 2019=100).

Source: elaborations of authors.

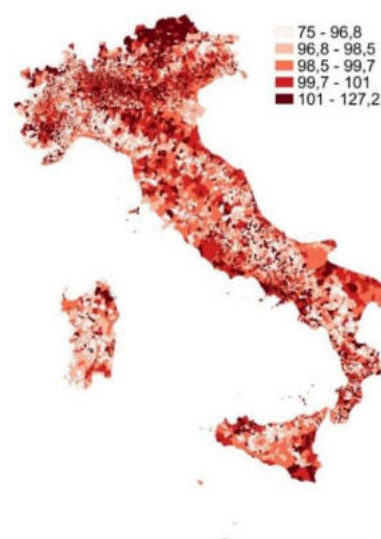
Directions of future work for this subject could be the followings: analysis of spatial correlations in composite index values; estimation of covariate effects using quantitative models.

Table 2 – DVI by geographical partitions, type of municipality, type of indoor area. Years 2019-2024 (base Italy 2019=100)

Territory	2019	2024
Italy	100.00	99.38
<i>Geographical partitions</i>		
North-Ovest	100.13	99.43
North-Est	100.27	99.59
Centre	99.84	99.15
South	99.96	99.47
Islands	99.67	99.16
<i>Type of municipality</i>		
Non provincial capital	99.89	99.33
Provincial capital	100.25	99.50
<i>Type of indoor area</i>		
Polo	100.27	99.51
Intermunicipal Centre	100.07	99.24
Belt	100.09	99.38
Intermediate	99.59	99.31
Peripheral	99.19	99.09
Ultra-peripheral	99.07	98.59

Source: elaborations of authors

Figure 6 - DVI by municipality. Year 2019 (base Italy 2019 = 100)



Source: elaborations of authors

Acknowledgements

The authors thank: Marco Marsili for all the suggestions provided in defining the conceptual framework underlying the calculation of the demographic vitality index; the anonymous referees for their suggestions that improved the clarity of the paper.

References

- BLANGIARDO G. 2013. Italians of today and tomorrow: awareness of next scenarios and search of new equilibrium, *RIEDS*, Vol. 67, No. 2, pp. 9-20.
- BOTTAZZI G., PUGGIONI G. 2013. Il malessere demografico. In REGIONE SARDEGNA (Ed), *Comuni in estinzione, gli scenari dello spopolamento in Sardegna*, Cagliari: Regione Sardegna, pp. 9 - 14
- CIPOLLONI C. 2021. Le politiche di contrasto al fenomeno dello spopolamento delle Aree interne, *Italian Papers On Federalism*, Vol. 3/2021, pp.52-79.
- COLANTONI A., HALBAC-COTOARA-ZAMFIR A., HALBAC-COTOARA-ZAMFIR C., CUDLIN P., SALVATI L, GIMENEZ MORERA A. 2020.

- Demographic Resilience in Local Systems: An Empirical Approach with Census Data, *Systems*, Vol 8, No. 34, pp.1-17.
- DE RUBENTIS S. 2019. Dinamiche insediative in Italia: spopolamento dei comuni rurali. In *Despoblación y transformaciones sociodemográficas de los territorios rurales: los casos de España, Italia y Francia*, Vol. 3, Lecce: Unisalento, pp.71-96.
- GESANO G., STROZZA S. 2011. Foreign migrations and population aging in Italy. *Genus*, Vol. 67, No. 3, pp. 83-104.
- GUARRACINO S. 2016. *Allarme demografico. Sovrappopolazione e spopolamento dal XVII al XXI secolo*. Milano: Il Saggiatore.
- KECK M, SAKDAPOLRAK P. 2013. What is Social Resilience? Lessons Learned and Ways Forward, *Erdekunde*, Vol 67, No. 01, pp. 5-19.
- MACCHI JANICA G. 2016. Desertificazione demografica dell'Italia: geografia dello spopolamento rurale nella penisola, *Trame nello spazio: quaderni di geografia storica e quantitativa*, Vol. 6, pp. 9-19.
- MAGGINO F. 2006. Gli indicatori statistici: concetti, metodi e applicazioni. Firenze: Firenze University press.
- MAZZIOTTA M, PARETO A. 2024. Statistica per gli indici compositi, Torino: Giappichelli editore.
- OECD. 2008. *Handbook on Constructing Composite Indicators. Methodology and user guide*. Paris: OECD Publications.
- RIZZO A. 2015. Declining, transition and slow rural territories in southern Italy Characterizing the intra-rural divides. *European Planning Studies*, Vol. 24, No. 2, pp. 231-253.
- SALONE C. 2017. Geografie italiane tra declino e resilienza urbana, *Urban Shrinkage*, Torino: Archivio Istituzionale Open Access dell'Università di Torino.
- SALVIA R., QUARANTA G. 2020. Place-Based Rural Development and Resilience: A Lesson from Small Community, *Sustainability*, Vol 9, No. 889, pp. 1-15.
- VALENTINI A. PARADISI. F. 2024, *Statistica ufficiale ed esigenze informative del territorio. Buone pratiche dal protocollo d'intesa tra Istat, Regioni e province autonome*, Anci e Upi, Roma: Istituto nazionale di statistica.

THE DIFFERENT ITALIES OF THE DEMOGRAPHIC DECLINE¹

Francesca Allegra, Paola Francesca Cortese, Graziella Fusaro, Giuseppe Stassi

Abstract. Italy's population decline is now more than a trend, it is an established (and accepted?) fact that policy seems unable to combat.

However, it does not affect the various territories in the same way: while the South and the Islands continue their significant population loss – as does the Centre, although to a much more limited extent – the North resists, even with some positive signs. This work aims to highlight the differences that have characterized the demographic trend in the Italian regions starting from 2014, the last year in which the national population was growing. The analysis of demographic trends and their effects on population structure will then be put in relation to the main socio-economic indicators released by Istat.

The statistical reading of territorial inequalities therefore aims to offer a useful cognitive contribution to identify any connections between demographic decline and economic vulnerability as well as the presumed links between some socio-economic and cultural characteristics and population decline.

1. Introduction

The demographic trend in Italy in the third millennium is currently characterised by a reversal that led our country towards a real demographic decline. Until 2014, the year in which the population peaked at 60,345,917 residents, the population had steadily increased. On the contrary, from 2015 to the present, there has been a continuous decrease in the population, with a drop of more than 1.4 million inhabitants (-2.3 percent). Only the population with Italian citizenship is decreasing, losing over 2 million individuals (-3.7 percent), while foreign residents continue to grow (+13.3). However, this positive net migration is unable to compensate for the negative natural change. In 2024, fertility reaches an all-time low (1.18 the average number of children per woman) and the birth rate drops from 8.3 (2014) to 6.3 per thousand; there is also a 15.3 percent drop in the female population of reproductive

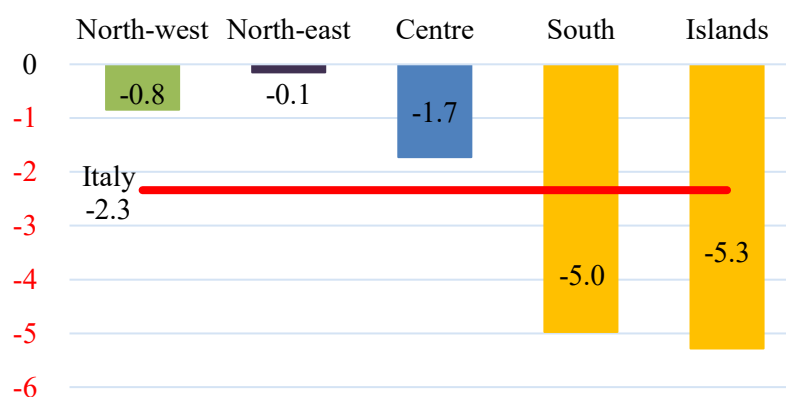
¹ Authors contributions: Francesca ALLEGRA paragraph 3; Paola Francesca CORTESE paragraph 5 and Conclusions; Graziella FUSARO Introduction and paragraph 2, Giuseppe STASSI paragraph 4. The authors' points of view expressed in the article do not necessarily reflect the official opinions of the Italian National Institute of Statistics.

age between 2014 and 2025. Italy remains the “oldest” country in the European Union (EU) with a quarter of the population over 65 and a growing imbalance in the age structure. In fact, the share of individuals over 65 years of age continues to increase year after year (24.7 percent in 2025 against 21.5 in 2014) and the weight of the youngest, under 15 years of age, continues to decrease (11.9 vs 13.9). The mean age of the population is 46.8 years and the elderly population is more than twice the size of the young population, with an ageing index of 207.6 percent. The growing dependency ratio, from 54.8 percent in 2014 to 57.8 in 2025, also shows a continued decline in the active age population.

2. Demographic decline: Macro-Areas and Regions

The demographic decline that began in 2014 affects all macro-areas but with differentiated intensity (Figure 1).

Figure 1 – Resident population on 1st January by macro-area. Years 2014-2025 (percentage change).



Source: Author's elaboration on Istat data

In the North-east, the resident population remains almost stable (-0.1 percent); in particular (Table 1), there is an increase in Trentino-Alto Adige (+3.2, especially in Bolzano +4.7) and Emilia-Romagna (+0.8) and a loss of population in Friuli-Venezia Giulia (-2.5) and Veneto (-1.1). In the North-west, only Lombardia records an increase in its residents (+1.1); Liguria and Valle d'Aosta suffered a population loss of more than 4 percent (-4.5 and -4.3 respectively). In the Centre, the decrease is -1.7 percent, specifically -4.5 percent in Umbria and -4.4 in Marche; the resident population in Lazio is almost unchanged (-0.2). The macro-areas most affected by

depopulation are the South (-5.0 percent) and the Islands (-5.3). There is a marked decrease in Molise and Basilicata (both -8.0 percent) and in Calabria (-6.4). In these last regions also the decrease in the female population of reproductive age is greater (potential mothers), structural factor that naturally affect the decline in births: Molise and Basilicata (-22.8 percent), Calabria (-20.2). The Sardegna region loses 5.5 percent of its inhabitants and 22.9 percent of its women of childbearing age.

Table 1 – Total resident population, female population of reproductive age and demographic indicators by region.

Regions and Italy	% Population change 2014-2025		Birth rate (per thousand) Year 2024 (provisional)	Population structure indicators (%) 1st January 2025 (estimate)			
	Total	F (15-49 years)		Ageing index	Dependency ratio	Mean age	> 65 years
Piemonte	-3.7	-15.8	5.8	239.8	61.4	48.1	26.9
Valle d'Aosta	-4.3	-17.9	5.2	227.1	59.2	47.7	25.8
Lombardia	1.1	-10.3	6.4	195.5	56.4	46.4	23.9
Trentino-Alto A.	3.2	-9.4	7.6	162.3	57.3	45.0	22.5
Veneto	-1.1	-14.9	6.2	211.9	57.9	47.1	24.9
Friuli-Venezia G.	-2.5	-15.8	5.8	252.3	62.3	48.6	27.5
Liguria	-4.5	-16.7	5.5	283.2	65.3	49.6	29.2
Emilia-Romagna	0.8	-10.2	6.3	210.8	58.0	47.1	24.9
Toscana	-2.2	-14.5	5.7	241.9	60.7	48.2	26.7
Umbria	-4.5	-17.3	5.5	246.6	62.3	48.4	27.3
Marche	-4.4	-17.0	5.6	235.5	60.8	47.9	26.6
Lazio	-0.2	-15.0	6.0	199.7	55.7	46.7	23.8
Abruzzo	-4.6	-19.0	5.8	228.1	59.8	47.6	26.0
Molise	-8.0	-22.8	5.4	259.0	60.3	48.3	27.1
Campania	-4.1	-16.5	7.4	161.6	53.1	44.5	21.4
Puglia	-5.0	-18.7	6.2	209.8	57.6	46.7	24.7
Basilicata	-8.0	-22.8	5.7	239.4	58.1	47.6	25.9
Calabria	-6.4	-20.2	6.9	196.2	58.5	46.2	24.4
Sicilia	-5.2	-18.1	7.0	184.3	57.5	45.7	23.7
Sardegna	-5.5	-22.9	4.5	281.4	59.2	49.2	27.4
Italy	-2.3	-15.3	6.3	207.6	57.8	46.8	24.7

Source: Author's elaboration on Istat data

In 2024, the lowest birth rate (4.5 per thousand) is found in Sardegna, followed by Valle d'Aosta (5.2) and Molise (5.4). Only five regions are above the national average: Trentino-Alto Adige (7.6), Campania (7.4), Sicilia (7.0), Calabria (6.9) and Lombardia (6.4).

The areas most affected by depopulation are also those characterised by the greatest imbalance in the age structure of the population. The strong ageing of Liguria is consolidated: individuals over 65 years of age make up 29.2 percent of the

total population, the ageing index reaches 283.2 percent and the mean age of the population is 49.6 years. Equally high is the incidence of the over-65s on the total population in Sardegna (27.4 percent) and Molise (27.1), regions with ageing indices of 281.4 and 259.0 percent respectively. The “youngest” regions, with much lower ageing indices, are Campania (161.6) and Trentino-Alto Adige (162.3); in these regions the proportion of the over-65s (21.4 and 22.5 percent) is below the national average. The dependency ratio is a measure of sustainability (ISTAT, 2024c) and high values signal the increasing socio-economic burden of the non-active population on the working age population. The highest indices are observed in Liguria (65.3 percent), Friuli-Venezia Giulia and Umbria (62.3 percent) while the lowest value is found in the region with the smallest elderly population, Campania (53.1 percent).

3. Education levels in the Italian regions

Increased education influences choices and shifts priorities: it can push people to migrate to places with greater opportunities for suitable employment and can impact the decision to have children. This section aims to provide an overview of education levels in Italy to offer possible explanations for the different demographic trends in its regions. The Italian regions present a very heterogeneous panorama concerning the achievement of a high level of education (Table 2). In 2024, in Italy, considering the population in the 25-64 age group, 66.7 percent had obtained at least an upper secondary school diploma. However, this is not a uniform figure across the country: the two largest islands and four regions of the South (Puglia, Campania, Calabria and Basilicata) are positioned with significant gaps below the national figure, while in this range we find only one region of the North (Valle d'Aosta) and none of the Centre. Thirteen regions are positioned above the national average, first of all Umbria (75.9 percent), Lazio (75.1) and Friuli-Venezia Giulia (74.9).

Within the population aged 25-64 who have obtained at least an upper secondary school diploma, gender favours women who, in Italy in 2024, exceed men by 5.4 percentage points. In this case too, substantial differences are found between the Italian regions, which present minimum gender gaps in Molise (1.7 percentage points in favour of women), Puglia (2.2), Campania (2.5) and Basilicata (2.9) and maximum in Sardegna (9.4), Valle d'Aosta (9.3), Toscana (8.8) and Marche (8.5).

Even in 2024, shifting the focus to the population in the 25-34 age group, 31.6 percent completed tertiary education. Among the nine regions that exceed the national value, Lazio is in first place (37.1 percent), followed closely by Emilia-Romagna (36.9), Umbria (36.6) and Veneto (36.3); the almost total absence of the South and the Islands is noted in the upper part of the ranking, represented only by

Abruzzo (32.5). In the last places for incidence of population aged 25-34 having completed tertiary education, we have six regions of the South: Molise (27.5 percent), Campania (27.3), Calabria (26.5), Sardegna (25.6), Puglia (24.4) and Sicilia (23.2).

Table 2 – Population by educational qualification obtained. Year 2024 (percentage values).

Regions and Italy	People with at least upper secondary education level (25-64 years old)			People having completed tertiary education (25-34 years old)		
	M	F	Total	M	F	Total
Piemonte	64.4	70.6	67.5	25.8	36.6	31.0
Valle d'Aosta	58.6	67.9	63.3	20.3	41.2	30.5
Liguria	68.9	74.1	71.5	21.7	37.8	29.5
Lombardia	66.3	72.6	69.4	26.6	44.4	35.2
Trentino-Alto Adige	70.9	75.8	73.4	21.8	36.7	29.0
Veneto	66.8	72.6	69.7	28.9	44.1	36.3
Friuli-Venezia Giulia	73.3	76.6	74.9	25.9	45.2	35.2
Emilia-Romagna	67.8	75.4	71.6	29.5	44.9	36.9
Toscana	63.1	71.9	67.6	25.8	38.9	32.2
Umbria	72.6	79.0	75.9	28.9	44.7	36.6
Marche	66.0	74.5	70.3	25.6	41.7	33.3
Lazio	72.7	77.3	75.1	29.3	45.3	37.1
Abruzzo	69.3	73.7	71.5	27.4	38.0	32.5
Molise	68.1	69.8	68.9	18.2	37.9	27.5
Campania	57.2	59.7	58.5	21.7	32.9	27.3
Puglia	55.8	58.0	56.9	18.7	30.3	24.4
Basilicata	64.5	67.4	66.0	20.6	39.8	29.8
Calabria	59.0	63.9	61.5	21.8	31.5	26.5
Sicilia	54.2	58.0	56.1	20.4	26.1	23.2
Sardegna	52.1	61.5	56.8	22.6	28.8	25.6
Italy	64.0	69.4	66.7	25.0	38.5	31.6

Source: Istat, Labour force survey.

In 2024 even among 25-34 year olds having completed tertiary education, women prevail, exceeding men by 13.5 percentage points. There are 12 regions where the gap is greater than the national one, two of which are in the South: Molise (19.7 percentage points in favour of women) and Basilicata (19.2). The differences recorded in Calabria (9.7), Sardegna (6.2) and Sicilia (5.7) are less large.

Early exit from the education and training system has a negative impact on the overall cultural level of a territory. In 2024, in Italy, the percentage of young people leaving education and training (ELET) early – that is, those aged 18 to 24 who have only achieved a low level of education – dropped to 9.8 percent, confirming a trend that has been ongoing for several years. Compared to 2018, the phenomenon has

decreased in all Italian regions, with the exception of Trentino Alto-Adige. In 2024, the highest percentages of people aged 18-24 years who have achieved only lower secondary (ISCED 2) and are not included in a training program were recorded in Sicilia (15.2 percent), Sardegna (14.5) and Campania (13.3). Below the national figure (with values ranging from 9.1 percent in Marche to 4.8 in Molise) are most of the regions of the North and all those of the Centre, as well as Basilicata and Abruzzo.

Early exit from the education and training system affects men more than women: at national level in 2024, 12.2 percent of men left the education and training system early, compared to 7.1 percent of women. At a regional level, the gender gap appears to be independent of the intensity of the phenomenon: limited differences can correspond to a high intensity of the phenomenon and vice versa. For example, in Sicilia the gap is 4.3 percentage points, while in Liguria - where the largest gap is recorded (11.4) - the percentage of ELET is lower than the national average.

Another characteristic that differentiates the Italian regions is the distribution of the percentage of people who are neither in education nor employed (NEET), that is the percentage of people aged 15-29 years that are not in education, employment, or training on total people aged 15-29 years. In 2024, in Italy, NEETs were 15.2 percent of the reference population, a decrease compared to the previous year, confirming the progressive reduction of the phenomenon (eight percentage points less than 2018). The data, however, clearly divide the South from the rest of Italy: all the regions of the South present values higher than the national figure, in particular in Calabria (26.2 percent), Sicilia (25.7) and Campania (24.9). Values very different from those of Emilia-Romagna (9.6), Veneto (9.0) and Trentino-Alto Adige (7.7).

The geography of the gender gap is more heterogeneous. In 2024, at a national level, the percentages of NEETs are 13.8 for men and 16.6 for women. Even for NEETs, the gender gap does not always correspond to a high intensity of the phenomenon: for example, in Emilia Romagna, women outnumber men by 5.7 percentage points, yet the NEET rate is among the lowest in the country; the situation is similar in Veneto. By contrast, in Campania – where the phenomenon is particularly widespread – the difference between men and women is minimal.

4. Economic conditions in the Italian regions

The dynamics of the labour market are closely interconnected with the demographic ones: the territories that offer the greatest employment opportunities are those that are most likely to attract population or, at least, to maintain the existing one; at the same time, having a job might facilitate parenthood.

In 2024, in Italy, the employment rate reached 62.2 percent (Table 3), a value that also marks a clear boundary between the North and the South of the country: Trentino-Alto Adige (72.7) and Valle d'Aosta (72.1) lead the ranking. No region in the South and Islands is above the national average, with significant disadvantages such as in Sicilia (46.8), Campania (45.4) and Calabria (44.8).

The gender gap - which in Italy, in 2024, was equal to 17.8 percentage points - affects the southern regions more, with values that in Basilicata, Campania and Puglia exceed 25 percentage points; the only exception is Sardegna (14.2). The smallest gap between men and women is recorded in Trentino-Alto Adige (10.9 percentage points) and Valle d'Aosta (7.5).

Table 3 – *Employment rate and Unemployment rate (15-64 years old). Year 2024 (percentage values).*

Regions and Italy	Employment rate			Unemployment rate		
	M	F	Total	M	F	Total
Piemonte	75.6	62.3	69.0	5.0	6.1	5.5
Valle d'Aosta	75.9	68.4	72.1	3.6	4.3	3.9
Liguria	74.8	59.8	67.3	4.8	6.4	5.5
Lombardia	76.3	62.3	69.4	3.3	4.3	3.7
Trentino-Alto Adige	78.1	67.2	72.7	2.3	2.5	2.4
Veneto	78.0	62.3	70.2	2.2	4.1	3.0
Friuli-Venezia Giulia	75.5	63.9	69.8	3.8	5.2	4.4
Emilia-Romagna	77.4	63.2	70.3	3.5	5.5	4.4
Toscana	78.1	63.7	70.9	3.2	5.2	4.1
Umbria	74.6	61.5	68.0	4.5	5.4	4.9
Marche	72.8	61.6	67.2	4.7	5.8	5.2
Lazio	72.3	55.8	64.0	5.4	7.6	6.4
Abruzzo	72.0	52.1	62.1	6.7	7.9	7.2
Molise	68.0	47.3	57.9	6.5	10.3	8.1
Campania	58.7	32.3	45.4	14.6	18.1	15.9
Puglia	64.9	37.6	51.2	8.4	11.2	9.5
Basilicata	68.7	42.9	56.0	5.3	9.6	6.9
Calabria	56.6	33.1	44.8	12.4	15.0	13.4
Sicilia	58.9	34.9	46.8	12.1	15.3	13.3
Sardegna	64.7	50.5	57.7	8.2	8.9	8.5
Italy	71.1	53.3	62.2	6.0	7.5	6.6

Source: Istat, Labour force survey.

If we look at the trend of the unemployment rate, we observe a situation similar to the one just described: values higher than the national one (6.6 percent in 2024) in the South and the Islands and lower in the rest of the country.

Even in terms of unemployment, the gender gap penalises women (1.5 percentage points in Italy in 2024), a gap that is often more marked in the southern territories.

Since the characteristics of the labour market are directly reflected in the economic well-being of the territories, it is not surprising that in all the regions of the South and the Islands the GDP per capita is lower than the national one (€ 36,077 in 2023), with values ranging from € 31,012 in Abruzzo to € 21,050 in Calabria.

The 2023 data on annual average households income (not including imputed rents) also suggest a disadvantage for those living in the South and the Islands, with values ranging from €33,343 in Sardegna to €28,131 in Calabria (compared to €37,511 in Italy). The same is true for median income: all southern regions are below the national average (€30,039 in 2023), with the highest figure in Basilicata (€27,922) and the lowest in Calabria (€23,210). Perhaps it is also based on income that, in 2024, in six southern regions the percentage of people dissatisfied with their economic situation exceeds the national figure (40.2 percent): from 41.9 in Campania to 51.4 in Sicilia.

5. Poverty in the Italian regions

The analysis of relative and absolute poverty and the risk of poverty are conceived as a further potential junction and multiplier of depopulation dynamics, particularly in those areas affected by a significant negative population balance.

In the following, poverty is emphasized as a key social and economic dimension that often co-occurs with demographic imbalances, lower education, and weaker labor market conditions. It is considered here as an additional interpretative lens, not as the sole or linear cause of demographic decline.

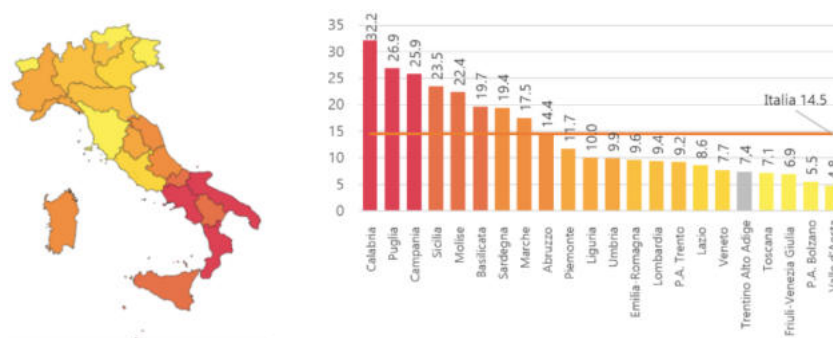
Poverty is not uniformly distributed across the Italian territory. Marked differences can be observed between:

- ☐ territorial divisions (North-West, North-East, Centre, South, Islands);
- ☐ individual regions;
- ☐ most notably, between small, medium-sized, and large municipalities.

In the southern regions, poverty reaches particularly high levels (Figure 2), often associated with demographic decline, lower levels of education, and higher unemployment. In Calabria, in 2023, about one in three residents lives in relative poverty; in Puglia and Campania, more than one in four. All eight southern regions occupy the top nine most critical positions in the national ranking. However, the relationship between poverty and demographic decline does not follow a single pattern. Some regions, such as Liguria and Umbria, despite experiencing significant demographic decline and population ageing, show nearly overlapping levels of

individual relative poverty (10.0 percent and 9.9 percent, respectively), but more contained compared to other regions with a strong demographic downturn, and still below the national average. The picture regarding individual relative poverty across Italian regions is largely confirmed by the data on individual absolute poverty and poverty risk levels, available for the five territorial divisions (Figure 3). These indicators also show Southern Italy as the area with the most critical levels, confirming the pattern already observed in education and labour market indicators. Although absolute poverty appears with relatively low variability across the divisions (ranging from a maximum of about 12 percent in the South and Islands to a minimum of 7.9 percent in the Centre), the high territorial inequality in the share of population at risk of poverty, highest in the South and Islands (31.5 percent and 35.8 percent, respectively) and lowest in the North-East (8.7 percent), points to a deep divide across a broad set of previously discussed indicators. Nonetheless, the critical levels reached by both statistical measures are evident and widespread throughout the country, including the North.

Figure 2 – Individuals in relative poverty by region. Italy, 2023 (percentage incidence).

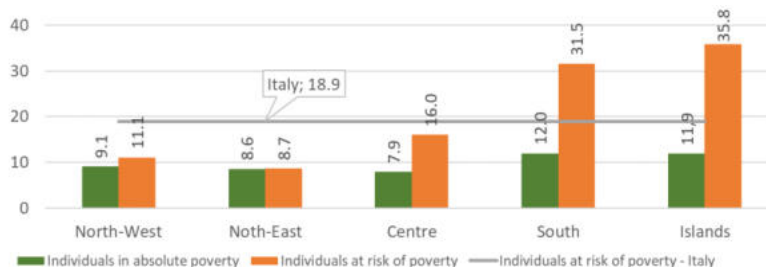


Source: Istat - Household Budget Survey (HBS). Authors' calculations.

To complement the regional analysis, a sub-regional perspective at the municipal level is introduced. This approach highlights vulnerabilities that averages may conceal, especially in smaller municipalities. The Municipal Fragility Index (Istat, 2021) is employed as a composite measure of demographic and socioeconomic conditions; reference is also made to the classification of Inner Areas (SNAI)² as examples of limited access to essential services. In fact, the existence of territorially differentiated vulnerabilities, although confirming the persistent weakness of the southern regions, does not spare other areas including the North-West and Central Italy, as shown in Figure 4 (map of the municipal fragility index).

² Inner Areas (SNAI): Italian national strategy (2013) targeting territories far from essential services, to counter demographic decline and marginalization.

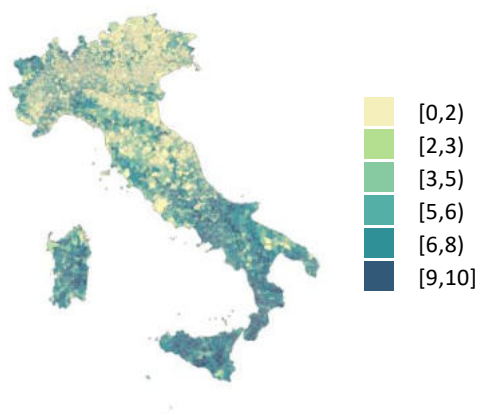
Figure 3 – *Individuals in absolute poverty and at risk of poverty by geographical area Italy, 2023 (percentage incidence).*



Source: Absolute poverty - Istat, Household Budget Survey (HBS); At-risk-of-poverty rate - Istat, EU-SILC. Authors' calculations.

Demographic dynamics and poverty levels are often observed together, with interactions that suggest mutually reinforcing effects rather than a one-directional causal link. In the most fragile areas, where population decline is pronounced and accompanied by a gradual reduction in the share of the working-age population (mainly small municipalities, particularly those classified as “inner areas”), the value of the municipal fragility index is consistently associated with levels of relative and absolute poverty (Figures 5 and 6), indicating very limited prospects for local and demographic development. Among the smallest municipalities (with up to 5,000 inhabitants), nearly 30 percent are highly fragile; this share decreases to 15.8 percent and 13.6 percent, respectively, in medium-sized and large municipalities.

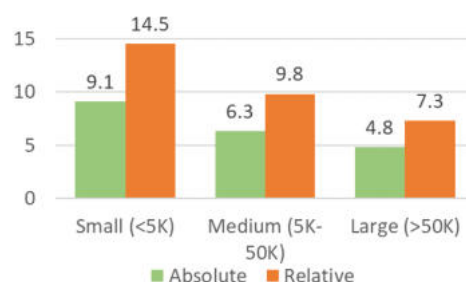
Figure 4 – *Composite Index of Fragility at Municipal Level. Italy, 2021.*



Source: Istat - Composite Index of Fragility at Municipal Level.

Figure 5 – Municipal Fragility Index by demographic size. Italy, 2021 (percent values).

Source: Istat - Composite Index of Fragility at Municipal level. Authors calculations.

Figure 6 – Absolute and relative poverty rate by type Municipality³, Italy, 2023 (percentage incidence).

Source: Istat, Household Budget Survey (HBS). Authors' calculations. Municipalities are classified by size (small $\leq 5,000$; medium 5,001–50,000; large $> 50,000$) and, where relevant, by Inner Areas (SNAI).

From a statistical perspective, poverty emerges as a sensitive indicator of a territory's ability to respond to ongoing demographic transformations. Its multiple dimensions require targeted policies capable of addressing both structurally marginalised areas and those where poverty manifests in more latent and invisible forms.

6. Conclusions

Depopulation is not merely a demographic phenomenon, but the result of structural imbalances that also involve education, employment, and economic

³ Municipalities are classified by demographic size (small $\leq 5,000$ inhabitants; medium 5,001–50,000; large $> 50,000$) and, where relevant, by belonging to the National Strategy for Inner Areas (SNAI). Poverty rates by type of municipality are based on HBS 2023 data; the Municipal Fragility Index refers to 2021 (Istat).

resources. Southern Italy (the Mezzogiorno) remains, dramatically, the most fragile area, where lower levels of schooling, lower participation in the labour market, lower income, and widespread poverty converge – factors that fuel outmigration and hinder territorial development. However, differentiated territorial models emerge: some regions in Central and Northern Italy, though affected by population decline and aging, demonstrate greater socio-economic resilience. In the most vulnerable areas, the loss of working-age population triggers vicious cycles of impoverishment and decline, weakening the capacity for response and regeneration. Depopulation thus appears to be linked to a broader territorial and generational crisis, which calls for sub-regional analyses and integrated approaches aimed at strengthening territorial attractiveness.

References

- BUBBICO R.L., MAZZOLA F., NISTICÒ R. 2021. Territorial Development and Human Capital: The Case of Southern Italy, *Italian Journal of Regional Science*, Vol. 20, No. 1, pp. 43–65.
- CERSIS – Università Cattolica del Sacro Cuore. 2022. *Rapporto sulla povertà in Italia*. Milano: Vita e Pensiero.
- ISTAT. 2024a. *Annuario statistico italiano 2024*. Roma: Istituto Nazionale di Statistica.
- ISTAT. 2024b. Bes | 2023. *Il benessere equo e sostenibile in Italia*. Roma: Istituto Nazionale di Statistica.
- ISTAT. 2024c. *Rapporto annuale 2024 – La situazione del Paese*. Roma: Istituto Nazionale di Statistica.
- ISTAT. 2025a. *Rapporto annuale 2025. La situazione del Paese*. Roma: Istituto Nazionale di Statistica.
- ISTAT. 2025b. Statistiche report, *Indicatori demografici | Anno 2024*.
- ISTAT. 2025c. Statistiche report, *Condizioni di vita e reddito delle famiglie | anni 2023-2024*.
- ISTATDATA, *La banca dati dell'Istituto Nazionale di Statistica*.
<https://esploradati.istat.it/databrowser/#/it>

Francesca ALLEGRA, Italian National Institute of Statistics, allegraf@istat.it
Paola Francesca CORTESE, Italian National Institute of Statistics, pacortes@istat.it
Graziella FUSARO, Italian National Institute of Statistics, fusaro@istat.it
Giuseppe STASSI, Italian National Institute of Statistics, stassi@istat.it

A TERRITORIAL READING OF HOUSEHOLDS AND FAMILIES CHANGES IN ITALY OVER THE LAST 50 YEARS¹

Mariangela Verrascina, Silvia Dardanelli, Antonio Guglielmi

Abstract. In recent decades, Italy has experienced significant family transformations, the patterns of formation, dissolution and reconstitution have become more heterogeneous and family boundaries more ambiguous. Population aging and the increase in relationship instability are associated with the consolidation of new family forms, and same-sex unions have been legally recognized (Cirinnà Law, N. 76 /2016).

The aim of the work is to study the changes in household/family types in Italy over the past half-century, by means of cartographic representation for a territorial reading of household/family models. The structure transformation is described using census data, from which types for smaller spatial units are constructed and compared in a time series.

The territorial analysis is carried out considering Provinces and Metropolitan Cities (MCs) as spatial units. The largest Municipalities tend to ‘drag’ the entire provincial area, for this reason an intermediate layer is constructed: the largest Municipalities are extrapolated from the Provinces/MCs and treated as separate territorial units.

Compared to the past, there is a decline in the traditional family and a consolidation of other forms. The different household/family types (e.g. classic nuclear family, one-person households, lone parent families) are represented on maps to display the evolution over time, to underline extreme values, to make visual comparisons in order to highlight territorial differences or whether there are similarities in household/family patterns across different areas of the country.

1. Process of transformation of the households and families

In recent decades, Italy has experienced significant household and family transformations. Families and households have changed in form and composition, as well as in size, but more in general, what has changed is the way people live in households and families.

¹ In the context of a joint and shared work, paragraph 1 is attributed to Mariangela Verrascina, paragraph 4 to Silvia Dardanelli, paragraph 3 to Antonio Guglielmi and paragraph 2 to Silvia Dardanelli and Mariangela Verrascina. Paragraph 5 is attributed to all the authors.

The aspects considered underlying the analysis are based on two fundamental definitions: the ‘(private) household’² and the ‘family nucleus’³, two concepts contained in the International Recommendations for the 2020 Censuses of Population and Housing (UNECE, 2015), but also in the Anagrafe Regulation in force in Italy.

Changes in family life forms reflect the demographic and social transformations still taking place in our country today. Different lifestyles, declining fertility, increasing separations and divorces, growing instability in couple relationships, and longer life expectancy facilitate the formation of smaller and smaller households and more flexible family structures that move away from the traditional model and are associated with the consolidation of new family forms. Patterns of formation, dissolution and reconstitution have become more heterogeneous and family boundaries more ambiguous. The process of transformation of the household/family involves its structure and the relationships among persons who compose it.

Today, in Italy, a true archipelago of family forms exists. For decades, a progressive and unstoppable process of family transformation has been underway. At the same time, there is an acceleration in the spread of new family models. Thus, our country represents a significant study context for the marked differences in the temporal and territorial distribution of the various family types.

The aim of this work is to study the changes in household and family types experienced by Italy over the past half-century through a territorial reading of family models. On one hand, it describes how traditional forms have changed and how they are distributed across the territory over the last 50 years; on the other hand, it shows the evolution of new family models over time in Italy. The goal is therefore to underline extreme values, make visual comparisons to highlight territorial differences or similarities in family patterns across different areas of the country.

2. Data and method

The ongoing transformation of household and family structures is described through census ‘pictures’, which also allow for a deeper understanding of the spatial dimension. Census data make it possible to identify household/family types for

² (Private) Household: Group of persons linked by marriage, civil partnership, kinship, affinity, adoption, legal guardianship or personal ties, who cohabit and share a place of usual residence (even if not already registered at the General Register Office). A household may be also constituted by one person.

³ Family Nucleus: People living in couples, with or without (resident) children, or lone parents with (resident) children. Two or more persons who belong to the same household and who are related as husband and wife (opposite sex), as partners in a registered partnership (same sex), as partners in a consensual union, without or with (resident) children, or as parent and (resident) child. The concept of family nucleus is more restrictive than the private household concept. Within a household there may be one or more family nuclei but there may be none (for example, one-person households).

smaller and more homogeneous spatial units and to capture patterns that might go unnoticed when considering broader spatial levels of analysis. The availability of detailed territorial data, as known, is a characteristic of the population census. The census enables a finer territorial mapping of households compared to other surveys; it records households according to the criterion of co-residence, meaning all those family types that result from the condition of co-habitation in the same dwelling, 'under the same roof'.

The census years considered depend on when a topic was introduced in the survey questionnaires and how widespread it was. Some forms have been present since the earliest censuses (Mastroluca, Verrascina, 2012), while other 'new' models began to emerge starting in the late 20th and early 21st centuries and became subject of survey and analysis only when they started to become 'visible'.

In order to respond to the need for a more in-depth knowledge of family structures, the question on the relationship to the household's reference person was expanded in the census questionnaire from 1981 onwards (the number of modes was gradually increased from 9 in 1981 to 23 in 2021). This made it possible to identify 'family nuclei' for which data had already been compiled in 1971 anyway. Thanks to the opportunities offered by the better articulation of the kinship question, in the latest censuses it has been possible, on the basis of the identification of nuclei, to arrive at a new typology of the family, more detailed and in step with the ongoing transformation of households (Cortese, 2011; Cortese, 1985). Since 2011, it has been possible to enumerate same-sex couples, and furthermore, the precise reference to the 'affective ties' referred to in the definition of family adopted today makes the enumeration of so-called 'de facto couples' less problematic (Cortese, 2007).

For indicators on households (Average number of components, Households with 5 members and over, One-person households) the time series of the past 50 years has been considered, i.e. the results of the last six decennial Population and Housing Censuses (from 1971 to 2021), while for indicators on family nuclei (Couples with Children, Lone parents, Couples in consensual union), the last three decennial censuses (2001 to 2021) have been taken into account. Lastly, an indicator on same-sex couples is presented based on the last two decennial censuses (2011 and 2021).

Similarities and differences over the territory, trends or observable regularities are sought through the cartographic representation of the spread of the phenomenon, or rather of the portion of the phenomenon captured by the 'snapshots' taken in Italy with the censuses.

Through the map sequences we try to answer some research questions concerning how household/family structures have changed in Italy, how the new structures have spread, whether the distribution is homogeneous on the Italian territory, whether the North-South dichotomy prevails, with the more 'innovative' North, where the spread

of new behaviours is advanced, and the more ‘traditional’ South, where such a spread still struggles to take hold, as well as whether sub-regional heterogeneities emerge.

We also wondered whether the more traditional forms, involving mutual support and co-residence/cohabitation for economic, housing and care needs, are still rooted in the regions of Southern Italy or whether pockets of ‘new’ household/family types can be observed.

The territorial analysis is carried out considering as spatial units 107 Provinces/Metropolitan Cities (MCs) existing in 2021. However the largest Municipalities (over 150,000 inhabitants or capitals of Metropolitan Cities)⁴ tend to ‘drag’ the entire provincial area, their value weighs heavily on the overall figure. So, the approach to the study consists of constructing an intermediate layer in which the large Municipalities are extrapolated from the Provinces/MCs and are treated as separate territorial units, to better highlight their peculiarities.

ArcGIS Pro is a GIS (Geographic Information Systems) software application developed by Esri (Environmental Systems Research Institute) for the analysis and management of geographic information. It offers advanced tools for spatial and geostatistical analysis and interactive visualisation; it allows to manage geodatabases and integrate data from multiple sources; and produce cartographic outputs. In this study, ArcGIS Pro is used to perform analyses, create the ‘rest of the Province/MC’ layer (through the Union function applied to municipal geographic data) and produce maps. For the 26 Provinces/MCs with large Municipalities, two areas were created: the large Municipality and the rest of the Province/MC. So, 133 geographical areas are considered.

3. Households are getting smaller

The size of households⁵ in Italy has decreased significantly over the last decades. Considering the indicator Average number of components (Figure 1), in 1971 households were composed on average of 3.4 components; this value has been steadily decreasing, reaching 2.2 components in 2021.

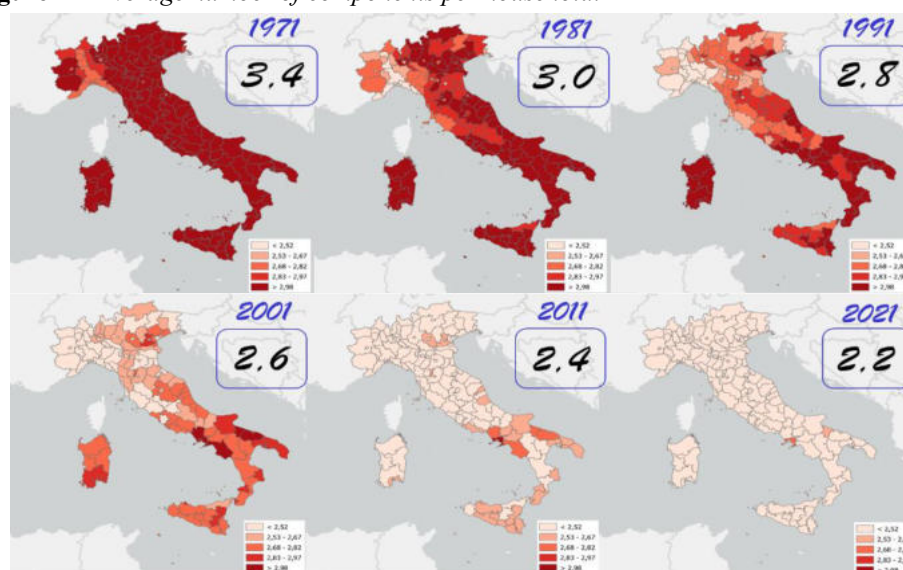
This phenomenon was initially visible only in a few areas in Northern Italy, until 1991, when a dichotomy emerged between the Centre-North and the South of the country, with most of the large Municipalities in the North recording the lowest values. The decrease in the average number of household members has continued to the present day, also affecting the Southern regions. In 2021, the only territories with

⁴ Turin, Milan, Brescia, Genoa, Verona, Venice, Padua, Trieste, Parma, Reggio Emilia, Modena, Bologna, Ravenna, Florence, Livorno, Prato, Perugia, Rome, Naples, Bari, Taranto, Reggio Calabria, Palermo, Messina, Catania, Cagliari.

⁵ See footnote 2.

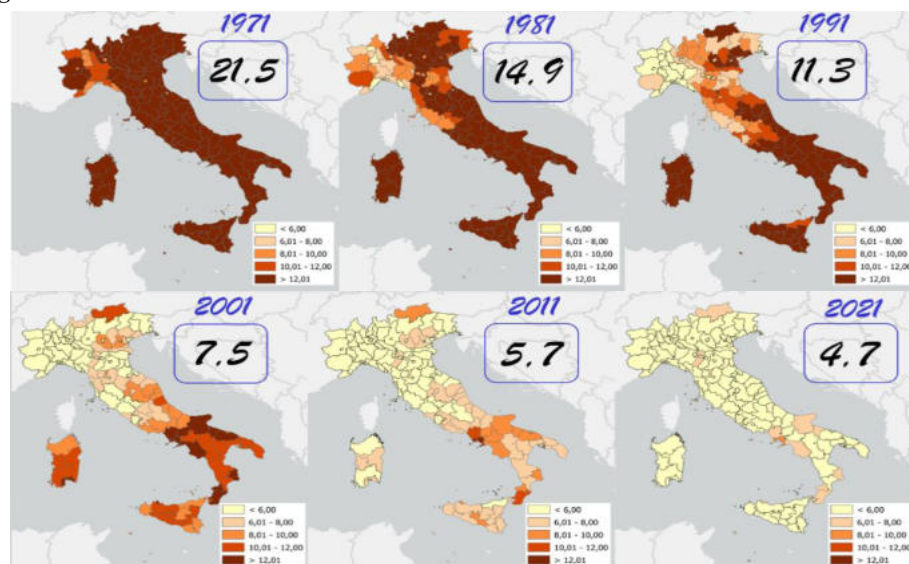
a higher average number of household members are the Provinces of Barletta-Andria-Trani and Naples, with an average of more than 2.5, while the large Municipalities, especially those in the North, continued to show the phenomenon more markedly, their values are lower than the Italian figure, with Bologna that recorded the lowest value (1.8).

Figure 1 – Average number of components per household.



Source: Istat, General Population Censuses (1971 to 2011) and Permanent Population Census 2021

The results for the percentage of Households with 5 or more members are in line with the Average number of components. The national value of households with 5 or more members fell from 21.5% in 1971 to 4.7% in 2021. As with the Average number of components, in 1971 this trend was initially visible only in the North. The phenomenon evolved in this direction and, from census to census, the percentage of households with 5 or more members decreased in the North and in the Centre of Italy, until 1991, the year in which it is possible to observe a divided Italy, with the South continuing to have a high percentage of more numerous households. In subsequent censuses, the South was also gradually affected by this phenomenon, aligning itself with the data for Northern and Central Italy, until 2021, when only the values for the rest of the Metropolitan City of Naples remains 9.3%. The large Municipalities of Northern Italy record values in most cases lower than the Italian value throughout the historical period analysed, with the absolute lowest value recorded in Trieste in 2001, equal to 2.0%.

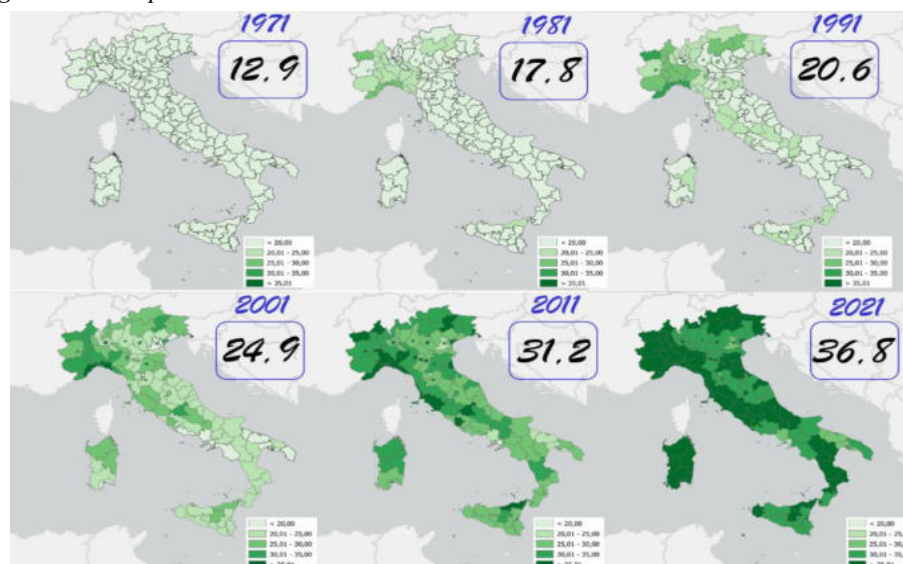
Figure 2 – Households with 5 members and over.

Source: Istat, General Population Censuses (1971 to 2011) and Permanent Population Census 2021

Households without nuclei, in which components do not form any kind of relationship as a couple or parent-child, increased especially due to One-person households. Persons living alone are becoming increasingly common across Europe where, on average, the share is 35.9% (Istat, 2022).

The living arrangements of the elderly, and more specifically living alone, are the result of the preferences and resources people have, together with the constraints they face as they age (Reher and Requena, 2018).

Starting with 1971, the phenomenon initially accounted for a small percentage of households, around 12.9%. In the following decades, one-person households have increased, and also in this case, the change is initially visible in Northern Italy. The trend then spread throughout Italy, until it almost doubled in 2001, when one-person households accounted for 24.9%. In 2011, the large Municipalities of Northern and Central Italy led the phenomenon, presenting the highest values of one-person households. These cities could differ by up to 10 percentage points from the national figure (31.2%), as in the case of Bologna, where the highest value of 47.3% was observed. In the later years, its relevance progressively extended not only to the Centre-North areas, but also to the South of Italy. In 2021, the percentage of persons living alone almost tripled compared to 1971, reaching 36.8%. The rest of the Metropolitan City of Naples is the only area least affected by this phenomenon, recording the lowest value of 24.8%.

Figure 3 – One-person households.

Source: Istat, General Population Censuses (1971 to 2011) and Permanent Population Census 2021

The different lifestyles, enhanced educational and employment prospects that characterize large urban centers also appear to favour the choice of living alone (Gallo, Dardanelli, *et al.*, 2023). In almost all the large Municipalities of Central-Northern Italy, the proportion of one-person households is above 40%, Milan standing out, where 54.0% of households are made up of one person. In the large Municipalities of Southern Italy, the phenomenon is less extensive, but still marked compared to previous decades, with roughly one household in three made up of persons living alone.

4. Family nuclei change forms

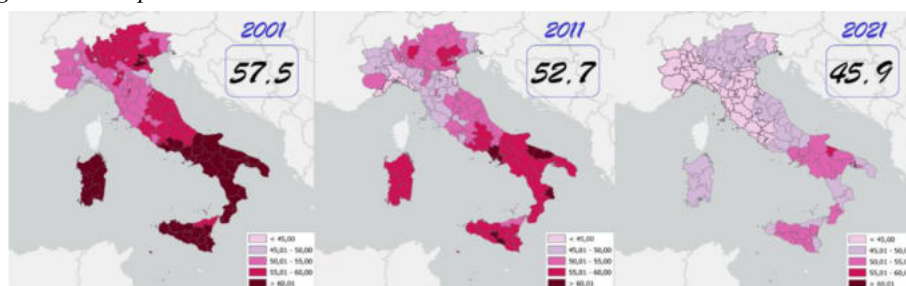
The demographic and social changes still taking place in our country today facilitate the formation of increasingly smaller households and more flexible family structures that move away from the traditional model, with a decline of the classic nuclear family. Couples⁶ with (resident) children decreased by more than 1.2 million, from 8,766,690 in the 2011 Census to 7,537,874 in 2021, confirming the downward trend already highlighted at the beginning of the new millennium (were more than 9,2 million in 2001).

⁶ See footnote 3.

The marked decline in couples with children is linked to the persistently low fertility rate, but especially to the advancing age of *boomers*, born in the years between 1955 and 1975. The significant decrease in couples with or without children is the combination of an increase in older couples and the sharp decline in younger couples (Dalla Zuanna, 2024).

In 2021, as in past censuses, a gap in families composition between the Southern and Northern areas is evident. Couples with children are more represented in the South, in particular Basilicata, Campania and Apulia; among the values lower than the national data, now widespread throughout the North and the Centre, the Valle d'Aosta, Piedmont and Liguria stand out, reaching a minimum for the Ligurian Provinces, which do not have more than 38.1% of couples with children.

Figure 4 – Couples with children.



Source: Istat, General Population Censuses (2001 and 2011) and Permanent Population Census 2021

In the decades, the fall has involved the whole of Italy indiscriminately, albeit with different intensity. Sardinia is the region that experienced the most marked reduction between 2011 and 2021, falling by about 10 percentage points in all the Provinces. In large Municipalities, in line with the differences highlighted between the Northern and Southern Italy, couples with children are more usual in the capital cities of the South and Islands. However, Palermo, Reggio Calabria and Bari, with values between 48.9% and 46.5%, are the only ones above the national figure. The lowest incidences are observed in Trieste, Genoa and Bologna (in 2021, 35.7%, 37.3% and 38.4% respectively), and in Cagliari (37.1%), which is in contrast with the territorial area to which it belongs.

Over the last three decades, partly offsetting the reduction in couples, both female and male lone parents (with one or more resident children) have increased, mainly due to growing marital instability. Comparison with the past shows a shift from an 'old' form of lone parenthood, originating especially from widowhood, to a new form, resulting, above all, from the voluntary dissolution of marriages, out-of-wedlock birth. In 2021, what has the greatest impact on this phenomenon is the growing marital instability; in fact, about half of lone parents are separated or

divorced, 30.7% are widowed, while 22.0% of lone parents have never married. In 2011, there was, on the contrary, a higher incidence (36.5%) of widows/widowers and a lower incidence (30.4%) of separated and divorced (ISTAT, 2024).

Also in the case of Lone parent families, the change compared to the past is generalised across the territory, with an increase affecting all the geographical areas considered (Figure 5). The number of lone mothers in 2021 is 2,967,420, showing an increase of 35.5% compared to 2011 Census, and the number of lone fathers is 855,049 with a change of about 85.0%. Lone parenthood is almost a female prerogative (8 out of 10 cases): women continue to live with their children following separation or divorce also because there is a strong preference for maternal custody in separations. Moreover, men are more likely to form a new union following a widowhood event.

In 2021, the highest percentages of lone parents out of the total number of families are recorded for Latium and Liguria, where the share exceeds 25.0% for all Provinces/MCs.

Figure 5 – Lone parents.



Source: Istat, General Population Censuses (2001 and 2011) and Permanent Population Census 2021

The large Municipalities are characterized by a process of fragmentation that in many cases is more accentuated than in the rest of the country. Different lifestyles and probably more unstable relationships seem to favour the formation of lone parent households. In all these cities there is a higher percentage of lone parents than the country as a whole. In many cases the large centres stand out compared to the rest of the Province/MC, particularly in the North and South, while in others (e.g. Central Italy, Sardinia, Liguria, some Provinces in Campania) the two areas show similar trends. In 2021, Rome, Cagliari, Catania and Naples are at the top of the list with lone parent shares above 30.0%.

Couples in consensual union increased in the decade 2001-2011 and then remained substantially stable until 2021 (Figure 6). The weight of these couples is much more evident in Northern and Central Italy than in the South and in the Islands. Here again, the dichotomy between the Centre-North and South of the country

clearly emerges, while Sardinia shows a separate trend from the Southern regions (8.5% for the rest of the Metropolitan City of Cagliari). The phenomenon already underrepresented in 2011 in the South and in Sicily has further thinned out (except for Catania and Taranto). Less than 2.5% of the couples living in Reggio Calabria and Agrigento are not married to each other, compared to about 15.0% of those living in Valle D'Aosta and the Autonomous Province of Bolzano.

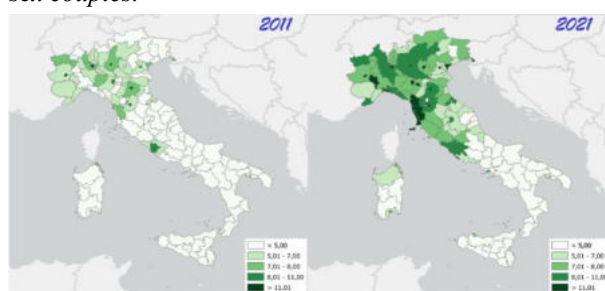
Figure 6 – Couples in consensual union.



Source: Istat, General Population Censuses (2001 and 2011) and Permanent Population Census 2021

Among the forms of couple life that emerge in the panorama of family models are those formed by persons of the same sex. These couples were first recorded at the 2011 Population Census (Dardanelli, 2015). Then, following the entry into force of the Cirinnà law regulating civil unions (No 76 of 20 May 2016), couples in civil unions were recorded at the permanent census in addition to those formed by same-sex partners in consensual union. These are families formed by individuals who have their usual residence in the same dwelling and who have declared themselves to be in civil union or cohabiting as a couple.

Figure 7 – Same-sex couples.



Source: Istat, General Population Census 2011 and Permanent Population Census 2021

Note: indicator per 10,000 couples

At the 2021 Census, the total number was 9,795, increased compared to the previous decade (7,513). The majority of couples formed by same-sex partners are

concentrated in Northern Italy, where more than 60.0% of them live, while in the Southern Regions and Islands the share stops at 15.2%. Civil unions represent the vast majority (86.3%) of the same-sex couples surveyed, and reside mainly in the North-West (44.2% of the national total) and the North-East (24.2%); instead, consensual unions, with 34.9%, are more represented in the Centre.

The gender analysis highlights the prevalence of those formed by men; in particular, men in civil unions are almost double than the number of women (Vitali, Dardanelli, *et al.*, 2025).

The large Municipalities of Northern Italy stand out for their higher quotas of same-sex couples compared to the rest of their Province/MC and the national value, in particular Milan, Bologna, Brescia and Turin have values of more than 23 per 10,000 couples (Figure 7).

5. Conclusions

The analysis of census data and the study of some types of households and family nuclei shows that there is in Italy a wide variety, with a broad combination of roles within the household/family. Compared to the past, there is a significant reduction in households with 5 and more members, and, more generally, in the classic nuclear family (composed of couples with children), the expansion of one-person households continues unabated over time and is distributed throughout the peninsula, lone parent families are growing as a consequence of the ageing population and the increase in relationship instability, same-sex couples, although underestimated, are rising within the forms of family life.

For the indicators considered, the dichotomy between North and South still prevails, but this division conceals substantial sub-regional and sub-provincial heterogeneities in the spatial distribution of family structures. Indeed, even in the most traditional regions, pockets of innovation are slowly gaining ground, while traditional post-war family models have lost ground. This trend is driven, as already mentioned, by profound changes in the demographic and social structure of our country over the last 50 years. Emerging family forms (childless couples, unmarried couples), that began to emerge in the last decade of the 20th century, seem to be preferred and prevalent not only among younger generations.

Only the comparison with future censuses and the analysis of the phenomena in the next few years will tell us if, even for the 'new' households and families, a convergence of the behavior patterns (from the territorial point of view) will come.

The permanent census makes it possible to arrive at a very fine territorial detail and to make more timely analyses thanks to the availability of data no longer every ten years but annual and multi-annual. In the future, it will be possible to conduct

more detailed analyses by sub-populations, including some demographic (age, gender, citizenship, marital status) and socio-economic (educational attainment, occupational status) characteristics, to study how different patterns of family life evolve and develop across the country.

References

- CORTESE A. 2011. *La conta degli italiani nei 150 anni dall'unità*. Roma: Istat.
- CORTESE A. 2007. Unioni civili e servizi demografici. I Servizi Demografici, No.3.
- CORTESE A. 1985. Le modificazioni della famiglia attraverso i censimenti. In *Annali di statistica*, serie IX, Vol. 6. Roma: Istat.
- DALLA ZUANNA G. 2024. Nuclei che cambiano: le nuove famiglie italiane. *Neodemos*.
- DARDANELLI, S., 2015. Tipologie familiari e coppie: le nuove informazioni del Censimento della popolazione 2011. In GHIGI R., IMPICCIATORE R. *Famiglie flessibili. L'arte di arrangiarsi ai tempi della crisi*, Neodemos, pp. 38-41.
- GALLO G., DARDANELLI S., MASTROLUCA S., PASQUALINI M. 2023. Famiglie e territorio. In TOMASSINI C. and VIGNOLI D. *Rapporto sulla popolazione. Le famiglie in Italia. Forme, ostacoli, sfide*, Il Mulino, pp. 143-176.
- ISTAT 2024. I nuclei familiari nei censimenti della popolazione - Anni 2011 e 2021. *Statistica Report* (ed. DARDANELLI S.). Roma: Istat.
- ISTAT 2022. Rapporto annuale 2022. La situazione del Paese. Roma: Istat.
- MASTROLUCA S., VERRASCINA M., 2012. L'evoluzione dei contenuti informativi del censimento della popolazione. In ISTAT *I censimenti nell'Italia unita. Le fonti di stato della popolazione tra il XIX e il XXI secolo*, Roma: Istat.
- REHER D., REQUENA M. 2018. Living alone in later life: a global prospective. *Population and development review*, Vol.44, No. 3, pp. 427-454.
- UNITED NATIONS ECONOMIC COMMISSION FOR EUROPE, 2015. *Conference of European Statisticians Recommendations for the 2020 Censuses of Population and Housing*. New York and Geneva: United Nations.
- VITALI A., DARDANELLI S., RINESI F., LO CONTE M., RUIU G. 2025. Nuove famiglie e famiglie "nuove tra le nuove". In PATERNO A. and VIGNOLI D. *Rapporto sulla popolazione. Verso una demografia positiva*. Il Mulino, pp. 79-106.

Mariangela VERRASCINA, Istat, verrasci@istat.it

Silvia DARDANELLI, Istat, dardanel@istat.it

Antonio GUGLIELMI, Istat, antonio.guglielmi@istat.it

STRUCTURAL HEALTH INEQUALITIES AND TERRITORIAL DISPARITIES: DRIVERS OF HEALTHCARE MIGRATION

Venera Tomaselli, Margaret Antonicelli

Abstract. Health-induced mobility is also tied to the distribution and availability of health care resources according to the regions and there is a balance between the supply and demand. Equity in access requires one to know the health profiles and needs of the population, so everyone gets an appropriate level of health treatment. The present study examines regional differences in the use of healthcare in Italy, particularly Medically Assisted Reproduction (MAR). Although, there has been improvement in MAR technologies, there are still inadequate public and private MAR centres in some places, and so many individuals must travel to undertake their treatments abroad as result of inequalities in service provision and regional policies. There is substantial financial burden on couples related to MAR, as travel, lodging and other costs can limit access, especially for those of lower income. To analyse these patterns in patient mobility, we utilise a finite mixture model using clustering techniques, which are widely used to analyse the population data. Results show that locally smooth General Mixture Models together with a normalised spectral cut-off criterion are good for clustering MAR related data. Notably, the migration toward Northern Italy is due to a larger presence of private centres, where generally more patients than public and/or accredited centres are treated. This seems to be shaped by rising demand for higher quality services and a strong preference for services from the private sector. These findings underscore the essential requirement for policy intervention to mitigate health access disparities and strengthen the resilience of health systems. District by district analysis of healthcare infrastructure is also essential in informing efforts to address this inequity in access to MAR services across the nation, and this inequity in the provision of MAR services has profound implications for both the reproductive rights of the individual, and broader demographic and socio-economic stability.

1. Introduction

The flows of health migration in Italy is increasing. Annual shifts remained below 1.2 million until the late 1990s, but since 2004, 1.3 million-plus has become routine. One turning point was in 2012, when the administrative procedures of registration of dwelling changes improved leading internal migration to exceed 1.5 million (Bonifazi et al., 2017; 2020). After a brief fall, migration has continued at well over 1.4 million, except for 2020, a pace that is 30% higher than in the 1990s. Patients

migrate in search of oncological, cardiac, transplant, and health treatment. However, the understanding of the relationship between sexual and reproductive health and migration is still fragmented, even if research has expanded to include rights, gender equality and socio-economic constraints (Alarcão et al., 2019). Needs of different populations have not been easily addressed.

The number of Medically Assisted Reproduction (MAR) enquiries for treatment has increased over the last 40 years. Delayed childbearing has elevated infertility in low-fertility societies and represents a challenge to public health systems as MAR has gained demographic and socio-economic relevance. Fertility rates remain low in Italy, too, yet there are fewer potential parents. MAR treatments have nearly doubled from 2005 and represent 4.25% of births in 2022. Estimated prevalence of using MAR was 3% (as a proportion of all 'births') and 13% amongst women aged 40 years and older from the 2021 SSN publication, reflecting healthcare, financial and social influences (3% for total fertility).

Public health in Italy is increasingly unable to guarantee equal access: the increase in private health out-of-pocket payments affects intentions regarding fertility, reproductive rights as well as public health. Unequal access to healthcare creates demand for migration in the health sector in response to the way in which the LEA is implemented. There are many public and private MAR centres in Lombardia and Toscana whereas few in the South, despite the large demand of health care. The present study analyses the domestic health migration related to MAR, and its goal is to provide an input to regional-based policies on access issues and demographic consequences of post-poned parenthood.

2. Public vs. Private MAR in Italy

A profound multifaceted gap of MAR services in quality and quantity, technological level, and regional coverage is recorded between public or accredited and private centres in Italy. Public and accredited centres are embedded in the Italian National Health System (SSN) in a model regulated by Law No. 40/2004 and by Ministerial Decree on Essential Levels of Assistance (LEA). Differences among regional autonomy lead to substantial differences in the availability of resources, publicly funded cycles, and reimbursement rates. Public centres follow budget limitations and prioritisation rules which are sometimes translated in the existence of waiting lists, in restricted reimbursed cycles and in reimbursement fees. Since the fees often do not cover the effective treatment costs, in turn they are not favourable to investments in high-end technologies and new treatment options.

The private MAR centres are legally and ethically regulated but are not under the direct financial regulation of the SSN and sustained largely by OP or private

insurance coverage. This allows private centres to offer more cycles, to decrease waiting times, to nest cycle types and personal treatment as well as providing technologies not available in public centres and also higher reported pregnancy rates, (although comparison continues to be complex, with variations in patient profiles and selection criteria). Many patients go to private centres looking for alternate therapies or certain high-tech procedures that may not be available in the public sector, so private health market is always increases.

The geography of MAR service provision the spatial coverage of MAR services is extremely uneven. Most high-volume centres are in Northern regions (Lombardia, Emilia-Romagna, Toscana), whereas most southern regions are characterised by scarce availability of certified centres, leading in turn to considerable health-migration. Patients commonly travel north for increased success rates, at a significant financial, emotional and logistical cost – and where socio-economic inequalities only compound access inequalities particularly disadvantaging poorer women. National harmonization Attempts such as the 2019 National Commission for updating the LEA notwithstanding, regional autonomy impedes national harmonization of MAR services. Effective policy interventions should target against the segregation of parallel private funding, the misalignment between tariffs and actual unit costs, the under investment in technology, the insufficiently clear data reporting, and the absence of a national benchmark to be used to constraint the pressure for quality driven solely by the market by avoiding the consolidation of a dual system that endangers equity of access to assisted reproductive technology services and demographic sustainability in Italy.

3. Research hypothesis

This paper explores the dynamics of intra-national mobility due to MAR procedures across Italian regions and focuses also on the role that geographic disparities and socio-economic issues play in influencing such dynamics. In addition to the total volume of MAR centres throughout the country, the inequalities of health-services at the regional level have a significant impact on the migration for healthcare in general and in the case of (non-resident) patients who seek fertility treatment outside their region of residence.

By accessibility data from the Italian National Registry, an unequal distribution of MAR centres is evident, largely concentrated in Northern and Central Italy with a significant decrease in the Southern areas. This geographic inequality generates substantial flows of health-related migration, as couples resident in the South must frequently travel to Northern centres. These movements are not only due to the lack

of the centres, but they also express perceptions of quality and success emphasised by social and economic discrimination that restricts access to poorer people.

Consistent with research objectives, the present analysis intends to: (i) measure socio-economic inequalities related to the territorial distribution of MAR services; (ii) evaluate migration flows for MAR treatments, specifically non-residents who have received procedures away from their home regions; (iii) investigate regional disparities in the supply of the Essential Levels of Assistance (LEA), a set of services aimed at ensuring equal access to reproductive treatment; and (iv) drive political actions to mitigate the consequences of postponed fertility and to assure homogeneous access of MAR treatment throughout the country. To study these 2 specific research questions, the analysis explores 2 primary points: *Q1*) the total, cumulative volume of MAR is much higher in the central and northern regions, due to both higher infrastructural capacity and demand; *Q2*) the mean volume of cycles *per* woman is much higher in the northern regions, due to unequal access and socio-economic status that affects access to the treatments. This evidence can enrich the policy-making process that is required to tackle territorial and social disparities in the reproductive healthcare in Italy.

4. Methodology

One popular clustering method, which is based on a formal statistical methodology for modelling the population distribution, is the finite mixture density model. This model supposes that the population has been divided into several subgroups, or clusters, beyond which the divergence can be considered minimal, and the elements in each cluster are drawn from a multivariate probability density function specific to that cluster. In this context, clustering amounts to estimating the parameters that define the mixture components and then calculating the probabilities that each observation belongs to the clusters.

A finite mixture model is Gaussian Mixture Models (GMMs), where the probability density function of a continuous random variable can be expressed as the sum of weighted Gaussian functions. Applications of GMMs are numerous, including biometric systems and epidemiological and health studies, since they are flexible and powerful tools for modelling complex data distributions. GMM is powerful because it approximates the underlying densities with any arbitrary shape using smooth and continuous functions facilitating the exposure of a wide range of data structures and patterns (Antonicelli et al., 2022; Reynolds, 2009). A GMM is defined as a weighted sum of G Gaussian component densities as in:

$$f(y; \Theta, \tau) = \sum_{k=1}^G \tau_k f_k(y_i; \Theta_k) \quad (1)$$

where f_k and θ_k are the density and the parameters of the k -th component of Gaussian mixture and τ_k is the probability that the observation y_i belongs to the k -th component (Antonicelli et al., 2022; Li and Reynolds, 2020)

$$(\tau_k \geq 0; \sum_{k=1}^G \tau_k = 1) \quad (2)$$

and f_k is a multivariate Normal density function, where θ_k is the parameter given by μ_k, Σ_k

$$l(\Theta, \tau, z_i | x) = \sum_{i=1}^n \log[\sum_{k=1}^G z_{ik} \tau_k f_k(y_i | \Theta_k)] \quad (3)$$

where z_i means that we have an unobservable vector z for each observation. These values must be estimated together with θ (where θ_k represents in this case the "joint parameter" (μ_k, Σ_k) and τ_k ($k=1, \dots, G$) (Antonicelli et al., 2022).

An EM algorithm is used to estimate unknown parameters and unobservable variables. The criterion used to select the number of components (clusters) of the Gaussian mixture is the Bayesian Information Criterion (BIC):

$$BIC = 2l(\hat{\Theta}, \hat{\tau}, \hat{z}_i | x) - (\#parameters) \log(n) \quad (4)$$

in which $(\hat{\Theta}, \hat{\tau}, \hat{z}_i | x)$ is the maximised value of the log-likelihood, $(\#parameters)$ is the number of parameters estimated, and n is the sample size. The BIC index is generally defined with the opposite sign compared to the definition used in this package (and therefore, smaller index $\Rightarrow$ better) (Antonicelli et al., 2022).

To evaluate the performance of the models, is important to measure accuracy (AC) (Cai et al., 2018). Given a point x_i , r_i , and s_i represent the obtained label and the label provided by the data set, respectively. The AC is defined as follows:

$$AC = \frac{\sum_{i=1}^N \delta(s_i, map(r_i))}{N} \quad (5)$$

where N is the total number of samples, $\delta(x, y)$ is the delta function that equals 1 if $x = y$ and equals 0 otherwise and $map(r_i)$ is the permutation mapping function that maps the obtained label r_i to the equivalent label from the data set.

5. Data collected

For this research, data were used that were made available in 2023 and referred to 2021, by the National Registry of Medically Assisted Reproduction, developed

through authorization of the Istituto Superiore di Sanità (ISS). The National Registry was established as an operational tool for the application of Law n. 40/2004 and it represents the official database for all information concerning MAR techniques in Italy. It compiles data from all MAR centres recognized by each Regional Health Authority and classifies centres in relation to the complexity of the services they provide, with a distinction between first level activity and second and third level activity. The National Registry aims to provide transparency on MAR practices and to stimulate uniformity in technical and organisational requirements among centres, as well to facilitate central monitoring of treatment efficacy, safety and outcome. The Registry also informs the community to make decisions regarding treatment and authorised activities, fosters scientific scholarship, supports long-term health follow-up studies of those born using MAR, and finally provides data on the number of embryos created and frozen. Consistently with the research goals of the present study, the 2021 data are employed, excluding data of due to the COVID-19 syndemic.

The geographical distribution of MAR centres is the following: 100 are public, 19 are private but affiliated to the National Health Service and 221 are private. Of these, 113 private and 89 public or affiliated centres offer second- and third-level treatments.

About 62% of level II, and III cycles with couples' own gametes are NHS funded as published by the ISS (2023). In 2021, the efficacy of treatments was moderately higher than in 2020. It was reported that pregnancies in fresh cycles had increased by +2.7% (32.6 vs 35.2%) and in frozen embryo/thawed oocyte cycles (FER/FO) by 0.6% (25.7 vs 26.3%). Furthermore, the use of pre-implantation genetic diagnosis increased, with 5,195 procedures carried out in 66 centres leading to 1,293 live births. It is a deliberate decision to concentrate on 2021 for the analysis. In relation to 2020, which experienced a considerable reduction in activity due to the COVID-19 syndemic and the protocols for containment, the number of treated couples and the total MAR treatment cycles carried out and the number of children born from these techniques in 2021 increased. Summit was excluded from comparisons due to the extraordinary disruption in 2020 and the potential for such a year to distort interpretation of longer-term trends.

6. Results

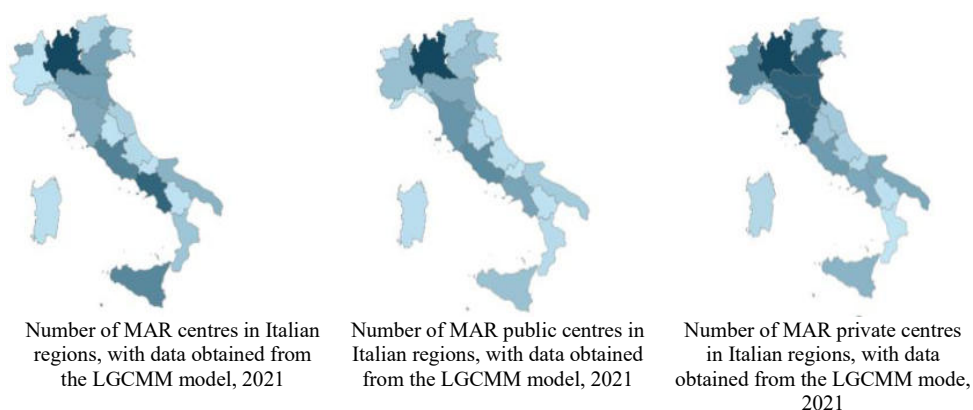
Regional discrepancies and healthcare migration related to MAR, are analysed using descriptive statistics and advanced clustering techniques. The aim is to map territorial inequalities in MAR services, to measure inter-regional differences in treatment intensity, and to understand how these disparities influence access to MAR

services. The findings provide nuanced interpretations of 4 cartographic analyses, each highlighting different dimensions of MAR centres and activities.

Descriptive statistics reveal a significant regional variability in MAR centres' distribution, treatment volumes, and the number of cycles *per couple*. The application of clustering methods such as the Locally Coherent Gaussian Mixture Model (LCGMM)¹ and the Spectral Normalised Cut (Ncut)² uncover clear spatial patterns in MAR centres' distribution. The measure of accuracy (AC) is employed to assess the best performance between LCGMM and Ncut models. LCGMM is particularly effective in capturing local variations in centres' distribution and treatment intensity, while Ncut in analysing the number of treatments.

The distribution of centres highlights a remarkable territorial heterogeneity. The regions are classified in 4 clusters (Figure 1) by LCGMM.

Figure 1 – *Compared analysis: MAR Centres.*



Lombardia stands out with the highest concentration of MAR centres, further subdivided internally into several sub-clusters (each includes from 4 to 16 centres). Campania also records a relatively high number of centres, showing strong local

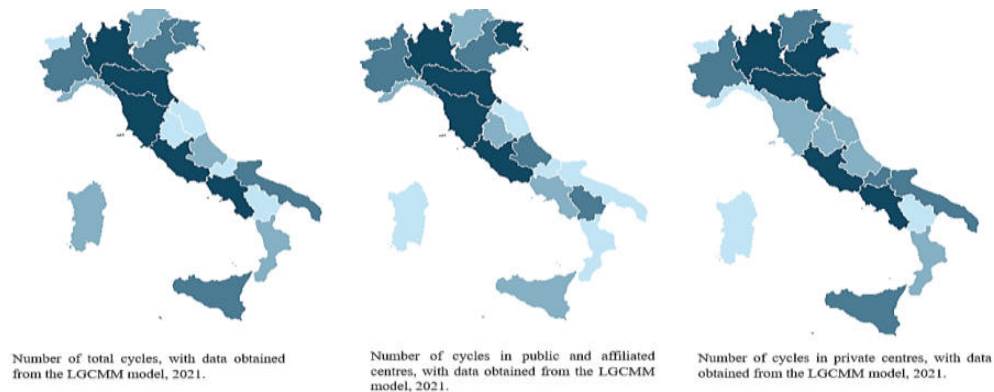
¹ Latent Class Growth Mixture Model (LCGMM) is a statistical modelling approach designed to capture unobserved heterogeneity in longitudinal data by identifying latent subpopulations that follow distinct developmental trajectories. Unlike traditional growth models, LCGMM allows for variability both within and between latent classes, providing a flexible framework for disentangling complex patterns of change over time.

² Normalised Cut (NCut) is a graph-partitioning method for clustering that formulates the segmentation problem as the minimization of a normalized cut criterion. This criterion balances the dissimilarity between clusters (minimizing inter-cluster connections) with the similarity within clusters (maximising intra-cluster coherence), thus avoiding the bias toward small or unbalanced partitions typically observed in standard graph cut methods.

demand and a potential role of attraction for neighbouring flows. Lazio and Sicilia form an intermediate cluster, suggesting a moderate infrastructural development. Veneto, Emilia-Romagna, Toscana, Puglia, and Valle d'Aosta are grouped together in another cluster, showing a balanced provision. Finally, Piemonte, Umbria, Molise, Basilicata, and Sardegna fall into the smallest cluster, suggesting structural limits or regional planning priorities. Overall, the cartogram indicates that, although Northern Italy generally presents better infrastructural endowment, exceptions exist, confirming the complexity of territorial distribution.

The analysis of treatment volumes (Figure 2) using the Ncut model identifies 5 distinct clusters. Lombardia is confirmed as the region with the largest number of cycles, followed by Toscana and Lazio. Piemonte, Veneto, Emilia-Romagna, and Campania form the second cluster, while Trentino-Alto Adige, Friuli Venezia-Giulia, Puglia, and Sicilia appear in an intermediate group. The remaining regions are assigned to the smallest clusters, emphasising once again the persistence of the territorial divide. Considering the number of cycles the LCGMM again classifies the regions into 5 clusters, with Lombardia maintaining its dominance. The territorial pattern changes, however, distinguishing between public and private centres. Lombardia confirms its leadership, combining strong public provision with a very active private sector.

Figure 2 – *Compared analysis: MAR Cycles in public and private centres.*

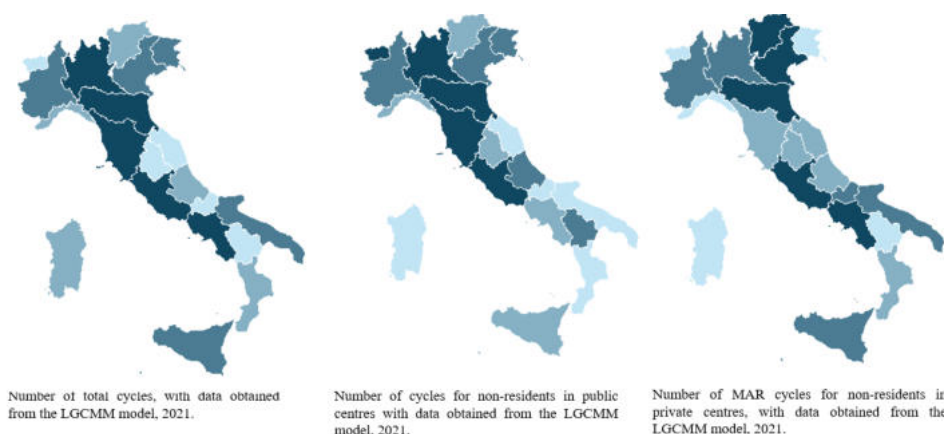


Campania, although characterised by a high number of centres, belongs to a cluster with smaller cycle volumes, together with Emilia-Romagna, Toscana, and Lazio. Piemonte, Veneto, Friuli Venezia-Giulia, Puglia, and Sicilia form intermediate groups. Besides Southern regions, such as Calabria and Basilicata, along with Sardegna, Valle d'Aosta, and Trentino-Alto Adige, are placed in the smallest cluster. Lazio constitutes a distinct intermediate cluster, marked by a

relatively balanced ratio between supply and demand. These results highlight that service use is influenced not only by the number of centres but also by organisational efficiency, financial constraints, and patient migration preferences.

The cartogram of MAR cycles performed for non-resident patients with couples' own gametes (Figure 3) confirms Lombardia as the main destination. Its centres combine high success rates, advanced clinical expertise, and a consolidated reputation, elements that strengthen its role as the leading hub for domestic migration. Toscana and Emilia-Romagna also show strong appeal, offering geographically closer alternatives and attracting patients who prefer to limit travel time while maintaining good expectations of quality. Lazio records an intermediate position: although it receives a portion of non-resident patients, it does not achieve the same level of national centrality, reflecting a more balanced but less specialised system.

Figure 3 – *Compared analysis: MAR cycles with couple's own gametes.*

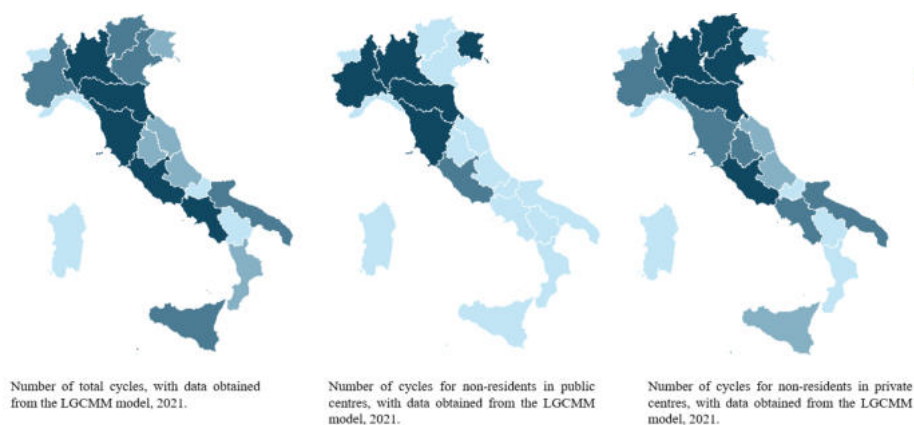


In contrast, the Southern regions appear at the margins of this phenomenon, with consistently low inflows of non-resident patients. Campania is a particularly significant case: despite its relatively high number of centres, it does not emerge as a national destination. This gap suggests that infrastructure alone is insufficient to generate interregional attractiveness if not supported by efficiency, technology, and perceived quality. Overall, the cartogram highlights the strong pulling power of the Northern areas, where both service capacity and patient trust converge in shaping mobility flows.

Finally, the analysis of MAR cycles with donated gametes (Figure 4) shows even stronger disparities. Lombardia confirms its absolute leadership, thanks to centres that combine advanced technology, specialised expertise, and the ability to manage

highly complex procedures. This makes the region the most important destination for couples requiring treatments with higher levels of medical and organisational complexity. Central regions, particularly Toscana and Emilia-Romagna, also attract a considerable share of non-resident patients. Their centres benefit from long-standing investments and a solid reputation for quality, placing them as the first alternatives to Lombardia. Lazio emerges as a moderate attractor: its centres are able to provide these services but their role seems more limited to local or neighbouring demand, without developing a comparable national attractiveness.

Figure 4 – *Compared analysis: MAR cycles with donated gametes.*



The South, by contrast, remains at the lowest levels of activity. Despite recent infrastructural improvements, centres in these regions struggle to provide complex procedures and compete in terms of patient perception. Campania offers a telling example: although it has a large number of MAR centres, its contribution to donated gametes treatments is limited, showing that the mere presence of infrastructure does not translate into the ability to deliver advanced services.

The evidence suggests that mobility for donated gametes procedures is even more selective than for treatments with couples' gametes. The access is concentrated in a few regions capable of combining advanced technology with patient trust, while the dual public-private system amplifies inequalities: private centres are quicker and more efficient to introduce innovation, whereas public centres often face budget constraints and waiting times. The result is a system where socioeconomic resources affect the access, leaving couples living in disadvantaged contexts with limited opportunities.

These findings underline that donated gametes treatments represent a critical test of the Italian MAR system's equity. The persistence of a clear North-South divide

reflects not only infrastructural shortages but also deeper organisational and socioeconomic disparities. Their overcoming requires both coordinated policies to strengthen public provision, spread high-complexity services beyond the traditional centres of excellence and also to harmonise standards nationwide, so that access is not affected by residence or income.

7. Conclusions

The present study reinforces the known fact that substantial geographical differences persist in the delivery of and access to MAR services in Italy. Using advanced statistical techniques like Locally Coherent Gaussian Mixture Models and Spectral Normalised Cut algorithms we depicted the uneven distribution of centres for MAR, the huge disparities in treatment volumes and the significant North-South gradient of patients mobility for MAR.

These disparities result from infrastructural inadequacies and socioeconomic inequities that restrict more South-based individuals and couples' access. Our results show that MAR institutions hosted in regions such as Lombardia, Emilia-Romagna and Toscana are still appealing not only for local patients but also for a considerable amount of non-resident patients, highlighting their role as national areas of reference for services related to MAR. On the other hand, passing districts are largely found in the south, where as the infrastructure of medical and socio-economic conditions limit access.

Territorial inequalities in MAR services have profound consequences well beyond individual reproductive rights: they shape demographic trajectories and gender relations and impose financial burden on families forced to travel for treatment. Evidence supports the need for policy interventions to equalise the working conditions for MAR services across the country, realigning tariffs with actual costs, investing in new technologies, and strengthening public sector capacity. Addressing these structural health disparities is of paramount importance in ensuring equal access to reproductive health services and in preserving population sustainability more broadly.

Research should seek to track evolving trends, determine the effect of recent policy changes in the Essential Levels of Care, and understand patient decision making at a deeper level. A better understanding of social determinants of health and quality perceptions would contribute to developing more effective strategies to minimize health migration, and to guarantee more adequately comprehensive reproductive healthcare as a benefit for all citizens living in any region irrespective of their economy.

References

- ALARCÃO V., STEFANOVSKA-PETKOVSKA M., VIRGOLINO A., SANTOS O., RIBEIRO S., COSTA A., NOGUEIRA P., PASCOA P.M., PINTASSILGO S., MACHADO F. L. 2019. Fertility, Migration and Acculturation (FEMINA): A research protocol for studying intersectional sexual and reproductive health inequalities. *Reproductive Health*, Vol. 16, No. 1, p. 140. Springer.
- ANTONICELLI M., RUBINO M., MAGGINO F. 2022. The Gaussian mixture model-based clustering for the comparative analysis of the Healthcare Digitalization Index in the Italian local health authorities. In A. Balzanella, M. Bini, C. Cavicchia, & R. Verde (Eds.), *Book of Short Papers SIS 2022 - 51th Scientific meeting of the Italian Statistical Society* (pp. 1732-1737). Pearson. ISBN: 9788891932310.
- BONIFAZI C., HEINS F., LICARI F., TUCCI E. 2020. The regional dynamics of internal migration intensities in Italy, in *Population, Space and Place*.
- BONIFAZI C., HEINS F. 2017. Internal migration patterns in Italy: continuity and change before and during the great recession, in *Rivista Italiana di Economia Demografia e Statistica*, Volume LXXI – No. 2 Aprile-Giugno.
- BONIFAZI C., HEINS F., TUCCI E. (2017), Italy: internal migration in a low-mobility country, In Champion, T., Cooke, T., & Shuttleworth, I. (Eds.) *Internal Migration in the Developed World*, Routledge.
- CAI D., HE X., HAN J. 2005. Document clustering using locality-preserving indexing. *IEEE Transactions on Knowledge and Data Engineering*, Vol. 17, No. 12, pp. 1624-1637. <https://doi.org/10.1109/TKDE.2005.198>.
- CAI L., SHI W., MIAO Z., HAO M. 2018. Accuracy assessment measures for object extraction from remote sensing images. *Remote Sensing*, Vol. 10, No. 2, p. 303.
- LI X., REYNOLDS A. C. 2020. A Gaussian mixture model as a proposal distribution for efficient Markov-chain Monte Carlo characterization of uncertainty in reservoir description and forecasting. *SPE Journal*, Vol. 25, No. 01, pp. 1-36.
- LOVASZ L., PLUMMER M. 1986. *Matching Theory*. Elsevier. ISBN: 9780080872322.

Venera TOMASELLI, Department of Economics and Business, University of Catania, venera.tomaselli@unict.it

Margaret ANTONICELLI, Department of Humanistic Studies, Faculty of Communication, IULM, Milano, margaret.antoniceili@iulm.it

INCOME, ENVIRONMENTAL POLLUTION AND HEALTH INEQUALITIES IN ITALY: A REGIONAL PERSPECTIVE IN THE ERA OF TRANSITIONS

Francesca Feoli

Abstract. Poverty and inequality are increasingly intertwined with territorial and environmental dimensions, especially in a context of profound demographic, environmental and technological change.

In particular, health inequalities reflect disparities in access to and quality of care among different population groups, which are shaped by socio-economic and environmental determinants. Among these, income and living conditions emerge as key factors influencing individual and collective vulnerability to health risks.

This study examines the interaction between income levels, environmental pollution and population health from a regional perspective. By integrating statistical indicators and multidimensional data - economic, social and environmental - the analysis aims to identify territorial patterns of disadvantage and their impact on health outcomes and access to care.

The proposed multidisciplinary approach contributes to a broader reflection on how structural inequalities intersect with environmental degradation and how these dynamics evolve in a period of environmental and social transition.

The study provides insights to support the design of more inclusive, sustainable and resilient public policies, capable of addressing multiple forms of vulnerability simultaneously and promoting equity across territories and populations.

1. Introduction

In recent years, the analysis of territorial and multidimensional inequalities has become central to the scientific and political debate, especially in light of the Sustainable Development Goals (SDGs) promoted by the United Nations. The growing complexity of social and environmental vulnerabilities has made it necessary to have an integrated approach that takes into account the multiple dimensions of well-being and quality of life (Sen, 1999; Stiglitz *et al.*, 2009).

From this perspective, this work aims to systematically analyze the interaction between poverty, environmental conditions, health inequalities, and employment dynamics, through a coherent set of recognized and comparable statistical indicators at the territorial level. As highlighted by Segre, Rondinella, and Mascherini (Segre *et al.*, 2011), measuring well-being requires a multidimensional vision that also

values the contribution of civil society, focusing on qualitative aspects of life and involving local communities in defining priorities. Their work emphasizes how the significance of regional differences in Italy must be addressed not only with economic data, but also with tools capable of capturing perceived well-being and local social dynamics.

Similarly, recent studies such as that of Yebetchou Tchounkeu (Yebetchou Tchounkeu, 2024) show how the efficiency of the public healthcare system significantly impacts the overall well-being of the population, revealing strong heterogeneity across Italian provinces. This evidence reinforces the need to analyze the territorial performance of public services—particularly healthcare—as fundamental determinants of living conditions and individual opportunities.

The data used, coming from Istat databases and referring to the year 2022, were analyzed at different territorial levels, from national to regional and autonomous provinces, in order to highlight the critical issues and disparities present between the different areas of the country.

The theoretical-methodological approach is inspired by Amartya Sen's (Sen, 1999) capabilities perspective, according to which well-being cannot be reduced to a single economic dimension, as well as by the most recent proposals for measuring well-being and quality of life that go beyond income alone as a measure of progress (OECD, 2020).

This is supported by the work of the Stiglitz-Sen-Fitoussi Commission, which has promoted the use of alternative indicators to GDP to measure social progress. "The Commission also recommends measuring well-being through a multidimensional approach that also takes into account aspects of citizens' subjective evaluation and considering indicators of sustainability, not only environmental, but also economic and social" (Stiglitz *et al.*, 2009).

At the national level, institutions such as Istat and CNEL have promoted multidimensional approaches to measuring well-being, as in the case of the BES – Equitable and Sustainable Well-being (Istat-Cnel, 2013) project, which proposes a set of indicators divided into twelve areas, including health, environment, work, and economic inequality.

This work refers to the scientific literature that studies the phenomena of poverty and inequality in an integrated way. In particular, reference is made to the studies of Brandolini and Saraceno (Brandolini *et al.*, 2007), who underline the importance of adopting a combined perspective to understand the conditions of material deprivation, and to those of Wilkinson and Pickett (Wilkinson *et al.*, 2009), who highlight the link between economic inequalities and worsening of public health indicators.

In summary, the aim of the study is to provide a territorial and comparative reading of social and economic fragilities in Italy, through an integrated analysis of

the most up-to-date data available. The choice of indicators reflects a targeted and theoretically founded selection, capable of providing a complex but readable picture of the structural inequalities that characterize our country.

This paper is structured as follows: Section 2 presents the data and methods. Section 3 introduces the statistical analysis results. Finally, section 4 contains the conclusions.

2. Data and methods

To carry out this study, I used a series of multidimensional data that allowed me to analyze in an integrated way the intersection between poverty, health inequalities, environmental conditions and territorial dynamics. The processing was carried out with Excel and XLSTAT, a statistical software that works as an add-in for Microsoft Excel.

The data, referring to the year 2022, were extracted from the Istat databases and analyzed by NUTS 2 level territorial units, including the 20 Italian regions and the 2 autonomous provinces of Trento and Bolzano, in line with the European statistical classification.

The main thematic areas examined are:

- Poverty
- Employment system
- Environment
- Health system

Table 1 - List of statistical indicators divided by thematic area.

Thematic area	Statistical indicators	Unit
Poverty	1. Relative family poverty incidence	percentage
	2. Homogeneity in the distribution of family net income	Gini index
	3. Average annual household income	Euro
Employment system	1. Labour force (15-64 years)	percentage
	2. Youth employment rate (15-29 years)	percentage
	3. Unemployment rate	percentage
Environment	1. Air quality - PM2.5	percentage
	2. Families reporting air pollution	percentage
	3. Families reporting unpleasant odours	percentage
	4. Service for the separate collection of municipal waste	percentage
Health system	1. Medical specialists active in the health system	For 10,000 inhab
	2. Hospital emigration index	percentage
	3. Current public health expenditure per inhabitant	Euro
	4. Avoidable mortality (0-74 years)	Years
	5. Healthy life expectancy at birth	Years
	6. Standardized mortality rate	For 10,000 inhab
	7. Infant mortality	For 1,000 inhab

3. Statistical analysis

3.1 Descriptive analysis

To perform the data analysis, I started using descriptive analysis techniques to obtain a preliminary understanding of the main characteristics of the dataset; these techniques represent the first step in the exploratory approach to the data and are essential to summarize the information in a simple, clear and effective way.

I calculated the descriptive measures of location, the measure of central tendency, the measure of dispersion and graphical representations (bar charts, cartograms) to better visualize the distributions and facilitate the interpretation of the data.

Table 2 - Descriptive Statistics.

Variable	Min	Max	Mean	Std. Dev.
Average annual household income	29807,00	51632,00	40673,73	6390,31
Homogeneity in the distribution of family net income	0,25	0,34	0,28	0,02
Relative family poverty incidence	5,10	30,00	11,37	6,79
Labour force (15-64 years)	51,12	75,82	66,18	7,93
Youth employment rate (15-29 years)	20,53	51,74	34,41	8,67
Unemployment rate	2,27	17,11	8,09	4,06
Medical specialists	24,40	40,50	32,35	4,46
Hospital emigration index	4,75	30,37	11,79	7,33
Avoidable mortality (0-74 years)	14,20	22,40	17,49	2,08
Current public health expenditure per inhabitant	2025,66	2914,22	2281,39	191,72
Healthy life expectancy at birth	53,10	69,30	60,28	2,95
Standardized mortality rate	75,93	104,91	89,77	6,70
infant mortality	1,40	6,40	2,60	0,99
Air quality - PM2.5	12,50	100,00	74,85	22,37
Families reporting air pollution	17,00	47,70	29,79	9,83
Families reporting unpleasant odours	8,60	28,60	16,67	4,81
Service for the separate collection of municipal waste.	32,10	95,50	63,86	19,37

Source: Elaborations on data from Istat databases

The indicator "Incidence of relative family poverty" presented two observations with missing data (P.A. Bolzano and Valle D'Aosta) that were estimated with the mean value. The analysis showed that the variables Average annual household income (in euro) Current public health expenditure per inhabitant are those that present the greatest variability between observations.

3.2 Thematic area Poverty

For the topic of poverty, since data for the indicator Average annual family income for the Trentino Alto Adige region were not available, I used data from the autonomous provinces of Trento and Bolzano. The national analysis of the main Italian economic and social indicators highlights significant aspects related to income distribution and the living conditions of the population. The average value of the total income received by families stands at €41,004, this figure being an arithmetic mean can be influenced by very high incomes in a narrow segment of the population, therefore it is useful to compare it with the inequality index.

The Gini index measures inequality in income distribution, on a scale from 0 (perfect equality) to 1 (maximum inequality). Italy has a value of 0.296 thus indicating moderate inequality. The relative poverty rate indicates the percentage of individuals who live in families with a disposable income lower than the threshold of 60% of the national median income.

A national value of 10.10% indicates that over a tenth of the Italian population lives with resources lower than the level considered necessary for a dignified life. This data highlights a persistent socioeconomic fragility.

Figure 1 – *Spatial distribution of the average annual household income, the Gini index and the incidence of relative family poverty. Year 2022 Values in Euro and percentages.*



Source: Elaborations on data from IstatData

Figure 1 illustrates the regional geographical analysis, which confirms the dualistic opposition between North and South in our country, specifically we see that the regions of the North with the most favorable socio-economic conditions are Emilia-Romagna, Trento, Toscana, Veneto, Lombardia, Friuli-Venezia Giulia, have Medium-high income between €43,000 and €48,000, low inequality (Gini < 0.270) and low relative poverty (5–6%)

While the most disadvantaged regions, with low income, high inequality and poverty are Calabria, Campania, Sicilia, Basilicata, Puglia have low income between €28,000 and 35,000, high inequality (Gini > 0.30) and high relative poverty (over 17%, up to 30%)

3.3 Thematic area Employment system

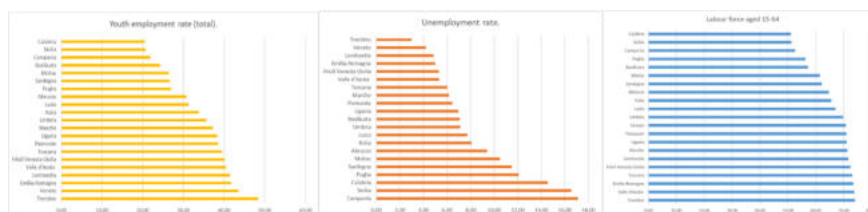
To analyze the issue of the employment system, I have selected three fundamental indicators that allow us to grasp in a complex way the dynamics of the labor market, with particular attention to active participation, the employment status of young people and the level of unemployment.

At the national level, the unemployment rate stands at around 8.07%, while participation in the labor market (active population between 15 and 64 years) reaches approximately 66%. As for young people (15-29 years), the employment rate is approximately 34%, highlighting a still limited participation of this age group in the world of work.

The regional analysis, shown in Figure 2, always highlights the gap between the North and the South of the country.

The Southern regions show low participation in the labor market, indicating a possible disincentive or lack of opportunities. Young people from the North find work more easily than their peers in the South. The North-South gap is also marked in the unemployment rate: the lowest values are recorded in the North, with Bolzano in the lead, while in the South the percentages often exceed 12%

Figure 2 – Regional Labour Market Indicators: Youth Employment, Unemployment and the Labour Force rates. Year 2022 Values in percentages.



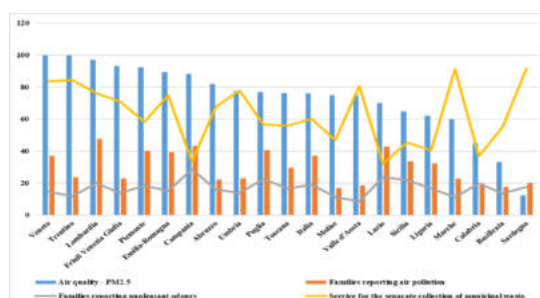
municipalities that exceed the threshold of 65% of separate waste collection, a value considered indicative of virtuous waste management. From a territorial point of view, as shown in Figure 3, significant differences emerge, the regions of Northern Italy (in particular Lombardia, Veneto and Piemonte) show generally positive performances in separate waste collection, but at the same time record high concentrations of PM2.5 and widespread perceptions of air pollution by citizens.

It is interesting to note how the subjective perception of pollution does not always coincide with objective data. Some regions, in fact, show measured levels of good environmental quality, but negative perceptions by the population, and vice versa. Trentino-Alto Adige, for example, has very high PM2.5 values (100%), but a low subjective perception of both air pollution and the presence of unpleasant odors.

Marche and Sardegna stand out positively both for the low negative perception by families and for the good objective quality of environmental services.

On the other hand, Campania represents one of the most critical cases: poor air quality, low levels of separate waste collection and strongly negative subjective perceptions are detected, signaling a particularly problematic environmental context.

Figure 3- *Perceived and measured environmental quality in the Italian regions: PM2.5, perception of pollution, odors and separate waste collection. Year 2022. Values in percentages.*



Source: Elaborations on data from *Bes of the territories 2024* and *We Italy 2024*, Istat

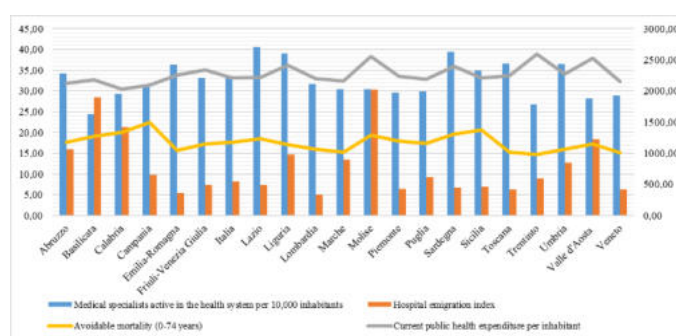
3.5 Thematic area Health system

The proposed statistical analysis focuses on a set of key healthcare system indicators, with the aim of assessing regional differences in service provision, system efficiency, and health outcomes. To this end, we use synthetic and standardized indicators, which are essential for accurately and comparably describing the population's health status and capturing crucial aspects such as quality of life and the effectiveness of regional healthcare systems.

Nationally, Italy has an average of 33.2 specialist doctors per 10,000 inhabitants, with per capita public healthcare spending of approximately €2,212.16. The hospital out-migration rate stands at 8.3%, indicating a significant proportion of patients traveling outside the region to receive treatment. Regarding health outcomes, the avoidable mortality rate in the 0-74 age group averages 17.6 deaths per 10,000 inhabitants, while the standardized mortality rate is 90.41 per 10,000 inhabitants. Healthy life expectancy at birth stands at 60.1 years, and the infant mortality rate is 2.5 deaths in the first year of life for every 1,000 resident live births.

The regional overview, Figure 4, shows that regions in the Centre-North (such as Lazio and Tuscany) tend to have a higher density of specialist doctors than many regions in the South (e.g., Basilicata, Calabria). However, some exceptions, such as Sardinia, indicate that this indicator does not follow a clear North-South division. Southern regions and some regions with low population density (e.g. Molise, Basilicata) show the highest levels of health emigration, indicating a likely deficiency in the quality or availability of local health services.

Figure 4 – *Indicators of the Italian Regional Health System: Medical Staffing, Hospital Mobility, Health Spending and Avoidable Mortality. Year 2022. Values in years, euro and percentages.*



Source: Elaborations on data from *Bes of the territories 2024* and *We Italy 2024*, Istat

Per capita spending is quite variable and not always higher in regions with better health outcomes or a low rate of hospital emigration. For example, Molise has high spending, but also a high rate of emigration and avoidable mortality.

Healthcare emigration, in this context, refers to patient mobility, i.e., the movement of Molise residents to other Italian regions to receive medical care that is unavailable, inaccessible, or perceived to be of higher quality than that provided locally. While this phenomenon can contribute to improving certain health outcomes, it also has significant economic and organizational consequences. Specifically, it translates into significant financial outflows from Molise to host

regions, as the national healthcare system provides interregional financial compensation based on patient mobility. This can further weaken the local healthcare system, diverting resources that could be invested in improving domestic provision and contributing to a vicious cycle of service impoverishment.

This suggests that the efficiency and quality of resource allocation are critical factors, in addition to the amount of spending. Avoidable mortality is significantly higher in southern regions, suggesting significant differences in the effectiveness of prevention, access to early care and overall quality of the health system.

3.6 Study of relationships between variables

In recent decades, the growing attention to environmental and social issues has highlighted the importance of understanding the interconnections between economic, environmental and health factors. In particular, individual or family income, the quality of the environment in which one lives and the state of health of people represent three fundamental dimensions of human well-being. The aim of this analysis is to investigate the correlations existing between these elements, to verify to what extent the level of income influences the quality of the surrounding environment and, consequently, the state of health of individuals.

Bivariate analyses were conducted to explore the relationships between the different pairs of elementary indicators. The following table 3 shows the correlation coefficients, with the statistically significant ones highlighted in bold.

It should be remembered that correlation analysis, by its nature, does not allow for the establishment of causal relationships between variables: it simply measures the intensity and direction of the link.

Table 3 – Correlations.

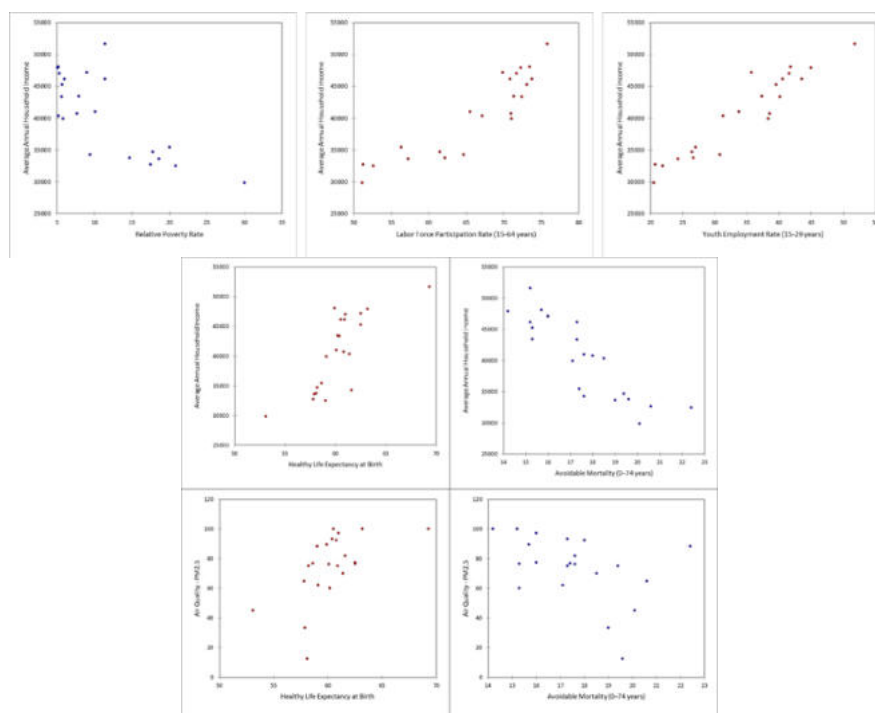
Variable	Average annual household income	Chi index	Relative family poverty incidence	Labour force aged 15-64	Youth employment rate	Unemployment rate	Medical specialists	Hospital migration index	Current public health expenditure per inhabitant	Healthy life expectancy at birth	Avoidable mortality (0-74 years)	Standardized mortality rate	Infant mortality	Air quality - PM2.5	Families reporting air pollution	Families reporting unpleasant odours	Service for the separate collection of municipal waste
Average annual household income	1																
Chi index	-0.544	1															
Relative family poverty incidence	-0.762	0.519	1														
Labour force aged 15-64	0.905	-0.623	-0.871	1													
Youth employment rate	0.946	0.553	0.779	0.943	1												
Unemployment rate	-0.870	-0.628	-0.772	-0.923	-0.913	1											
Medical specialists	-0.061	0.234	-0.299	0.070	-0.112	0.368	1										
Hospital migration index	0.439	-0.114	0.481	-0.346	-0.421	0.179	-0.400	1									
Current public health expenditure per inhabitant	0.427	-0.347	-0.161	0.448	0.482	-0.412	-0.045	0.009	1								
Healthy life expectancy at birth	0.770	0.442	0.614	0.714	0.780	-0.674	-0.047	-0.419	0.597	1							
Avoidable mortality (0-74 years)	-0.366	0.621	0.724	-0.336	-0.871	0.871	0.115	0.200	-0.241	-0.437	1						
Standardized mortality rate	-0.829	0.623	0.697	-0.824	-0.839	0.880	0.125	0.235	-0.265	-0.606	0.942	1					
Infant mortality	-0.181	0.231	0.317	-0.179	-0.185	0.217	-0.191	0.230	0.043	-0.221	0.319	0.310	1				
Air quality - PM2.5	0.618	-0.347	0.486	0.491	0.628	0.430	-0.227	-0.391	0.139	0.585	-0.474	-0.406	-0.153	1			
Families reporting air pollution	0.119	0.260	-0.246	0.095	0.079	0.076	0.259	-0.856	-0.322	0.056	0.027	0.119	-0.160	0.428	1		
Families reporting unpleasant odours	0.514	0.705	0.311	0.683	0.559	0.679	0.334	-0.353	0.555	-0.369	0.592	0.595	-0.022	-0.064	0.700	1	
Service for the separate collection of municipal waste	0.593	-0.657	-0.461	0.581	0.592	-0.590	-0.220	-0.216	0.211	0.410	-0.649	-0.728	-0.072	0.142	-0.293	-0.617	1

Source: *Elaborations on data from Istat databases.*

Table 4 shows the significant correlations; the average income indicator shows a rather strong negative correlation with the relative poverty rate (-0.76), suggesting that regions with a higher average income tend to record lower levels of poverty.

This confirms the role of income, especially if equally distributed, as a determining factor in reducing economic inequalities.

Table 4 – Significant correlations.



Furthermore, average income is positively associated with both the labour force participation rate and the level of youth employment, highlighting a link with a greater vitality of the labour market. Average income also has a positive correlation with healthy life expectancy and a negative correlation with avoidable mortality.

This suggests that regions with higher income levels tend to associate greater healthy longevity and a lower incidence of avoidable deaths, probably due to better access to health services, more favourable living conditions and a greater capacity for prevention. The indicator for air pollution shows a positive correlation with both average per capita income and healthy life expectancy, and a negative correlation with avoidable mortality. This apparent paradox can be explained by the fact that

regions with higher levels of pollution often coincide with urbanized and economically developed areas, where average income is higher.

In such contexts, greater availability of health services, modern infrastructure and favorable socio-economic conditions contribute to improving health outcomes, partly mitigating the negative effects of exposure to air pollutants.

4. Conclusions

The analysis conducted highlights profound territorial inequalities among the Italian regions, with the South presenting the greatest structural criticalities. The regions of the South, in particular Calabria and Sicily, are characterized by low levels of per capita income, high economic inequality and widespread relative poverty. Added to these conditions is a fragile employment situation, especially among young people: in regions such as Campania and Calabria, youth employment rates are less than 30%, among the lowest in the country.

Signs of vulnerability also emerge in terms of health. Campania has the highest avoidable mortality rate, while Molise, Basilicata and Calabria show high health emigration, a symptom of deficiencies in local health services.

From an environmental point of view, air pollution is generally less critical in the South, with the exception of Campania. However, separate waste collection remains insufficient in many areas of the South, indicating a delay in sustainable waste management practices.

On the contrary, the Northern regions, such as Trentino-Alto Adige, Lombardia and Veneto, stand out for their overall positive performance.

These territories have an average income higher than the national average, low levels of poverty and, in particular Veneto and Trentino, low unemployment rates. In terms of healthcare, Lombardia, Emilia-Romagna and Veneto show a high level of hospital self-sufficiency, retaining the majority of patients within their own healthcare facilities. The Alpine and North-Eastern regions (in particular Trentino, Veneto, Friuli Venezia Giulia and Lombardia) offer very favorable economic and healthcare conditions, despite presenting environmental criticalities linked to air pollution, especially in urbanized and industrialized areas. On the other hand, the North confirms its virtuousness in separate waste collection, with results significantly higher than the national average.

Overall, the data analyzed highlight the need for differentiated and territorially targeted public policies, aimed at reducing regional inequalities and strengthening socio-economic, healthcare and environmental conditions in the most disadvantaged areas, promoting greater territorial cohesion and justice.

References

- BRANDOLINI A., SARACENO C. 2007. *Povert  e diseguaglianza: nuovi approcci alla distribuzione del reddito*. Il Mulino.
- ISTAT-CNEL. 2013. BES – Il Benessere equo e sostenibile in Italia. Roma: Istat.
- OECD. 2020. How's Life? Measuring Well-being. OECD
- SEGRE E., RONDINELLA T., MASCHERINI M. 2011. Well-being in Italian regions, measures, civil society, *Social Indicators Research*, Vol. 102 No. 1, pp. 47-69
- SEN A. 1999. *Development as Freedom*. Oxford University Press.
- STIGLITZ J. E., SEN A., FITOUSSI J.P. 2009. Report by the commission on the measurement of economic performance and social progress
- WILKINSON R. G., PICKETT K. 2009. *The Spirit Level: Why More Equal Societies Almost Always Do Better*. Allen Lane
- YEBETCHOU TCHOUNKEU R. A. 2024. The impact of public health efficiency on well-being in Italian provinces. *Journal of Economic Studies*, Vol. 51, No. IX, pp. 232-248.

HEALTH MOBILITY AMONG THE OLDER ADULTS IN ITALY: A REGIONAL INEQUALITY PERSPECTIVE

Giuseppe Venere

Abstract. As Italy faces rapid demographic aging, understanding the healthcare mobility of older adults (over 65) has become a crucial challenge for regional planning and ensuring equitable access to care. This study examines interregional health migration among individuals aged 65 and over, shedding light on the patterns of elderly patients moving across Italian regions in search of hospital services.

The main objective of this research aims to explore the determinants of health-related mobility for older adults and assess the territorial inequalities that drive these flows. Specifically, it investigates whether demographic factors, economic capacity, healthcare quality, and geographic proximity affect the direction and intensity of elderly patient mobility between regions.

The analysis is based on integrated data from Istat, the Italian Ministry of Health, and AGENAS (National Agency for Regional Health Services). The methodological approach employs count gravity models (Poisson and Negative Binomial), with interaction effects between healthcare quality – measured through LEA (Essential Level of Care) scores – and economic development (GDP per capita) of the receiving regions. These models help to assess how both the performance of regional healthcare systems and the economic capacity of regions influence the decisions of elderly patients to move in search of medical care.

Preliminary findings reveal significant disparities across regions. Older adults are more likely to move from Southern to Northern and Central regions, driven by better healthcare performance and infrastructure. The interaction between higher LEA scores and regional wealth strengthens a region's attractiveness.

1. Introduction

Aging of the population is one of the most pressing issues for healthcare and welfare systems in highly industrialized countries, like Italy. The increasing share of individuals aged over 65 years has generated increased pressure on the demand for healthcare services, particularly concerning chronic illnesses, multimorbidity, and continuity of care (Savaş ., 2023; King, 2024). In this respect, the mobility of the elderly among healthcare beneficiaries is a central element, not only as proof of inefficiencies and geographic holes in the delivery of healthcare but also as a survival and adaptation choice followed by the most disadvantaged groups (Williams *et al.*, 2000; Warnes, 2009; Ciobanu *et al.*, 2017).

In Italy, access to healthcare is controlled by a decentralised universalistic system, where regional administrations are granted broad organisational and managerial autonomy. While this organization has been more responsive to regional needs, it has also generated important inequities regarding service quality, waiting lists, and services provided (Berta *et al.*, 2021; Carnazza *et al.*, 2025). These inequities are clearly evident in the interregional hospital mobility flows and constitute a multifaceted phenomenon that makes the most attractive areas trap a high percentage of patients from poorly performing areas (Levaggi *et al.*, 2004; Frischhut *et al.*, 2025). These interregional movements are not solely the result of inefficiencies, but also reflect a growing willingness among patients to wait and travel in order to access care perceived as higher in quality (Bruni *et al.*, 2021). Moreover, it has been shown that the main factors influencing hospital mobility include hospital capacity, service organization, quality of care provided, and the availability of advanced medical technologies (Balía *et al.*, 2018), all of which contribute to making certain regions systematically more attractive than others.

In recent years, the issue of Essential Levels of Care (Livelli Essenziali di Assistenza - LEA) has turned out to be one of the most effective tools for ascertaining the adequacy of healthcare services delivered at the regional level. The LEA scores, provided by the Ministry of Health, summarize regional performance in ensuring the minimum bundle of services required by national standards taking into account several dimensions such as prevention, community care, and hospital support. The scores act as a monitoring mechanism to ensure that fundamental care is assured universally across the country (Alfiero *et al.*, 2021; Spano *et al.*, 2022; Betti *et al.*, 2023).

At the same time, other structural determinants - like per capita Gross Domestic Product (GDP) and geographic distance between regions - may be significant determinants of regional attractiveness and repulsion (Levaggi and Zanola, 2004). GDP can be a measure of the region's economic capacity to provide for and finance healthcare services, and therefore its ability to meet healthcare demand (Gan and Frederick, 2011). Distance, however, contributes to the expense burden for older individuals to travel to access care in another region, with the potential to limit access for less well-off individuals (Glinos *et al.*, 2010).

The overall purpose of this study is to track and examine interregional hospital-related healthcare mobility patterns amongst the population aged 65 and above, with a goal to observe the drivers that compel older adults to be treated outside their home region. Specifically, the analysis will investigate whether structural variables such as the LEA score and regional GDP can be considered principal drivers of healthcare mobility, using gravity models. To this end, the analysis revolves around two general research questions:

RQ.1 To what extent do structural characteristics of regional healthcare systems, as measured by LEA compliance and regional GDP, influence the direction and intensity of interregional hospital mobility among the elderly population?

RQ.2 What is the most appropriate gravity model specification for capturing the determinants and patterns of interregional hospital mobility among the elderly?

Drawing on administrative data and synthetic indicators, this work takes a data-driven, demography-oriented perspective to provide a comparative and detailed interpretation of the phenomenon, feeding into ongoing scientific and policy discussions on territorial equity in healthcare. The findings also aim to be of practical use for the planning and improvement of the balance between healthcare supply and demand, with specific reference to ageing populations.

2. Rethinking Elderly Mobility in Healthcare: A Literature-Based Perspective on Italy's North-South Divide

Italy is also characterized by a clear territorial diversification of the supply of healthcare services, historically expressed in the form of a persistent North–South divide in terms of infrastructures, economic resources, and performance indicators (Alfiero *et al.*, 2021; Betti *et al.*, 2023). Though all regions are required to guarantee the Essential Levels of Care (LEA), effective compliance is rather dissimilar: while Centre-North regions are consistently at the top of national performance rankings, Southern regions fall below minimum standards (Spano *et al.*, 2022). This means a potentially more disadvantaged population that is less able to effectively access the right care pathways. At the same time, the increasing use of outgoing healthcare mobility testifies to a widespread feeling of distrust towards local healthcare systems.

Migration flows of older individuals, for too long confined to the role of marginal epiphenomenon, are now included in active ageing and life course optimisation processes. The notion of inactive old age is challenged by data showing an increasing tendency to migrate in old age, both within one's own country and outwards to other countries (Savaş *et al.*, 2023; King, 2024). The reasons for this are several: from the search for more favourable climates (Bolzman *et al.*, 2021) to the migration away from healthcare systems perceived as inefficient (Warnes, 2009; Gao *et al.*, 2021).

The elderly migrant is not an inert individual, but a conscious person who makes informed decisions regarding quality of life, access to care, and the economic sustainability of his or her own ageing path (Ciobanu *et al.*, 2017). This capacity for self-determination emerges clearly in the growing literature on the mobility of older people, which interprets such moves not only as responses to immediate needs but as conscious strategies of adaptation to vulnerability, aimed at living well and in good health.

Mobility in healthcare is not only an expression of escape from disadvantaged environments but is also linked to attraction to places with greater availability and quality of services. The literature shows that regions with higher performing healthcare can

attract patients not only due to the presence of clinical excellence, but also for organizational efficiency, shorter waiting lists, and greater transparency (Levaggi and Zanola, 2004; Berta *et al.*, 2021).

In particular, LEA score is a suitable measure for summarizing the quality of healthcare delivery at the territorial level, while per capita GDP is employed as a proxy for the structural endowment of the system (Alfiero *et al.*, 2021; Frischhut and Levaggi, 2024). As a matter of fact, hospitals in Northern Italy exert a strongly attractive function, generating a competitive care market in which health benefits represent an important discriminator that has important returns in economic terms (Carnazza *et al.*, 2025). However, this polarisation reinforces existing inequalities, with some areas being strengthened by the additional income generated by interregional hospital admissions, while others are increasingly disadvantaged, with a decrease in the efficiency and reliability of their local healthcare systems (Spano *et al.*, 2022; Betti *et al.*, 2023).

Healthcare mobility therefore has a double meaning: on the one hand it represents an opportunity, on the other hand it entails a number of challenges. For elderly patients, moving to receive care often results in a complex emotional, economic and logistical undertaking. Studies on medical tourism (Glinos *et al.*, 2010; Hanefeld *et al.*, 2015) show that the choice of destination is influenced by social networks, perceived quality of care, affordability and relational support.

At the same time, mobility can enhance health inclusion when the place of origin fails to provide adequate care. In the context of cross-border healthcare, for instance, European policies uphold the right to seek medical treatment abroad (Wismar *et al.*, 2011). National healthcare systems are therefore expected to facilitate these flows, ensuring that freedom of choice in accessing care is both meaningful and practicable (Jacobsen *et al.*, 2023).

To conclude, the literature suggests that, if well managed, this phenomenon can produce economic and human capital returns for host communities (Mainil *et al.*, 2017; Suess *et al.*, 2018).

3. Data sources and methodological approach

The study is based on the integration of multiple official data sources, with the aim of ensuring analytical consistency and the robustness of results. The data come primarily from the Italian National Institute of Statistics (Istat) and refer to three specific domains: the “Health for All” database, which provides structured indicators on regional healthcare systems; resident population tables, which help contextualize healthcare demand; and hospital mobility data, which allow for the tracking of interregional patient flows. Some information was obtained through customized tables to refine the demographic and territorial analysis. These data are supplemented by indicators provided by the Ministry of Health, in particular with regard to the evaluation of the Essential Levels of Care (Livelli Essenziali di Assistenza - LEA), and by information

from the National Agency for Regional Health Services (Agenas), in particular the occupancy of hospital beds and the observed interregional health mobility in the year 2022 with a focus on the over-65 age group.

The dataset used for the analysis refers to the year 2022 and consists of 441 directional observations, representing all possible origin–destination combinations among the 21 Italian regions, including intra-regional flows, i.e., cases where hospital admissions occurred within the same region of residence.

The unit of analysis is the number of hospital admissions of individuals aged 65 and over who received care either within their own region or in a different one, depending on the recorded flow. The data refer exclusively to hospital mobility recorded in 2022.

These is a summary table of the variables included in the model, referring to both the region of origin and the region of destination, and used for the estimation of the gravity models.

Table 1 *Overview of the Variables Included in the Models.*

Variable	Type	Role	Meaning
origine	String	Descriptive	Region of origin
destinazione	String	Descriptive	Region of destination
flusso	Numeric	Dependent	Number of flows in 2022
log_pop_origine	Continuous (log)	Independent	Log of the population in the region of origin
log_pop_destinazione	Continuous (log)	Independent	Log of the population in the region of destination
log_pil_origine	Continuous (log)	Independent	Log of GDP in the region of origin
log_pil_destinazione	Continuous (log)	Independent	Log of GDP in the region of destination
LEA_origine	Continuous	Independent	LEA score of the region of origin
LEA_destinazione	Continuous	Independent	LEA score of the region of destination
log_distanza	Continuous (log)	Independent	Log of the distance between regions
stessaregione	Dichotomous (dummy)	Independent	1 = same region; 0 = different region
confine	Dichotomous (dummy)	Independent	1 = bordering regions; 0 = non-bordering regions

Methodologically, the analysis is structured on multiple levels. To construct composite indicators, or to aggregate the multidimensionality of the LEA score (preventive, community-based, and hospital care), Principal Component Analysis (PCA) was initially applied. This technique allowed for the reduction of informational complexity with maximum preservation of explained variance, with a single composite variable remaining to be included in the gravity models.

The empirical study is based on the application of four different specifications of the gravity model; this method is widely applied in the literature for the study of spatial flows, and specifically for the study of health mobility.

The Poisson Model was initially applied to examine the relationship between healthcare mobility flows and regional structural determinants. However, evidence of overdispersion - where the variance exceeds the mean - indicated that a Negative

Binomial model would be more appropriate, as it better accommodates such data characteristics. To allow for greater flexibility in modelling dispersion, a Generalized Negative Binomial model was ultimately adopted, in which the dispersion parameter ($ln\alpha$) was modelled as a function of the population of the origin region and the log-transformed distance between regions.

4. The LEA scores

The evaluation of the Essential Levels of Care (Livelli Essenziali di Assistenza, hereafter referred to as LEA) is one of the most important tools for analyzing territorial disparities within the Italian National Health System. Established by the Ministry of Health, the LEA defines the set of healthcare services and provisions that must be guaranteed uniformly to all citizens across the national territory, regardless of their region of residence. Its primary goal is to ensure a minimum, standardized level of health protection, financed mainly through general taxation and, in part, through user co-payments (ticket)¹.

The choice to include the LEA score as a key explanatory variable in the model stems from its nature as an official composite indicator developed by the Italian Ministry of Health. The LEA score integrates a wide range of dimensions related to healthcare quality, accessibility, and resource allocation across regions². It encompasses several structural components of supply - such as hospital bed availability, coverage of primary and community care, number of medical staff per patient, adherence to prevention protocols, and unmet health needs - thereby providing a holistic and standardized measure of healthcare system performance. Including individual indicators (e.g., hospital beds per capita, staff density, or specific morbidity measures) alongside the LEA score would have risked redundancy and multicollinearity, as confirmed by Spearman correlation tests and VIF diagnostics performed in preliminary analyses. Furthermore, the inclusion of selected indicators - such as elderly mortality or specific chronic disease rates - might fail to capture the broader spectrum of morbidity and service provision relevant to older populations, thereby introducing a partial and potentially biased representation. For these reasons, the LEA score was retained as the primary proxy for regional healthcare quality, ensuring parsimony, coherence, and conceptual robustness within the model

¹ <https://www.salute.gov.it/new/it/tema/livelli-essenziali-di-assistenza-lea/> accessed on May 2025

² As a robustness check, additional model specifications were tested by including individual variables commonly used in the literature to account for healthcare needs and supply, such as mortality rates among older adults, the number of hospital beds per inhabitants, and regional public expenditure on health and social care services. While descriptively relevant, these variables showed a high degree of correlation with the dimensions already incorporated within the LEA score, leading to multicollinearity and conceptual redundancy.

specification and representing an innovative indicator compared to relevant studies that have not used it such as Fabbri & Robone (2010) and Balia *et al.* (2018).

Figure 1 - Italian map of LEA scores calculated using Principal Component Analysis and the Min-Max Scaling technique.



Source: Italian Ministry of Health, National Health Report 2025.

The “LEA scores” are constructed based on indicators grouped into three functional macro-areas: collective prevention and public health, district-level care (including primary and community-based services), and hospital care. These dimensions are monitored annually across all regions and autonomous provinces, producing a composite index that ranges from 0 (indicating maximum inefficiency) to 1 (indicating maximum efficiency), expressed on a normalised scale. In this study, LEA scores were further synthesised using Principal Component Analysis (PCA), in order to reduce redundancy among sub-indicators and generate a single standardised index, subsequently transformed through Min-Max Scaling.

The map in Figure 1 clearly illustrates the territorial distribution of the LEA scores across Italy, showing a very high territorial gradient.

The best scores are recorded in northern regions such as Emilia-Romagna (0.94), Veneto (0.93), and Lombardy (0.92), indicating high overall efficiency in their regional health systems. In these cases, services tend to be more accessible, delivered more promptly, and are widely perceived as more reliable by citizens, as highlighted in recent studies (Signorelli *et al.*, 2017, 2020; Alfiero *et al.*, 2021; Spano *et al.*, 2022; Betti *et al.*, 2023).

Conversely, southern regions such as Calabria (0.24), Sicily (0.28), and Campania (0.30) rank at the lower end of the index, reflecting persistent structural shortcomings - from shortages of medical personnel and inadequate healthcare facilities to limited managerial capacity and inefficient resource allocation. This imbalance plays a

significant role in driving outbound healthcare mobility flows and stands among the primary factors contributing to health disparities based on place of residence.

5. Results

The analysis of healthcare mobility flows among the elderly population (aged 65 and over) between Italian regions was conducted using gravity models adapted to the healthcare context. These models estimate flows between two territories based on their attractive or repulsive characteristics, such as population size, geographical distance, and quality of healthcare services. Three model specifications were tested: the Poisson model, the Negative Binomial model, and the Generalized Negative Binomial model.

The dataset comprises 441 directional observations, capturing all “from-to” combinations among the 21 Italian regions (19 regions with the autonomous provinces of Trento and Bolzano), including intra-regional flows (i.e., movements within the same region).

5.1 Initial Modelling Attempts: From Poisson to Negative Binomial

The baseline model applied was the Poisson specification, which assumes equality between the mean and the variance of the dependent variable. Initial results revealed significant associations between healthcare mobility flows and key regional characteristics, such as the LEA score of the destination region and the presence of a shared border.

$$E(Y_{ij}) = \exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k)$$

where Y_{ij} is the expected number of hospitals flows from region i to region j ; X is the vector of independent variables; β is the vector of estimated coefficients.

However, the analysis of standardised residuals and the Pearson χ^2/df ratio (366.4) indicated substantial overdispersion, violating the Poisson model's core assumptions. This outcome is consistent with the broader literature on healthcare mobility, which notes the limitations of the Poisson framework in contexts characterised by high heterogeneity and spatial dependency (Silva & Tenreiro, 2006; Burger *et al.*, 2009).

To account for overdispersion, the Negative Binomial model was subsequently adopted. This specification introduces a dispersion parameter (α) to better capture unobserved heterogeneity.

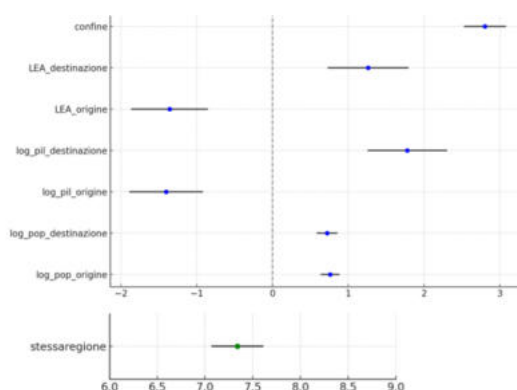
$$Y_{ij} \sim \text{NegBin}(\mu_{ij}, \alpha)$$

Where μ_{ij} is the expected mean of the healthcare flow from region i to region j , modelled through an exponential function of the socio-economic and structural characteristics of the origin and destination regions.

The model fit improved substantially, as shown by a significant drop in AIC (5,280) and BIC (5,313), as well as a marked increase in pseudo- R^2 (0.1247). Residual analysis revealed a more symmetrical distribution with fewer outliers. However, one notable finding was that the log-transformed geographical distance variable lost its statistical significance, suggesting a complex interaction between spatial proximity and unobserved regional factors.

These limitations highlighted the need for a more flexible modelling approach capable of directly incorporating structural sources of dispersion into the estimation process (Burger *et al.*, 2009).

Figure 2 - Generalised Negative Binomial estimates for elderly hospital mobility.



5.2 The Generalised Negative Binomial Model: A Robust and Comprehensive Solution

To overcome the limitations of the previous specifications, the Generalised Negative Binomial model was applied. This approach allows the dispersion parameter (α) to be modelled as a function of one or more covariates. Such a specification not only helps to control for residual heterogeneity but also enables the identification of variables that may be driving the overdispersion.

$$Y_{ij} \sim \text{NegBin}(\mu_{ij}, \alpha_{ij}) \quad \text{with} \quad \log(\mu_{ij}) = X_{ij}\beta, \quad \log(\alpha_{ij}) = Z_{ij}\gamma$$

Where Z_{ij} is the vector of predictors used to model overdispersion (in this case: $\log\_pop\_origine$, $\log\_pop\_destinazione$, and $\log\_distanza$).

The results show a further improvement in model fit: both the AIC and BIC are the lowest among all estimated models, confirming the model's high parsimony and statistical coherence. The boxplot of residuals reveals an almost complete absence of outliers, with minimal residual dispersion and no evident skewness.

This model also demonstrates that a portion of the overdispersion can be attributed to the logarithmic distance between regions ($P > |z|^{***}$) and to the logarithm of the elderly population in both origin ($P > |z|^{***}$) and destination regions ($P > |z|^{***}$). When included in the $\ln \alpha$ component, these variables contribute to a more accurate modelling of dispersion (Silva and Tenreyro, 2006; Burger *et al.*, 2009). Meanwhile, the LEA and GDP variables remain statistically significant, with the LEA score of the destination region exhibiting a particularly strong effect.

6. Discussion and conclusion

This study investigated hospital healthcare mobility among the population aged 65 and over in Italy, employing gravity models to assess the impact of regional structural differences on interregional patient flows. The primary objective was to determine whether regional healthcare performance, as measured by LEA scores, and economic prosperity, proxied by per capita GDP, influence mobility patterns among elderly patients seeking higher quality and more accessible care.

The findings confirmed that regions with high-performing healthcare systems act as strong attractors, whereas lower-performing areas tend to experience patient outflows. Economic development also plays a complementary role: wealthier regions with better infrastructure are more effective in attracting and retaining patients.

To empirically validate these patterns and quantify the role of structural determinants in shaping mobility flows, three gravity model specifications were tested. The Poisson model was inadequate due to overdispersion; the Negative Binomial model improved the fit, while the Generalised Negative Binomial model offered the best balance of simplicity, robustness, and explanatory power.

However, despite consistent results, the study has limitations. It excludes zero-flow observations and overlooks social, cultural, and individual factors, such as trust in local services, family support, or indirect costs, that are crucial to understanding elderly patients' decisions. Nevertheless, even within these constraints, it provides valuable evidence on the underlying structural drivers of elderly healthcare mobility. These choices go beyond service quality, highlighting broader structural divides, access issues, and subjective perceptions. Reducing these disparities remains a central challenge for regional health policy in Italy.

References

- ALFIERO S., BRESCIA V., BERT F. 2021. Intellectual capital-based performance improvement: a study in healthcare sector, *BMC Health Services Research*, Vol. 21, pp. 1-15.
- BALIA S., BRAU R., MARROCU E. 2018. Interregional patient mobility in a decentralized healthcare system, *Regional Studies*, 52.3: 388-402.

- BERTA P., GUERRIERO C., LEVAGGI R. 2021. Hospitals' strategic behaviours and patient mobility: Evidence from Italy, *Socio-Economic Planning Sciences*, Vol. 77, 101030.
- BETTI M., DE TOMMASO C.V., MAINO F. 2023. Health Inequalities in Italy. Comparing regions among prevention, community health services and hospital assistance, *Social Development Issues*, Vol. 45, No. 1, pp. 61-76.
- BOLZMAN C., FOKKEMA T., GUISSÉ I., VAN DALEN D. 2021. Starting a new life in the South? Swiss, Dutch and Flemish ageing in Morocco: A lifecourse perspective, *Ageing & Society*, Vol. 41, No. 6, pp. 1240-1266.
- BRUNI M., UGOLINI C., VERZULLI R. 2021. Should I wait or should I go? Travelling versus waiting for better healthcare. *Regional Science and Urban Economics*, 89: 103697.
- BURGER M., VAN OORT F., LINDERS G.J. 2009. On the specification of the gravity model of trade: zeros, excess zeros and zero-inflated estimation, *Spatial Economic Analysis*, Vol. 4, No. 2, pp. 167-190.
- CARNAZZA G., LAGRAVINESE R., LIBERATI P., TORRINI I. 2025. Monetary flows for inter-regional health mobility: The case of Italy, *Papers in Regional Science*, Vol. 104, No. 1, 100063.
- CIOBANU R.O., FOKKEMA T., NEDELCU M. 2017. Ageing as a migrant: Vulnerabilities, agency and policy implications, *Journal of Ethnic and Migration Studies*, Vol. 43, No. 2, pp. 164-181.
- FABBRI D., ROBONE S. 2010. The geography of hospital admission in a national health service with patient choice, *Health Economics*, 19.9: 1029-1047.
- FRISCHHUT M., LEVAGGI R. 2024. With a little help from my (neighbouring) friends. 'Border region patient mobility' in the European Union: A policy analysis, *Health Policy*, Vol. 146, 105114.
- GAN L.L., FREDERICK J.R. 2011. Medical tourism facilitators: Patterns of service differentiation, *Journal of Vacation Marketing*, Vol. 17, No. 3, pp. 165-183.
- GAO L., PENNING M.J., WU Z., STERRETT S.J., LI S. 2021. Internal migration and the health of middle-aged and older persons in China: the healthy migrant effect reconsidered, *Research on Aging*, Vol. 43, No. 9-10, pp. 345-357.
- GLINOS I.A., BAETEN R., HELBLE M., MAARSE H. 2010. A typology of cross-border patient mobility, *Health & Place*, Vol. 16, No. 6, pp. 1145-1155.
- HANEFELD J., LUNT N., SMITH R., HORSFALL D. 2015. Why do medical tourists travel to where they do? The role of networks in determining medical travel, *Social Science & Medicine*, Vol. 124, pp. 356-363.
- JACOBSEN F.F., GLASDAM S., SCHOPMAN L.M., SODEMANN M., VAN DEN MUIJSENBORG M.E., ÅGOTNES G. 2023. Migration and health: exploring healthy ageing of immigrants in European societies, *Primary Health Care Research & Development*, Vol. 24, e10.

- KING R. 2024. International retirement migration: who, where, when and why? In *Handbook of Human Mobility and Migration*, Edward Elgar Publishing, pp. 163-181.
- LEVAGGI R., ZANOLA R. 2004. Patients' migration across regions: the case of Italy, *Applied Economics*, Vol. 36, No. 16, pp. 1751-1757.
- MAINIL T.J.G.M.J., EIJGELAAR E., KLIJS J., NAWIJN J., PEETERS P.M. 2017. Research for TRAN committee—health tourism in the EU: a general investigation. *European Parliament, Directorate General for Internal Policies, Policy Department B: Structural and Cohesion Policies, Transport and Tourism*.
- SAVAŞ E.B., SPAAN J., HENKENS K., KALMIJN M., VAN DALEN H.P. 2023. Migrating to a new country in late life: A review of the literature on international retirement migration, *Demographic Research*, Vol. 48, pp. 233-270.
- SIGNORELLI C., FARA G.M., ODOE A., ZANGRANDI A. 2017. The reform of the Italian Constitution and its possible impact on public health and the National Health Service, *Health Policy*, Vol. 121, No. 1, pp. 90-91.
- SIGNORELLI C., ODOE A., ORADINI-ALACREU A., PELISSERO G. 2020. Universal Health Coverage in Italy: lights and shades of the Italian National Health Service which celebrated its 40th anniversary, *Health Policy*, Vol. 124, No. 1, pp. 69-74.
- SILVA J.S., TENREYRO S. 2006. The log of gravity, *The Review of Economics and Statistics*, pp. 641-658.
- SPANO A., ARONI A., TAGLIAGAMBE V., MALLUS E., BELLÒ B. 2022. Performance and expenditure in Italian public healthcare organizations: does expenditure influence performance?, *Public Money & Management*, Vol. 42, No. 2, pp. 79-86.
- SUESS C., BALOGLU S., BUSSE J.A. 2018. Perceived impacts of medical tourism development on community wellbeing, *Tourism Management*, Vol. 69, pp. 232-245.
- WARNES T. 2009. International retirement migration. In *International Handbook of Population Aging*, pp. 341-363.
- WILLIAMS A.M., KING R., WARNES A., PATTERSON G. 2000. Tourism and international retirement migration: new forms of an old relationship in southern Europe, *Tourism Geographies*, Vol. 2, No. 1, pp. 28-49.
- WISMAR M., PALM W., FIGUERAS J., ERNST K., GINNEKEN E.V. 2011. *Cross-border health care in the European Union: mapping and analysing practices and policies*. World Health Organization on behalf of the European Observatory on Health Systems and Policies.

LATENT STEREOTYPES IN CONTEMPORARY SOCIETY: TEACHERS' STRATEGIES TO PROTECT CHILDREN FROM GENDER DISCRIMINATION IN SICILIAN SCHOOLS¹

Simona Ballabio, Arianna Carra, Paola Maddalena Chiodini, Daniela Corso,
Stefania Quartarone, Elena Sorba, Flavio Verrecchia

Abstract. “La Femme naît libre et demeure égale à l’Homme en droits ...”. Olympe de Gouges’ declaration was the first document advocating legal equality for women. It opposed the Declaration of the Rights of Man, which granted rights only to men, excluding women from political participation, property ownership, and professional opportunities. In 1793, de Gouges was executed by guillotine, accused of “forgetting the virtues of her sex” and interfering in politics. Robespierre later banned women’s associations, closing their clubs and newspapers. As she was led to execution, de Gouges allegedly said: “Women have the right to mount the scaffold; they must also have the right to mount the rostrum.” Over two centuries later, gender stereotypes persist. Like a time machine, they replicate past accusations and consequences. Gender-based biases continue to shape education, professional advancement, and social dynamics. This study examines how teachers in Sicily address gender discrimination in schools. A CAWI survey conducted by Telefono Arcobaleno Onlus gathers data on how teachers detect pupil distress and intervene in cases of bias and inequality. Schools play a key role, educators observe the formation of stereotypes at an early stage and can act to counter discrimination. The findings aim to improve intervention strategies, provide practical tools for teachers, and reinforce education’s role in protecting children from gender discrimination.

1. Introduction

The *Telefono Arcobaleno* association is an international organization dedicated to the protection of children and adolescents. Certain initiatives have been structured into distinct annual programs, reflecting the evolving needs of the region. Within this framework, the survey “*Teachers Facing Students*”, is presented. This investigative study – a collaborative product of specialists from Telefono Arcobaleno, senior researchers from the National Institute of Statistics, and academics in socio-economic and statistical fields – targets teachers in kindergarten, primary, and middle schools. Its primary objective is to ascertain the capacity of

¹ Even if the article is the joint responsibility of the authors, the following individual contributions can be distinguished: paragraph 1 is attributable to Verrecchia; paragraph 2 is attributable to Carra; paragraph 3 is attributable to Corso; paragraph 4 is attributable to Sorba (up to Table 1 included) and Chiodini (after Table 1) and paragraph 5 is attributable to Ballabio (up to Table 3 included) and Quartarone (after Table 3).

Sicilian teachers to observe, interpret, and respond promptly to signs of distress manifested by their students, thereby ensuring their protection. Specifically, the study aims to meticulously analyse the perspectives, experiences, and intervention strategies for child protection adopted by Sicilian educators concerning child abuse, bullying and cyberbullying, and gender stereotypes. The present study focuses exclusively on the section related to gender stereotypes.

2. About stereotypes

In 1791, in the Declaration of the Rights of Woman and of the Female Citizen, Olympe de Gouges asserted the equality between men and women. This resulted in her demise: she was guillotined in 1793 for having "forgotten the virtues of her sex." This is just one example of how powerful stereotypes can be in influencing the recognition of rights and freedoms.

Gender stereotypes—sets of conventional patterns of behavior and attitudes, based on simplistic and preconceived ideas—pervade society, producing concrete effects at both the micro and macro levels (Ellemers, 2018), and have extremely deep roots (Carra *et al.*, 2025). They are so deeply embedded in history that they have become an “invisible” barrier and a “presupposition,” capable of powerfully conditioning even the orientation and, consequently, the legal apparatus of societies, to the point of “legitimizing violence” against women. They are rooted in a long history of inequalities in which men and women have received different forms of recognition in terms of freedom, citizenship, and rights (Scott, 1986).

Gender stereotypes constitute the cultural humus that contributes to fueling and even justifying violence against women, from its most overt forms to the more subtle and symbolic ones. Italian court cases provide significant examples, such as the 1978 rape trial in which the defense attempted to blame the victim for her behavior (RAI, 1979), demonstrating the persistence of secondary victimization (Romito, 2005). At the legislative level, the concept of femicide has made explicit the connection between discrimination and lethal violence against women (Russell & Radford, 1992), but the path toward full recognition remains long.

The effects of stereotypes unfold across the entire life course: from educational and occupational inequalities (Charles & Bradley, 2009; Blau & Kahn, 2017), to underrepresentation in decision-making roles (Paxton *et al.*, 2007), and to the persistent unequal distribution of care work (Hook, 2010). Schools represent one of the most fertile grounds for the reproduction of stereotypes and, beginning especially in the 1980s, numerous studies and research projects began to address the issue of gender in education, contributing to raising public awareness of the impact of stereotypes in the educational field and their consequences in the world of work (see, for example, Acker, 1995; Sabbe & Aelterman, 2007).

Despite the different approaches that can be taken to addressing gender issues in school, the conclusion remains the same: “*teaching is imbued with gender*” (Sabbe and Aelterman, 2007), and power dynamics, stereotypes, and inequalities can profoundly affect the educational paths of girls and boys (Carlana, 2018).

In fact, education is a vehicle through which gender stereotypes tend to produce and reproduce “*a sexual division of labour whereby women are locked into low paid*” positions (Acker, 1995)—a condition that, in its most severe forms, can lead to what is defined as “economic violence”, a form of abuse in which control over financial resources is used as a means of exercising power and control within a relationship (Di Bella, 2023), a form of violence explicitly recognized by the Convention on Preventing and Combating Violence against Women and Domestic Violence (the so-called “Istanbul Convention”), adopted by the Council of Europe in May 2011 (Council of Europe, 2011).

To simplify, one of the chains linking the effect of gender stereotypes in schools to economic inequalities shaped by gender starts with teachers—especially mathematics teachers—who hold stronger “implicit” stereotypes about the belief that math is more difficult for girls. These have a significantly negative impact on girls (Carlana, 2018), who tend to achieve lower results in the subject and to self-select for “less demanding” high schools (Carlana, 2018).

Even though women may also “outperform” men in tertiary education, they remain a minority in the most lucrative fields such as science, technology, engineering, and mathematics (Acker, 1995; Carlana, 2018), and thus end up being “underrepresented”, especially in the most profitable sectors (Carlana, 2018).

Ultimately, since performance in mathematics is considered “a good predictor of readiness for STEM universities” (Carlana, 2018), it follows that results in this subject can be seen as “predictors” of future employment in the highest-paying sectors.

3. The contents of the survey

A subtle thread connects the enduring persistence of gender stereotypes over time, the emergence of gender-based violence and its legitimization in relationships, as well as the importance of preventing it from the earliest stages of schooling through comprehensive information and training programs aimed at teachers and students at all educational levels. In this direction, the Istanbul Convention actively encourages member states to include specific curricula on gender equality in school programs, addressed both to school staff and students, thereby constituting a crucial tool for preventing discrimination and gender-based violence.

Teachers, in fact, observe dynamics related to gender stereotypes already during the early stages of identity formation. Consequently, schools represent not only a

privileged context of observation but also an environment with strong transformative potential and, therefore, considerable preventive capacity.

It is within this framework that the research project “Teachers Facing Students”, promoted by Telefono Arcobaleno and specifically focused on the school environment, is situated. The association has consistently supported the search for solutions to the complex challenges affecting minors and, for years, has maintained a close relationship with educational institutions, recognizing them as crucial settings for the early detection of signs of distress. Consequently, schools are regarded as fundamental actors in the prevention and counteraction of the various forms of violence that can hinder the healthy development of children and adolescents.

Within the survey, gender stereotypes and gender discrimination emerge as foundational themes and constitute the central focus of the present work. The section dedicated to gender stereotypes pursues a dual objective: on the one hand, to detect their possible prevalence among students from the observational perspective of teachers; and on the other hand, to gather respondents’ views on the contexts and channels of learning (e.g., family, school, sport, culture, religion) through which minors internalize such stereotypes. In addition, the analysis investigates the possible repercussions of stereotypes on educational and professional pathways, on identity and self-esteem, as well as on the propensity to legitimize violent behaviors in peer interactions, and it also seeks to identify the intervention measures implemented within schools to prevent and combat gender discrimination.

Based on the analysis of the collected data, the paper pursues two main descriptive objectives: first, to understand whether and to what extent gender stereotypes are already widespread among students in the early grades of schooling, in which contexts they are learned, and how they are addressed within the school environment; second, to assess whether the ability to detect them varies according to teachers’ characteristics, that is, whether sensitivity to the issue is evenly distributed or instead influenced by the observers’ own cognitive frameworks, with particular attention to the dimension of gender.

This survey was conducted on an experimental basis and recorded a relatively low response rate. A broader-scale implementation is planned with the aim of increasing participation. Despite the limited response rate, calibration strategies were applied, allowing for the identification of relevant tendencies and indicative patterns. Nevertheless, given the low response rate, the resulting sample should be regarded as self-selected. It therefore offers only a blurred snapshot of reality—yet still a valuable one—of a phenomenon that is inherently difficult to capture, both because of its highly sensitive nature and because it concerns minors who can hardly be interviewed directly. It is likely that those teachers who chose to respond were particularly sensitive to the topic; however, this very aspect strengthens some of the

findings, such as the recurrent association of stereotypical characteristics with female and male pupils.

4. Data Collection Instrument, Sample, and Calibration Procedures

The survey was preceded by a pre-test phase, the objective of which was to verify the effectiveness and adequacy of the questionnaire in the field (Istat, 1989). In this phase, an initial prototype of the instrument was submitted, involving a selected sample of teachers, sector experts, and methodology specialists. The selection of participants was designed to ensure a diverse range of perspectives, thereby enabling a comprehensive evaluation of the instrument. The primary objective of the pre-test was to evaluate the quality of the questionnaire prior to its large-scale distribution.

The questionnaire, administered through the CAWI (Computer-Assisted Web Interviewing) technique, is systematically structured to elicit responses derived from both personal reflection and direct professional experience. Teachers are instructed to base their responses on their professional experience spanning the preceding five years. There are preliminary questions designed to ascertain the respondent's professional profile and contextual information. Specifically, information is solicited regarding the province and affiliated educational institution, school level, age, gender, academic qualifications, subject taught, length of service, and professional role. The concluding questions of the questionnaire aim to determine whether educational institutions benefit from the professional contributions of qualified and specialized personnel (e.g., psychologists, psychotherapists, pedagogists) and whether established operational protocols exist for preventing and managing the emergence of violence and bullying in adult-minor relationships or among peers. They are asked whether they deem specialized training beneficial for augmenting their competencies in the thematic areas of interest.

The target population for this survey comprised the teaching personnel of primary, and lower secondary educational institutions within the Sicily Region. To facilitate data collection, invitations to participate were disseminated to the school principals of all eligible institutions across the region, collectively representing over 700 entities, approximately 60,000 teaching professionals, and 430,000 enrolled students (Table 1).

Table 1 – Overall population (values in thousands).

	Students	Teachers	Of which females	Of which support	Of which < 45 years old
Kindergarten	96	11	11	3	2
Elementary school	202	27	26	9	6
Middle school	133	21	16	6	6
Total	430	60	53	17	14

Despite the provision of three separate reminders during the period under review (April-June 2025), it had to be accepted that the response rate among teaching staff would only be comparable to that of self-selected sample surveys. In fact, despite the school response rate was 6,7% the teachers response rate was 0.8%.

It is well known that the more sensitive the topics under investigation, as in this case, the more one must take into account the self-selection of respondents, which, from a purely statistical point of view, means that the results cannot be considered representative of the entire teaching population, but only of those members of the target population who decided to participate in the survey. Nevertheless, as with other surveys on sensitive issues, they are so useful in terms of information that they are also conducted by official statistics agencies. One example is the survey on LGBT+ (Istat, 2023).

In the practice of statistical institutes, when calibration is possible using known population totals even with low response rates, references are made to models that implicitly conform to the simple random sample, having a theoretical basis according to which the relative errors of absolute frequency estimates are a decreasing function of the values of the estimates themselves, as in the case of the Survey on Gender Role Stereotypes (ISTAT, 2018). In this survey, ISTAT reports non-sampling errors as errors due to non-response, with self-selection problems that also seem to derive from design factors, considering the sample representative. According to this second perspective, the calculation of the error (Corbetta, 1999, p. 318) is given by²

$$e = z \sqrt{\frac{pq}{n-1}} \sqrt{1 - \frac{n}{N}}.$$

In any case, to mitigate the distorting effects of self-selection, statistical calibration was implemented, based on known totals relating to the proportional distribution of teaching staff by school level and on socio-demographic variables such as gender (Table 2). The “sample weight” column demonstrates the relative weight of the stratum (by gender and school level) of respondents in comparison to the same stratum total of the population. The final column displays the relative weight of the respondent, which is defined as a measurement of the influence that each individual respondent's response exerts on the stratum total.

In addition, considering the suboptimal response rate and problems related to self-selection, it was deemed useful to adopt a ‘cautious calibration’ approach that uses the minimum value between the observed and the weighted data for the dissemination of results for polarising response modalities. This allow preventing

² Where z , with a confidence level of 95%, is equal to 1.96, n respondents, N target population, n/N is the sampling fraction, p is the proportion in the sample (e.g. favourable over total units), $q = 1-p$.

sensationalist perspectives. In the tables presented in the following paragraph, only the precautionary calibrated values will be reported.

Table 2 – Weight Distribution of the sample and the population.

	Gender	Sample weight (%)	Population weight (%)	Respondent unit weighting
<i>Kindergarten</i>	Female	14.50	18.48	160
	Male	0.63	0.27	53
<i>Elementary school</i>	Female	36.76	43.51	148
	Male	0.21	2.28	1358
<i>Middle school</i>	Female	41.18	26.38	80
	Male	6.72	9.08	169
Total		100.00	100.00	

5. Preliminary results

It should be noted that the section of the questionnaire concerning stereotypes was submitted only to primary and secondary school teachers.

The initial findings (Table 3, 4 and 5) indicate that teachers actively engage with the topic of gender stereotypes and discrimination, and that, in some cases, they also address it at an experiential level.

The level of schooling appears to be a significant factor. Middle schools report the highest engagement (69.9%), followed by primary schools (43.3%). This trend suggests that such issues become more apparent—or are more readily perceived—as students grow older. Many teachers, when asked to report how frequently certain forms of gender discrimination occur among their students, occasionally observe difficulties faced by female students in assuming leadership roles or in non-conforming to gender stereotypes. At the same time, many teachers more frequently encounter situations in which male students are victims of gender stereotypes and discrimination, particularly when they feel negatively judged for engaging in behaviours traditionally considered “feminine”.

Moreover, male students are often described as consistently exhibiting adherence to stereotyped gender norms in peer relationships. Several teachers even report instances in which male students appear to feel entitled to judge their female peers based on physical appearance or, in some cases, to engage in aggressive or demeaning behaviour towards them. This occurs even though schools—albeit with some difficulty—make efforts to provide opportunities for reflection and implement educational activities aimed at combating gender discrimination. According to teachers, gender stereotypes are predominantly transmitted within the family, as well as through online content and broader cultural references. Although the school environment is considered influential, not all teachers regard it as a context that could actively contribute to the transmission of gender stereotypes. There is broad awareness among teachers that gender stereotypes influence fundamental aspects of individuals' lives and relationships, particularly during the developmental years. According to the data, teachers believe that such stereotypes affect self-esteem (88.9%), expectations regarding the roles that males and females are expected to fulfil (82.2%), and even the willingness to tolerate or legitimise violence (73.3%).

Table 3 – *Experience of the topic, learning context, opinions on effects, interventions, and training needs by educator's gender (Percentages of affirmative responses).*

	Total	Female	Male
<i>Experience of the topic</i>	48.9	46.0	61.1
Primary school	43.3	-	-
Lower secondary school	69.9	-	-
<i>Internalization of stereotypes:</i>			
within the family	90.0	90.4	84.8
in the school context	62.7	61.5	63.6
in the sports context	66.3	66.3	66.8
within cultures	75.9	76.5	66.7
within religions	60.4	64.5	35.0
through the internet and social media	85.8	86.3	78.8
<i>Stereotypes can:</i>			
influence the choice of studies and careers	75.5	74.4	78.8
affect identity and self-esteem	88.9	92.0	69.9
determine expectations regarding male and female roles	82.2	86.2	57.4
lead to the legitimization of violent behaviors	73.4	75.6	59.9
<i>Implementation of interventions</i>	75.6	77.0	67.4
<i>Interventions carried out:</i>			
meetings with families	81.9	84.6	64.9
discussions among teachers and the Headmaster	85.8	85.1	87.9
reflection activities with individual students	86.4	89.1	69.9
educational activities – whole class group	85.0	88.3	64.9
<i>Presence of a psychologist</i>	38.2	37.3	41.7
<i>Presence of an intervention protocol:</i>	32.1	30.6	38.9
<i>Need for training</i>	90.1	91.1	77.8

Table 4 – *Educators' experience of stereotypes, discrimination and behaviors considered legitimate (Percentage of responses "Often").*

	Total	Female	Male
<i>Observed stereotypes and discrimination:</i>			
difficulty with girls' leadership	11.7	11.2	15.0
girls conforming to stereotypes	23.5	24.0	15.2
boys conforming to stereotypes	34.4	34.0	27.3
perception of negative judgment of boys showing "feminine" behaviors	42.3	42.2	42.5
<i>Behaviors considered legitimate by students towards females:</i>			
aggressive behaviors	3.7	3.9	2.5
judging based on physical appearance	13.4	13.6	12.5

Table 5 – *Students' characteristics, school-life difficulties and importance of physical appearance (Percentage of responses "Equally in both genders").*

	Total	Female	Male
<i>Students' characteristics:</i>			
jealousy	43.1	44.0	33.3
strength	28.2	30.3	12.1
sensitivity	54.2	56.7	36.4
gruffness	55.4	55.8	51.5
kindness	61.8	62.0	60.0
generosity	77.5	79.3	65.0
superficiality	63.9	65.0	57.5
empathy	60.4	63.1	51.5
tendency to dominate	51.7	52.3	48.3
<i>School-life difficulties</i>	94.9	94.8	95.0
<i>Importance of physical appearance</i>	47.5	47.2	51.5

This latter, particularly alarming data suggests a widespread perception that stereotypes are not merely abstract social constructs, but rather phenomena with tangible and potentially harmful consequences. When asked which characteristics are most frequently associated with students by gender, many teachers provided responses largely free of rigid or exclusive attributions. Nevertheless, a portion of teachers continued to associate specific traits with one gender over another: i. female students are associated with jealousy, empathy, kindness, and sensitivity; ii. male students are associated with strength, tendency to overpower, superficiality, and grumpiness. These representations, even when unintended, may contribute to the perpetuation of gender stereotypes. Such stereotypes can influence the developmental, educational, and relational trajectories of children and adolescents. These findings underscore the need to establish structured opportunities for reflection, as well as targeted training on the subject. Teachers, for their part, express a strong demand for such training. While they are acutely aware of their responsibilities, they frequently report lacking the tools necessary to respond

effectively. They also call for the implementation of clear protocols and the support of specialised professionals—such as psychologists and pedagogists—who are stable, accessible, and well-integrated into the school system. With regard to intervention strategies addressing incidents of gender discrimination in schools, teachers generally report implementing targeted actions, despite the absence of formal operational protocols. These actions typically involve all key actors engaged in such dynamics. Priority is given to reflective interventions targeting the student responsible for the discriminatory behaviour, alongside educational initiatives directed at the wider class group. Similarly, considerable importance is attributed to internal discussions among colleagues and with the school principal, as well as to maintaining open dialogue with the families of those involved. Furthermore, the survey reveals, alongside elements of awareness, significant cultural and structural challenges that may undermine the school context's ability to effectively safeguard minors. The analysis of teachers' responses highlights a widespread awareness of the existence and effects of gender stereotypes, with a general tendency toward shared views between women and men. However, some significant differences emerge: female teachers demonstrate greater consistency, confidence, and sensitivity in recognizing the contexts and consequences of stereotypes, while male colleagues more frequently express uncertainty or hesitation. The main domains in which stereotypes are perceived as being learned (family, school, sport, media, religion) reveal greater firmness in the responses of women. Similarly, the consequences of stereotypes—on identity, self-esteem, educational choices, and even the legitimization of violence—are acknowledged more decisively by female teachers. In observing school dynamics as well, women appear more attentive to forms of discrimination and stereotypical behaviors among female and male pupils, whereas men seem more uncertain and, at times, less inclined to recognize them. Nevertheless, both genders show a good level of engagement in educational and preventive actions, with established practices such as internal discussions among colleagues and individual educational interventions.

6. Conclusions

When considered as a whole, the questionnaire presents a multifaceted and detailed depiction of the school experience, highlighting both the awareness and the practical challenges that teachers encounter in addressing situations of student distress. Its purpose extends beyond the mere collection of data, serving also as a stimulus for professional reflection, collective awareness, and the orientation of training and institutional interventions. Although this study does not provide a definitive conclusion, it advocates for the construction of an educational environment equipped to detect and respond to signs of distress. The establishment of alliances, the allocation of resources, and the existence of a shared educational

vision are identified as essential components. Teachers are responsible for observation, listening, and the protection of their students. However, they cannot fulfil this role in isolation. A support system is therefore required to provide training, resources, and ongoing guidance. The data highlight a teaching staff that is aware yet often isolated in dealing with complex issues. The school represents a privileged vantage point for observing signs of student distress; however, there is a need for more operational tools, ongoing training, and stronger partnerships with families and local services. Building on this foundation, it is possible to design concrete interventions to protect minors and to strengthen the educational role of the school as a space for protection and prevention. The survey reveals a school system that is sensitive, yet still insufficiently equipped at both cultural and organisational levels. Resistance to intervention, stereotyped representations internalised by teachers themselves, and a widespread culture of minimisation or self-limitation in assuming educational responsibility, render systemic intervention necessary. It is essential to reinforce the training of teachers on relational, legal, and psychological dynamics; to ensure the presence of qualified professionals (such as psychologists, educators, and mediators); and, above all, to foster a shared school culture that transcends the perception of these matters as being outside one's professional remit.

Acknowledgements

The authors are grateful to the participants of the 61st SIEDS Conference and referee for their suggestions, which led to a substantial improvement of the work.

References

- ACKER S. 1990. Gender issues in schooling. In ENTWISTLE N. (Ed) *Handbook of Educational Ideas and Practices*, Routledge, Abingdon, Oxon, pp. 91-99.
- BLAU F. D., KAHN L. M. 2017. The Gender Wage Gap: Extent, Trends, and Explanations. *Journal of Economic Literature*, Vol. 55, No. 3, pp. 789-865.
- CARLANA M. 2019. Implicit Stereotypes: Evidence from Teachers' Gender Bias, *The Quarterly Journal of Economics*, Vol. 134, No. 3, pp. 1163-1224.
- CARRA A., CHIODINI P.M., IMPALLOMENI C., SORBA E. VERRECCHIA F. 2025. Labour market and gender role stereotypes: the effects of the pandemic, *RIEDS - Rivista Italiana di Economia e Demografia e Statistica*, Vol. LXXIX, No.2, pp. 79-90. SIEDS, Roma.
- CHARLES M., BRADLEY K. 2009. Indulging our gendered selves? Sex segregation by field of study in 44 countries. *American Journal of Sociology*, Vol. 114, No. 4, pp. 924-976.
- CORBETTA P. 1999. *Metodologia e tecniche della ricerca sociale*. Bologna: Il Mulino.

- COUNCIL OF EUROPE 2011. Convention on Preventing and Combating Violence against Women and Domestic Violence (Istanbul Convention). Istanbul, May 11, 2011.
- DI BELLA E. 2023. La violenza economica sulle donne. GENere2023. Istat e Università di Genova. Genova, Albergo dei Poveri, 5 dicembre 2023. <https://www.istat.it/evento/genere2023-la-misurazione-della-violenza-contro-le-donne-e-delle-disuguaglianze-di-genere/>
- ELLEMERS N. 2018. Gender Stereotypes. *Annual Review of Psychology*, Vol. 69, pp. 275–298.
- HOOKE J. L. 2010. Gender inequality in the welfare state: Sex segregation in housework, 1965–2003. *American Journal of Sociology*, Vol. 115, No. 5, pp. 1480–1523.
- ISTAT. 1989. *Manuale di tecniche di indagine. 2 – Il questionario: progettazione, redazione e verifica*. Roma: Istat.
- ISTAT. 2018. *Stereotipi sui ruoli di genere e l'immagine sociale della violenza*. Nota metodologica. Online.
- ISTAT. 2023. *L'indagine ISTAT-UNAR sulle discriminazioni lavorative nei confronti delle persone LGBT+*. Online.
- PAXTON P., KUNOVICH S., HUGHES M. M. 2007. Gender in politics. *Annual Review of Sociology*, Vol. 33, pp. 263–284.
- RAI 1979. Processo per stupro. Rai Teche – RaiPlay. Online.
- ROMITO P. 2005. *A deafening silence: Hidden violence against women and children*. Policy Press.
- RUSSEL D., RADFORD J., 1992. *Femicide: The politics of woman killing*. Twayne.
- SABBE E., AELTERMAN A. 2007. Gender in teaching: A literature review, *Teachers and Teaching: theory and practice*, Vol. 13, pp. 521–538.
- SCOTT J. W. 1986. Gender: A useful category of historical analysis. *The American Historical Review*, Vol. 91, No. 5, pp. 1053–1075.

Simona BALLABIO, Istat, North-West Area Office, ballabio@istat.it

Arianna CARRA, Istat, North-West Area Office, carra@istat.it

Paola Maddalena CHIODINI, Università degli Studi di Milano-Bicocca – Dipartimento di Statistica e Metodi Quantitativi, paola.chiodini@unimib.it

Daniela CORSO, Telefono Arcobaleno, daniela.corso@telefonoarcobaleno.org

Stefania QUARTARONE, Telefono Arcobaleno, stefania.quartarone@telefonoarcobaleno.org

Elena SORBA, Istat, North-West Area Office, sorba@istat.it

Flavio VERRECCHIA, Istat, North-West Area Office, verrecchia@istat.it

DO FAMILY, HEALTH AND JOB PERCEPTIONS SHAPE WORKERS' WELL-BEING? A JOB SATISFACTION ANALYSIS IN EUROPE¹

Alessandra Di Bello, Alex Pieroni

Abstract. In an evolving European context, the boundaries between professional and personal life are becoming increasingly important in shaping individual subjective well-being. The growing emphasis on Work-Life balance reflects broader societal transformations, including changes in labour market structures, shifting family dynamics, and evolving cultural attitudes toward employment. While previous works have analysed employment conditions for immigrants, few studies have focused on their perception of job satisfaction comparing them with natives.

This study analyses perceived job satisfaction among workers using data from the 10th round of the European Social Survey (2020-2022). A series of linear regression models is applied to analyse the satisfaction of workers with low, medium and high skilled jobs among natives, second-generation migrants, and individuals with a migration background. The focus is centred on the effect on work satisfaction of three domains: job characteristics, sociality and household dynamics, and perceived health. Using the Work-Life balance index to divide countries into groups, it was found that states with a low balance experience more pronounced effects, with job skill levels playing a much more significant role in shaping outcomes.

1. Introduction

Job satisfaction represents a central dimension of individual well-being, as well as an important indicator for understanding job quality and inequalities in the labour market. It is a complex, multidimensional, and interdisciplinary concept influenced by a variety of factors both internal (values, expectations, psychological capital) and external (working conditions, organizational context, remuneration) (Aziri, 2011; Luthans *et al.*, 2007). Based on major theoretical models, job satisfaction emerges as the result of the interaction between personal, environmental, and organizational characteristics. Within this framework, the national context plays a crucial role, as welfare systems, work culture, and Work-Life balance policies significantly influence individual perceptions (Esser and Olsen, 2012; Hauff *et al.*, 2015).

This contribution aims to comparatively analyse the role of both work-related and non-work-related factors in determining job satisfaction, with particular attention to the migration dimension and Work-Life balance in European contexts. In particular, studying how job satisfaction differs among individuals with a migration background is

¹ This article is the result of a collaborative effort among the authors.

essential to understanding integration processes and inequalities in the labour market. Using data from the European Social Survey (Round 10th), the analysis focuses on three groups: natives, second-generation migrants and migrants. Using linear regression models and the construction of a synthetic Work-Life balance index, developed using the Mazziotta–Pareto index (MPI), differences in job satisfaction among groups with and without migrant background are examined, considering occupational skill level, and controlling for gender, age, and educational attainment. We analyse perceptions of job satisfaction by considering additional perception-based variables, measuring how satisfaction varies across three domains of individuals' lives: perceived health, household and sociality, and work.

The objectives are threefold: (1) to verify whether significant differences in job satisfaction exist between natives and individuals with a migration background; (2) to assess the moderating effect of Work-Life balance across different European countries; (3) to explore the impact of extra-work factors, such as perceived health, family pressure, and social networks. This integrated approach allows for a better understanding of the mechanisms underlying occupational well-being and advances factors about possible latent inequalities in European labour markets. This article is divided into four sections: the theoretical background of the main literature on the topic, the data and methods used, the results obtained, and the conclusions.

2. Theoretical background

Well-being can be evaluated following two main approaches: objective or subjective measures. The first primarily uses indicators related to economic and social status, providing easily comparable metrics across different studies and datasets. On the other hand, subjective measures sacrifice this comparability in order to capture the significance for the respondent, allowing individuals some freedom in interpreting the question and managing their answers according to personal priorities. A thorough review of the literature dealing with the relationship between work and subjective well-being (SWB) shows that influencing factors can be grouped into two broad categories: work-related and non-work-related factors (Wang and Jing, 2018). These factors can mediate the effect of the job on satisfaction for both migrants and natives. Satisfaction is a complex and multidimensional concept, encompassing fields such as psychology, sociology, and economics. This complexity is similarly reflected in job satisfaction (Büssing and Bissels, 1998).

The first aspect analysed in the review concerns a more straightforward relation with working conditions. Job characteristics are key to job satisfaction for both natives and migrants. It has been shown that for migrants, satisfaction significantly increases when salary levels for the same job in the host country exceed those in the home country (Itzhaki *et al.*, 2013). Furthermore, an appropriate workload and the possibility to

exercise control, organisation, and autonomy in the job are factors associated with higher job satisfaction among migrant workers (Itzhaki *et al.*, 2013; Magee and Umamaheswar, 2011). Regarding work-related skills, Baernholdt and Mark (2009) suggest that high job complexity can have a detrimental effect on job satisfaction. The work environment clearly influences job satisfaction, as workplace discrimination leads to poorer outcomes over time (An *et al.*, 2016; Magee and Umamaheswar, 2011). Moreover, perceiving one's contribution as valuable is essential for greater job satisfaction (An *et al.*, 2016). Using SWB measures allows an assessment at a personal level of the effect of "personal work-related factors", such as overqualification, which disproportionately affects individuals with immigrant backgrounds compared to natives (McGuinness and Byrne, 2014). Another important element is the connection between physical or mental health and job satisfaction, which has been shown to be crucial for understanding differences between individuals with similar characteristics (Aazami *et al.*, 2015; Datta Gupta and Kristensen, 2007).

Turning to factors less directly related to the job position, typical demographic factors play a significant role in shaping job satisfaction. Age and gender are found to favour, respectively, older individuals and males (Au *et al.*, 1998; Fugl-Meyer *et al.*, 2002). Diving more deeply into "cultural factors", proficiency in the host country language significantly affects well-being at work, as it allows for better communication with colleagues and more effective problem-solving; language proficiency also mediates access to better jobs, which are associated with higher satisfaction (Bloemen, 2013; Hakak *et al.*, 2010). This effect is also driven by employers' tendency in host countries to prefer candidates with higher local language skills, enabling migrants to access more, and potentially better, job opportunities (Hainmueller and Hopkins, 2015). Migrants usually have different frameworks for evaluating job satisfaction, not based solely on wages (Walczak and Vallejo-Martín, 2021). This phenomenon, often referred to as the "immigrant paradox in job satisfaction", suggests that migrants often report equal or higher levels of job satisfaction compared to natives despite facing structural disadvantages and barriers (Lu *et al.*, 2001). This paradox highlights the importance of considering cultural and subjective factors when analysing job satisfaction among individuals with migration backgrounds.

Finally, "community and policy factors" strongly influence both overall and job satisfaction. Multiple studies emphasise the importance of national contexts, particularly welfare regimes, as key determinants of job satisfaction (Esser and Olsen, 2012; Hauff *et al.*, 2015). Furthermore, the strength of an individual's social network (family, friends, acquaintances) plays a key role in alleviating negative aspects of work and enhancing a sense of belonging and support (Cross and Cummings, 2004; Hakak *et al.*, 2010). The perception of being accepted into the host society is also relevant, as experiences of discrimination outside the workplace can affect job satisfaction (Esses, 2021; Hakak *et al.*, 2010). Participation in socio-cultural activities has been shown to have a significantly

positive impact on job satisfaction, at least in Germany and the United Kingdom (Giovanis, 2021). To complete the picture of influencing factors on job satisfaction, previous studies underline the importance of family, especially partners, and the consequences of work on the possibility to interact and enjoy shared time and activities, as tensions in the couple may be generated by problems or stressful workplaces (Boles *et al.*, 2001; Shirmohammadi *et al.*, 2023).

Considering the findings of previous research, three main hypotheses have been formulated and will be tested in the following sections.

HP1: By jointly considering job skills and job satisfaction, we hypothesise that the variability in job satisfaction is greater among natives than among individuals with a migrant background. This may be because more complex jobs tend to reduce satisfaction, while migrants generally report higher levels of job satisfaction under similar conditions.

HP2: We hypothesise that the national context plays a significant role in shaping job satisfaction. Specifically, we expect that individuals living in countries with higher levels of work–life balance will report greater job satisfaction compared to those residing in countries with lower levels of work–life balance.

HP3: We hypothesise that subjective factors related to individual perceptions in domains such as health, household and sociality, and the work context significantly influence job satisfaction and contribute to variations in overall well-being.

It is important to underline that this research does not aim to evaluate the effect of the migration event *per se*, but rather to describe the differences present between natives and people with a migration background.

3. Data and Methods

This study is based on data from the 10th Round of the European Social Survey (ESS), conducted in 2020 and 2022. Since the main outcome of interest is job satisfaction, the analytical sample is limited to individuals who were employed at the time of the survey, resulting in 31,295 observations. Individuals are categorised into three groups according to their migration background: natives (84% of the sample); second-generation migrants (8%), that is, individuals born in the country with at least one foreign-born parent; and migrants (8%) born abroad to foreign-born parents.

To capture cross-national differences in work-related institutional and cultural contexts, we constructed a Work–Life Balance Index (WLB) using official statistics as Eurostat and the OECD (additional information available on request). The index integrates various indicators related to work and well-being, including public holidays, duration of paid maternity leave, national happiness scores, levels of LGBTQ+ inclusivity, average weekly working hours, the prevalence of long working hours, and the incidence of atypical work schedules such as Sunday and night shifts, and indicators of work-related

mental and physical health risks. These variables were aggregated and standardized using the Mazziotta–Pareto Index (MPI), a widely used composite index in case of geographical units that works by normalizing and summing up the variable through the mean, applying a penalty factor in case of unbalanced units. All the used variables assume the same weight in the process by construction. The resulting Work–Life Balance Index ranges from 88 to 108 across countries. We classified countries into three groups: High Work–Life balance (scores above 102), Medium (scores between 98 and 102), and Low (scores below 98). Countries classified in the High Work–Life balance group include Lithuania, Germany, Norway, Czech Republic, Netherlands, Bulgaria, Estonia, Hungary, Finland, Poland, and Iceland. The Medium category comprises Belgium, Slovenia, Austria, Latvia, France, Sweden, Spain, Ireland, Slovakia, and Italy. The Low Work–Life balance group includes the United Kingdom, Switzerland, Portugal, Bosnia and Herzegovina, North Macedonia, Serbia, Greece, and Montenegro.

To examine variations in job satisfaction, which is the continuous dependent variable of the analysis ranging from 0 to 10, simple linear regression models are employed. A first model is estimated on the overall sample, without distinguishing countries by their level of Work–Life balance. Subsequently, three separate models are estimated for each group of countries classified according to the Work–Life balance Index: High, Medium, and Low. Control variables include gender, age, language spoken at home, and educational attainment. The analysis compares natives with individuals of migrant background, considering the interaction between groups and the type of occupation, classified by low, medium, and high skill levels (ISCO classification) to assess whether job satisfaction also varies according to occupational skill level. The sample is composed of 50% high-skilled workers and 43% medium-skilled workers, with a balanced percentage distribution between natives and individuals with a migrant background (with a slight difference in percentage points for first-generation migrants). Low-skilled workers represent 7% of the sample, with a higher proportion among first-generation migrants (13% of this group) compared to natives and second-generation migrants (6% each).

Additional variables related to individual perceptions and experiences, aggregated into macro categories, are grouped into three thematic domains. The not work-related category is the health and subjective well-being domain, that include self-assessed general health and overall life satisfaction. The household and social sphere, identified as semi-work related category includes variables such as the frequency of social interaction (not shown in the Results, available on request); how often partner or family feel overwhelmed by the respondent's job; how often the job prevents time investment in the partner or family; how often individuals are too tired after work to enjoy personal activities; perceptions of the household's current income; and religiosity. Finally the work-related variables identified as work environment domain that includes objective variables such as the type of employment contract and the total number of hours

normally worked per week (not shown in the Results, available on request), and variables of individual's perception whether they are allowed to decide how their daily work is organised, and whether they take on extra responsibilities without additional pay.

4. Results

In Table 1, the results are presented for the main variable of interest, which combines individuals' migration background with their job skill level. Starting from the model without distinguishing by WLB and using natives with medium job skill levels as the reference category, we observe a gradient effect based on skill level, particularly pronounced among natives. A similar pattern appears for individuals with at least one foreign-born parent, although it is not always statistically significant, likely due to the smaller sample size of this group. When considering migration background as a variable to assess changes in job satisfaction, its influence appears limited, as there are no significant differences between coefficients within the same skill level. These two findings together suggest that job skill level has a greater impact on job satisfaction than migration background.

When shifting to models divided by WLB, we observe that natives experience a greater penalty in job satisfaction when working in low-skill jobs in countries with High or Medium WLB. Conversely, this factor does not affect countries with low WLB. Holding a high-skill job has a positive effect, with the strongest impact observed in Low-balance countries. These results suggest that better jobs exert a stronger positive influence on satisfaction in lower-performing countries, as if they were able to compensate more significantly. Further evidence of this can be found in the significant effect of the second generation-high skill combination, which is only relevant in this latter group of countries.

Looking at different migrant generations, we find that second-generation migrants are significant only in Low WLB countries, with a positive effect in the high-skill job category mentioned above, and a negative effect in the medium-skill category. Being a migrant does not influence job satisfaction in the case of high-skill jobs, partly due to the limited number of individuals with these specific characteristics. However, migrants show the largest absolute negative effect when combined with low-skill jobs in Low WLB countries, with a reduction in job satisfaction of nearly 0.4 points.

Table 2 presents the results for the mediating variables within the three domains previously identified. The table reports the absolute changes in the coefficients between the overall model and the WLB models, indicated using symbols for increase, decrease, or stability (+; -; $\approx$).

Table 1 – Results of Linear Regression Models for migration background and level of skill job: Overall Model, Country-Specific Models Grouped by Work-Life Balance Index, showing coefficients, significance (p-values) and intervals of confidence.

Skill job & Groups	Mod. All Countries Coef.; [int. conf.]	Mod. High W.L.B. Country Coef.; [int. conf.]	Mod. Medium W.L.B. Country Coef.; [int. conf.]	Mod. Low W.L.B. Country Coef.; [int. conf.]
Ref. Medium skill – Native				
High skill - Native	0,144*** [0,090;0,197]	0,104** [0,028;0,180]	0,083 [-0,014;0,181]	0,269*** [0,150;0,387]
High skill - Second G	0,150** [0,039;0,261]	0,125 [-0,037;0,287]	0,064 [-0,136;0,264]	0,254* [0,025;0,483]
High skill - Migrant	0,080 [-0,038;0,198]	0,003 [-0,183;0,189]	0,140 [-0,067;0,346]	0,096 [-0,132;0,325]
Medium skill – Second G	-0,063 [-0,185;0,058]	-0,062 [-0,238;0,155]	0,076 [-0,157;0,309]	-0,272* [-0,511;-0,033]
Medium skill - Migrant	-0,053 [-0,180;0,073]	-0,254* [-0,476;-0,032]	0,000 [-0,202;0,201]	0,067 [-0,176;0,310]
Low skill - Native	-0,286*** [-0,385;-0,186]	-0,363*** [-0,513;-0,214]	-0,282** [-0,463;-0,100]	-0,177 [-0,371;0,017]
Low skill - Second G	-0,095 [-0,400;0,211]	0,170 [-0,280;0,621]	-0,285 [-0,813;0,242]	-0,581 [-1,260;0,098]
Low skill - Migrant	-0,248* [-0,455;-0,041]	0,001 [-0,440;0,442]	-0,188 [-0,502;0,126]	-0,399* [-0,756;-0,042]
Cons	7,385	6,203	6,170	6,230
n. Total {mean Job Satisfaction}	29.388 {7,38}	14.361 {7,40}	8.825 {7,41}	6.202 {7,30}
n. Natives {mean Job Satisfaction}	24.742 {7,39}	12.478 {7,41}	7.234 {7,43}	5.030 {7,29}
n. Sec Gen {mean Job Satisfaction}	2.277 {7,38}	1.070 {7,42}	676 {7,37}	531 {7,30}
n. Migrants {mean Job Satisfaction}	2.369 {7,29}	813 {7,21}	915 {7,34}	641 {7,34}
Fisher	177,08	89,62	52,1	43,88
Adj. R ²	0,248	0,25	0,24	0,272

Note: Statistical significance of the relationship is marked by *if $p < 0.05$, ** if $p < 0.01$, *** if $p < 0.001$. Source: our elaborations on ESS data Round10th.

Table 2 — *Results of Linear Regression Models for health, household and sociality, work variable: Overall Model Coefficients and Significance (p-values); Country-Specific Models Grouped by Work-Life Balance Index, showing Significance (p-values) and $\pm 5\%$ Variation from the Overall Model Coefficients.*

Variables	Mod. All Countries Coef.; P-value	Mod. High W.L.B. Country 5% change; P-value	Mod. Medium W.L.B. Country 5% change; P-value	Mod. Low W.L.B. Country 5% change; P-value
<i>Subjective health (Ref. Very good/good)</i>				
Health	Fair	-0,125 ***	— ***	+ —
	Bad/Very bad	-0,303 ***	— ***	+ *
	<i>Satisfied with life (Ref. Unsatisfied)</i>			
	Satisfied	0,863 ***	+ ***	— ***
	Extremely satisfied	1,523 ***	$\approx$ ***	+ ***
<i>Partner/family fed up with pressure of your job (Ref. Never/Hardly ever)</i>				
Household & sociality	Sometimes	-0,223 ***	— ***	— ***
	Often/Always	-0,679 ***	— ***	$\approx$ ***
	<i>Tired after work to enjoy things like doing at home (Ref. Never/Hardly ever)</i>			
	Sometimes	-0,199 ***	— ***	+ *
	Often/Always	-0,635 ***	— ***	+ ***
	<i>Job prevents you from giving time to partner/family (Ref. Never/Hardly)</i>			
	Sometimes	-0,197 ***	+ ***	$\approx$ ***
	Often/Always	-0,407 ***	$\approx$ ***	— ***
	<i>Feeling about household's income nowadays (Ref. Comfortably)</i>			
	Difficult/Very Difficult	-0,439 ***	+ ***	$\approx$ ***
	<i>Religiosity (Ref. Not Religious)</i>			
	Low	0,022	+ ***	— ***
	Medium	0,131 ***	+ ***	+ ***
	High	0,352 ***	+ ***	+ ***

Table 2 (cont.)— *Results of Linear Regression Models for health, household and sociality, work variable: Overall Model Coefficients and Significance (p-values); Country-Specific Models Grouped by Work-Life Balance Index, showing Significance (p-values) and $\pm 5\%$ Variation from the Overall Model Coefficients.*

Variables	Mod. All Countries Coef.; P-value	Mod. High W.L.B. Country 5% change; P-value	Mod. Medium W.L.B. Country 5% change; P-value	Mod. Low W.L.B. Country 5% change; P-value
<i>Allowed to decide how daily work is organised (Ref. No influence)</i>				
Influence	0,114 ***	+	+	—
Control	0,619 ***	$\approx$ ***	+	— ***
<i>Extra responsibilities at work without being paid more (Ref. No)</i>				
Sometimes	0,278 ***	— ***	+	+
Yes	0,627 ***	— ***	+	$\approx$ ***

Note: For Cons, Obs., Fisher, and Adj. R^2 see Table 1

Statistical significance of the relationship is marked by *if $p < 0.05$, ** if $p < 0.01$, *** if $p < 0.001$. Source: our elaborations on ESS data Round 10th.

Confident intervals and standard errors available upon request

Starting with the health domain, the most influential variable is overall life satisfaction. Its effect is somewhat smaller in countries with Medium levels of WLB. Regarding subjective health, the negative impact of belonging to the worst-off group is particularly pronounced in countries with Higher WLB, as indicated by a consistently negative coefficient. In the household and social domain, all variables show a significant impact. Variables related to the partner appear especially influential, penalizing individuals whose job limits the time available for household responsibilities or creates tensions with a partner who is dissatisfied with the respondent's job. The effects range between -0.4 and -0.7 , with a greater impact observed in Low WLB countries for the first variable, and in High WLB countries for the second. Religiosity exhibits a stronger positive effect in Medium and High WLB countries, reaching approximately 0.35 among individuals reporting the highest levels of religiosity. Turning to work-related characteristics, having greater control over work organization positively affects satisfaction, with an estimated effect of 0.6 points. However, this effect is less pronounced in countries with the lowest WLB. Individuals who accept increased responsibilities without corresponding financial compensation tend to report higher levels of job satisfaction, although this pattern is less evident in countries with the highest Work-Life Balance.

5. Conclusions and Limitations

This study contributes to the understanding of job satisfaction in Europe by analysing how both Work-related and Non-work-related factors shape individual experiences across natives, second-generation migrants, and first generation. Findings reveal there is no significant difference between groups with a migration background; instead, the difference lies in the level of job skill, partially confirming our first hypothesis. Among natives, disparities in satisfaction are more pronounced at the extremes of the skill distribution (high and low). The reason can be found in the fact that migrants tend to be more satisfied with their work, confirming the immigrants' satisfaction paradox, as they tend to compare themselves with individuals in their country of origin (Shen and Kogan, 2020). In this cross-sectional dataset, we don't know whether work satisfaction increases or decreases depending on the duration of stay in the country or the length of the employment episode.

Overall, our second hypothesis is not totally confirmed, because substantial cross-country differences don't emerge using the Work-Life Balance Index, but countries with Low Work-Life Balance scores displayed stronger inequalities between individuals with a migration background, particularly related to occupational skill. The limitation of the reduced sample size for migrants and second-generation migrants could influence the robustness of group-specific findings. Non-work-related factors, especially self-perceived health and overall life satisfaction, emerged as having a strong effect on job satisfaction, particularly more pronounced in countries with High Work-Life Balance. In the domains of sociality and household, although no substantial differences emerge across countries based on the Work-Life Balance Index, all variables still show a significant impact on job satisfaction. This suggests that social connections, family dynamics, and domestic responsibilities play a consistent role in shaping individuals' work satisfaction, which has consequences on all the other aspects of life, confirming our third hypothesis. Key variables such as overqualification and ethnic origin, potential factors of dissatisfaction for migrants, and stress-related work variables were not included due to data constraints. Despite these limitations, the study highlights the multifaceted nature of job satisfaction and the importance of considering both structural and subjective dimensions in labour market research.

Acknowledgements

We thank Prof. Giuseppe Gabrielli, Prof. Roberto Impicciatore and the participants of the LXI SIEDS Congress for their valuable feedback on this paper. This research was co-funded by Next Generation EU (PNRR NGEU - PE08 Age-It, CUP E63C22002050006). Usual disclaimers apply. ESS Round 10: European Social Survey Round 10 Data (2020). Data file edition 3.0. Sikt - Norwegian Agency for Shared Services in Education and Research, Norway – Data Archive and distributor of ESS data for ESS ERIC. doi:10.21338/NSD-ESS10-2020.

References

- AAZAMI S., SHAMSUDDIN K., AKMAL S., AZAMI G. 2015. The Relationship Between Job Satisfaction and Psychological/Physical Health among Malaysian Working Women. *Malays J Med Sci*, Vol. 22, No. 4, pp. 40-6.
- AN J.-Y., CHA S., MOON H., RUGGIERO J.S., JANG H. 2016. Factors Affecting Job Satisfaction of Immigrant Korean Nurses. *Journal of Transcultural Nursing*, Vol. 27, pp. 126–135.
- AU A.Y.W., GAREY J.G., BERMAS N., CHAN M.M. 1998. The relationship between acculturation and job satisfaction among Chinese immigrants in the New York city restaurant business. *International Journal of Hospitality Management*, Vol. 17, pp. 11–21.
- AZIR B. 2011. Job Satisfaction, a Literature Review. *Management Research and Practice*, Vol. 3, pp. 77–86.
- BAERNHOLDT M., MARK B. 2009. The Nurse Work Environment, Job Satisfaction and Turnover Rates in Rural and Urban Nursing Units. *Journal of nursing management*, Vol. 17, No. 8, pp. 994–1001
- BLOEMEN H. 2013. Language Proficiency of Migrants: The Relation with Job Satisfaction and Matching. *SSRN Electronic Journal*.
- BOLES J. S., HOWARD W. G., DONOFRIO H. H. 2001. An Investigation Into The Inter-Relationships Of Work-Family Conflict, Family-Work Conflict And Work Satisfaction. *Journal of Managerial Issues*, Vol. 13, No. 3, pp. 376–390.
- BÜSSING A., BISSELS T. 1998. Different Forms of Work Satisfaction. *European Psychologist*, Vol. 3, pp. 209–218.
- CROSS R., CUMMINGS J.N. 2004. Tie and Network Correlates of Individual Performance in Knowledge-Intensive Work. *Academy of Management Journal*, Vol. 47, pp. 928–937.
- DATTA GUPTA N., KRISTENSEN N. 2008. Work environment satisfaction and employee health: panel evidence from Denmark, France and Spain, 1994–2001. *Eur J Health Econ*, Vol. 9, pp. 51–61
- ESSER I., OLSEN K.M. 2012. Perceived Job Quality: Autonomy and Job Security within a Multi-Level Framework. *European Sociological Review*, Vol. 28, pp. 443–454.
- ESSES V.M. 2021. Prejudice and Discrimination Toward Immigrants. *Annual Review of Psychology*, Vol. 72, pp. 503–531.
- GIOVANIS E. 2021. Participation in socio-cultural activities and subjective well-being of natives and migrants: evidence from Germany and the UK. *International Review of Economics*, Vol. 68, pp. 423–463.
- HAINMUELLER J., HOPKINS D.J. 2015. The Hidden American Immigration Consensus: A Conjoint Analysis of Attitudes toward Immigrants. *American Journal of Political Science*, Vol. 59, pp. 529–548.

- HAKAK L.T., HOLZINGER I., ZIKIC J. 2010. Barriers and paths to success: Latin American MBAs' views of employment in Canada. *Journal of Managerial Psychology*, Vol. 25, pp. 159–176.
- HAUFF S., RICHTER N.F., TRESSIN T. 2015a. Situational job characteristics and job satisfaction: The moderating role of national culture. *International Business Review*, 24, 710–723.
- ITZHAKI M., EA E., EHRENFELD M., FITZPATRICK J.J. 2013. Job satisfaction among immigrant nurses in Israel and the United States of America. *International Nursing Review*, 60, 122–128.
- LI Y., 2024. Vehicle ownership, sustainable mobility and well-being in rural China. *Environment, Development and Sustainability*, Vol. 26, pp. 12545–12568.
- LU L., GILMOUR R., KAO S. F. 2001. Cultural Values and Happiness: An East-West Dialogue. *The Journal of Social Psychology*, Vol. 141, No. 4, pp. 477–493.
- LUTHANS F., AVOLIO B.J., AVEY J.B., NORMAN S.M. 2007. Positive psychological capital: Measurement and relationship with performance and satisfaction. *Personnel Psychology*, Vol. 60, pp. 541–572.
- MAGEE W., UMAMAHESWAR J. 2011. Immigrant Group Differences in Job Satisfaction. *Race and Social Problems*, Vol. 3, pp. 252–265.
- MCGUINNES S., BYRNE D. 2014. Examining the Relationships between Labour Market Mismatches, Earnings and Job Satisfaction Among Immigrant Graduates in Europe. *IZA Journal of Migration*, Vol. 4, No. 17.
- SHEN J., KOGAN I. 2020. Immigrants' relative income and life satisfaction: Comparison groups from a multi-generational perspective. *Acta Sociologica*, Vol. 63, No. 1, pp. 82–102.
- SHIRMOHAMMADI M., BEIGI M., RICHARDSON J. 2023. Subjective well-being among blue-collar immigrant employees: A systematic literature review. *Human Resource Management Review*. Vol. 33, Issue 1.
- WALCZAK R., VALLEJO-MARTIN, M., 2021. Working conditions and their impact on work satisfaction in migrating and non-migrating workers. Factor structure of the Polish version of the Working Conditions Questionnaire, *Health psychology report*, Vol. 9, No.1, pp. 87-100.
- WANG Z., JING X. 2018. Job Satisfaction Among Immigrant Workers: A Review of Determinants. *Social Indicators Research*, Vol. 139, pp. 381–401.

Alessandra DI BELLO, University of Florence - University of Naples “Federico II”,
alessandra.dibello@unifi.it

Alex PIERONI, University of Florence - Alma Mater Studiorum, University of Bologna, alex.pieroni2@unibo.it

GENDER EQUALITY AT THE TOP MANAGEMENT OF THE ITALIAN NATIONAL INSTITUTE OF STATISTICS¹

Simona Peia, Giuseppina Sola

Abstract. The present study aims to analyze the role of women occupying the top positions at the Italian National Institute of Statistics (Istat). The study opens with an exploration of pertinent national and internal regulations. The text then proceeds to examine the distinctive characteristics that define the managerial role within Istat. These characteristics include both administrative and technical domains. Furthermore, the text provides illustrations of its multifaceted functions and tasks. This study employs internal management data to provide an assessment of the representation of women in senior leadership positions. Utilising the management roles held, the study aims to establish hypotheses concerning the capacity of women to influence the management agenda and the organisation's internal decision-making processes. To summarise, this study is driven by two principal objectives. First, it seeks to enhance comprehension of the manner in which women contribute to the leadership and management of Istat. Secondly, it is designed to assess their representation and their impact on decision-making processes.

1. Female Representation in Top Public Administration Management

Numerous studies have demonstrated that gender diversity enriches organizational culture, fosters innovation, and enhances operational efficiency. Women tend to demonstrate a greater tendency for innovation and introduce a variety of leadership styles that promote creativity and transformative solutions. A prevailing argument in leadership studies suggests that female leaders often cultivate cultures that emphasize inclusivity and collaboration. These cultures have the potential to enhance interpersonal relationships, thereby increasing overall productivity. Furthermore, these factors have been linked to more deliberate decision-making processes and more effective risk management strategies (Kuteesa, 2024).

Nonetheless, gender stereotypes - that is, unconscious biases influencing perceptions, expectations, and evaluations in the workplace - continue to represent a

¹ This article reflects a joint and equal contribution from all authors. The views expressed do not necessarily represent the official position of Istat.

significant barrier to women's access to top-level positions (Fedi, 2017). Leadership is frequently associated with masculine traits such as competitiveness and assertiveness, while women are more often perceived as collaborative and empathetic. This phenomenon gives rise to various challenges, including difficulties in attaining the initial promotion in comparison to male peers, often referred to as the "broken rung"; limitations in roles within organizations, frequently relegated to peripheral positions, a phenomenon termed the "glass wall"; and the selection for leadership roles in crisis contexts where the probability of success is low, leading to an elevated risk of failure and subsequent attribution of blame to pre-existing issues, often referred to as the "glass cliff."

These barriers are further compounded by the need for women to balance professional and domestic responsibilities, due to the disproportionate burden of unpaid care and household work. According to the recent Istat-Cnel report, in 2024, the number of women who were inactive in the labor market exceeded 7.8 million, constituting 63.5% of all inactive individuals aged 15 to 64. The predominant reasons cited for this phenomenon included family responsibilities, which constituted 33.9% of the sample, and engagement in educational or training activities, which accounted for 28.6%. Conversely, among male respondents, inactivity was primarily attributed to education (45.7%) or other factors (17.7%), with only 2.8% attributing it to family-related issues.

The implementation of work-life balance policies and organizational models based on flexible work arrangements (e.g., remote work, telecommuting, home working), along with strengthened parental support measures, can help alleviate the burden on women and facilitate their access to managerial positions. In contrast, the absence of such support may lead to burnout or to the difficult decision to entirely abandon leadership trajectories, further widening the gender gap in top-level roles.

In Italy, despite legislative and social progress over the past decades, women remain significantly underrepresented in leadership and decision-making positions. The second Gender Report by the Inps Supervisory Board confirms the male predominance in managerial and manager roles: in 2023, only 21.1% of private sector managers were women, compared to 78.9% men; among mid-level managers, women represented 32.4% versus 67.6% men (Inps, 2025).

In the public sector, by contrast, women are numerically predominant: they make up 60.7% of the 3.6 million public employees in Italy, with particularly high representation in the education (78.4%) and health (69.4%) sectors (Inps, 2025). However, this numerical prevalence does not extend to top positions: in 2023, only one in three senior public managers was a woman. According to the Gender Equality Index (GEI) of the European Institute for Gender Equality (EIGE), the share of women in top decision-making positions within ministries and other public administrations, though improved over the past decade, remains significantly below

the EU average: 33.1% in Italy versus 45.4% in the EU-27 - almost 8 percentage points lower (Table 1).

Table 1 – *National administrations: Senior administrators all administrative positions.*

	2014	2017	2018	2019	2020	2021	2022	2023
EU 27	38,2	41,8	41,9	42,7	43,5	44	44,5	45,4
Italy	32,4	30,8	36,2	37,9	37,9	32,1	35,5	33,1

Source: EIGE, *Women and men in decision-making (WMID)*, 2024.

This is an alarming statistic, considering that 40% is generally regarded as the minimum threshold for ensuring a meaningful gender balance. At the European level, this benchmark is exceeded in 29 countries, including Croatia (62%), Slovenia (61%), Greece (58.9%), Finland (54.2%), Portugal (51.3%), Romania (51%), and Sweden (52.5%). Conversely, the lowest rates are found in Denmark (29.6%), Czechia (28.2%), Hungary (18.9%), and Luxembourg (29.7%)².

In Italy, data from the Istat Permanent Census of Public Institutions confirm that gender parity in leadership remains an unachieved objective: in 2021, only 16.3% of institutions were headed by a woman (Istat, 2022). Significant disparities persist across regions: Southern Italy records the lowest share of female leadership (10.9%), while the Northeast reports the highest (20.9%) (Istat, 2022).

The underrepresentation of women in top positions within public administration becomes even more evident when focusing on appointments in ministries or the Prime Minister's Office. An analysis by Openpolis shows that female presence in these roles has sharply declined from 2019 to 2023. At the end of 2019, 41.4% of senior positions were held by women. This share dropped to 35.9% by the end of 2021, then slightly recovered to 37.6% by mid-2022. As of mid-2023, only 37 out of 122 top manager roles (30.3%) were occupied by women—less than one-third. Moreover, in 9 of the 15 ministries and the Prime Minister's Office, female representation decreased during this period.

The public research sector (EPRs) mirrors the structural inequalities observed in broader public administration. Despite women making up nearly half (48.3%) of all staff due to their academic success and capability, their advancement into senior scientific roles remains rare. In 2022, only 4% of all women employed in EPRs held manager positions. Notably, while female employment in the sector increased between 2015 and 2022, the number of female managers declined. Total staff rose from 20.570 in 2015 to 24.092 in 2022. The number of managers (excluding general directors) fell slightly from 107 to 103 - a 3.7% decrease driven entirely by a 10.6%

² All data are available at: https://eige.europa.eu/gender-statistics/dgs/indicator/wmidm_adm_nat_wmid_natadmin/datatable

drop in female managers. Meanwhile, non-manager staff grew by 17.2%, with a 25.2% increase among women (from 9.261 to 11.597). Consequently, the ratio of female managers to non-manager female staff changed from 1:435 in 2015 to 1:571 in 2022.

Table 2 – Public Research Employees by professional position.

Position	2015			2022			Var. %		
	M.	W.	T.	M.	W.	T.	M.	W.	T.
Director General	11	2	13	11	4	15			
Level 1 Administrators	13	9	22	11	12	23			
Level 2 Administrators	47	38	85	50	30	80			
Managers	60	47	107	61	42	103	1,7	-10,6	-3,7
Researchers/ Technologists	5.828	4.572	10.400	7.258	6.667	13.925			
Other personnel	5.361	4.689	10.050	5.119	4.930	10.049			
No managers	11.189	9.261	20.450	12.377	11.597	23.974	10,6	25,2	17,2
Total	11.260	9.310	20.570	12.449	11.643	24.092	10,6	25,1	17,1

Source: Annual Personnel Accounts, IGOP – State General Accounting Office

Promoting gender equality within public research institutions is not only a matter of social justice but also crucial for enhancing the potential, quality, and effectiveness of scientific research. Gender diversity introduces a range of perspectives and approaches that can drive innovation and improve the quality of both research and the policies it informs. Increasing the presence of women also makes the research sector more representative of the society it serves. Women contribute unique ideas and methodologies that enrich the scientific landscape. Furthermore, women in leadership and research positions can serve as role models for younger generations, inspiring more girls to pursue careers in science and technology.

This paper analyzes the presence of women in decision-making roles within the Italian National Institute of Statistics (Istat) to examine their career trajectories and assess their influence in redefining the structures governing the production of official statistics and research organization - thus fully harnessing their professional and intellectual potential.

2. ISTAT and its top management

Istat is a public research institution responsible for the production of official statistical information and for directing and coordinating the National Statistical

System, pursuant to Legislative Decree No. 322 of 1989. It fulfills its mandate - to serve society - through the production and communication of statistical data, analyses, and forecasts, in accordance with rigorous ethical-professional principles and the highest international standards. ISTAT also bears responsibility for coordinating, at the national level, all activities related to the development, production, and dissemination of European statistics.

The "administrative manager" and the "technical manager" were introduced by the Istat to align with the management rules set in Legislative Decree 165 of March 30, 2001 and Presidential Decree 166 of September 7, 2010. Administrative and technical managers perform management and coordination functions, albeit in different domains. Administrative managers oversee the administrative and organizational management of the Institute, particularly in areas such as budgeting, human resources, procurement, contracts, and legal affairs. They also provide support for technical and scientific activities. Technical managers, by contrast, possess specialized expertise in statistical, economic, IT, or scientific domains and are responsible for coordinating and supervising Istat's technical-scientific statistical production.

As of December 31, 2024, the Institute's organizational structure includes a maximum of 71 manager offices, as outlined in the following breakdown. This is in accordance with Istat's Statute, Presidential Decree No. 166/2010, and the numerical limits on administrative managers set by the D.P.C.M. of January 22, 2013. The 71 managerial offices were:

- a. the General Directorate with three central legal and administrative directorates, classified as first-tier administrative offices;
- b. three departments and twelve central directorates, classified as general technical offices;
- c. eight legal-administrative service units, classified as second-tier administrative offices;
- d. forty-four technical service units, including territorial offices, classified as non-general technical offices (ISTAT, 2024).

Administrative managers are selected from Istat's internal manager personnel or, pursuant to Article 19 of Legislative Decree No. 165/2001, from manager personnel of other public administrations (paragraph 5-bis), external candidates with specific professional, cultural, or scientific expertise (paragraph 6), or from Istat's own researchers and technologists (paragraph 6-quater).

General technical managers are appointed from among research managers, technological managers, managers of other public administrations, or recognized subject-matter experts.

Despite differences in specialization, administrative and technical managers are equivalent with respect to appointment procedures, the public nature of comparative

selection processes, and scope of responsibility - all of which are ultimately determined by Istat's internal organizational decisions.

However, certain legal provisions - such as the right to a manager appointment - apply exclusively to administrative managers and not to technical managers.

When vacancies arise, Istat publicly announces the number and type of manager positions available, along with selection criteria. It then gathers expressions of interest and evaluates the candidates.

In assigning each manager position, consideration is given to the candidate's aptitude and professional abilities, past performance within the administration (and associated evaluations), organizational competencies, and any prior leadership experience - whether gained internationally, in the private sector, or in other public administrations - provided that such experience is relevant to the post in question.

2.1. Administrative managers

Administrative managers play a critical role in ensuring the effective functioning of the Institute. They are responsible for the optimal management of human, financial, and material resources and for supporting technical and operational activities. Their efforts help create the conditions necessary for the timely and reliable production of statistics. Their main duties include:

- Human resources management, with particular attention to workforce planning, personnel policies, training, performance evaluation, and skills development;
- Financial administration, including budget preparation and monitoring, cash flow management, and the effective use of economic resources;
- Logistical and infrastructure support, including oversight of the tools and technologies used throughout the Institute;
- Legal and contractual supervision, encompassing public contract management, procurement, and compliance with administrative regulations;
- Transparency and anti-corruption oversight, with a focus on implementing policies to promote transparency, integrity, and anti-corruption compliance;
- Collaboration with technical managers and institutional leadership in defining the Institute's strategic direction.

Administrative managers must possess a wide range of technical, managerial, and interpersonal skills. Key qualifications include appropriate academic credentials, supplemented by specialized courses or master's degrees; in-depth knowledge of administrative law, public budgeting procedures, and public procurement regulations; and expertise in strategic planning, leadership, and the coordination of multidisciplinary teams. Additionally, they must demonstrate strong problem-

solving abilities and the capacity to propose innovative solutions to improve institutional processes.

2.2. *Technical managers*

The role of technical manager at Istat requires a highly qualified professional profile, characterized by a solid academic background, experience in scientific and technological fields, the ability to coordinate interdisciplinary teams and manage complex projects, and familiarity with national and international regulations governing statistical production.

The core functions of technical managers include:

- The development of statistical methodologies, through the design and implementation of advanced data processing and analysis techniques;
- Management of information and communication technologies, using advanced ICT infrastructure to collect, process, and disseminate data securely and efficiently;
- Data quality assurance, by monitoring data collection and analysis processes to ensure statistical accuracy and reliability;
- Support for strategic projects, in collaboration with national and international institutions, aimed at developing new indicators and statistical tools;
- Data quality monitoring, through the assessment of statistical accuracy, consistency, and reliability in accordance with international standards;
- Technological innovation, by promoting the use of emerging technologies such as artificial intelligence and big data analytics to enhance Istat's analytical capabilities.

3. Analysis of executive appointments in the decade 2015-2024

In a context marked by an ever-increasing demand for statistical information from stakeholders, growing attention to data protection and cybersecurity, and persistent budgetary constraints, gender balance in leadership positions is an issue of rising significance.

This section analyzes general and non-general manager appointments conferred over the 2015–2024 decade, with a focus on their gender distribution. As previously noted, the position of Director General is classified as a first-level administrative manager position, in accordance with the D.P.C.M. of January 22, 2013, which outlines three such roles at Istat and equates the Director General's appointment to this level.

It is worth noting that the total number of manager structures was 73 from January 1, 2015, to November 30, 2019, but decreased to 71 starting from December 1, 2019, following a reorganization that eliminated two technical manager roles - one general, one non-general.

An analysis of the appointments made during the decade reveals that gender distribution in leadership roles at Istat varies by position. The feminization rate of each role - defined as the percentage of women in that position - indicates that women are predominantly concentrated in lower-tier managerial roles, particularly as heads of service units, where they significantly outnumber their male counterparts.

Specifically, throughout the decade, the role of Director General has been held exclusively by men. In the Institute's near-centennial history, a woman has served in this role only once, between 2012 and 2015³. The 2019 reorganization marked the historical low point of female representation in Istat's administrative leadership: only 1 in 4 administrative managers was a woman. From 2020 onward, the share of women has gradually increased, reaching 8 out of 12 administrative managers in 2024. However, this growth primarily reflects an increase in women appointed to second-level administrative positions (i.e., heads of service units) rather than to central director roles (see Table 3).

Table 3 – *Administrative Management position by type and gender rate. Years 2015-2024.*

Year	Director General	Level 1 Administrators			Level 2 Administrators			All Administrative Positions		
	M.	W.	M.	a.v	W.	M.	a.v	W.	M.	a.v
2015	100	33,3	66,7	3	57,1	42,9	7	45,5	54,5	11
2016	100	50,0	50,0	2	66,7	33,3	6	55,6	44,4	9
2017	100	50,0	50,0	2	62,5	37,5	8	54,5	45,5	11
2018	100	50,0	50,0	2	50,0	50,0	8	45,5	54,5	11
2019	100	33,3	66,7	3	25,0	75,0	8	25,0	75,0	12
2020	100	33,3	66,7	3	62,5	37,5	8	50,0	50,0	12
2021	100	50,0	50,0	2	62,5	37,5	8	54,5	45,5	11
2022	100	66,7	33,3	3	62,5	37,5	8	58,3	41,7	12
2023	100	100,0	0,0	2	62,5	37,5	8	63,6	36,4	11
2024	100	66,7	33,3	3	75,0	25,0	8	66,7	33,3	12

Source: authors' elaborations based on Istat administrative data

A more balanced gender representation is evident in the technical directorate: since 2019, the feminization rate has exceeded 54%. Within the technical sector, women are more prevalent among service heads (6 out of 10) than among central directors (4 out of 10). Notably, since the 2019 reorganization, the position of

³ Notably, the position of President has never been occupied by a woman.

Department Director has been evenly split between men and women, with the sole exception of 2022, when both posts were held by women.

Table 4 – *Technical Management position by type and gender rate. Years 2015-2024.*

Year	General Technical Director			Non General Technical Administrators			All Technical Positions		
	W.	M.	a.v.	W.	M.	a.v.	W.	M.	a.v.
2015	28,6	71,4	14	47,7	52,3	44	43,1	56,9	58
2016	16,7	83,3	12	43,9	56,1	41	37,7	62,3	53
2017	16,7	83,3	12	51,2	48,8	43	43,6	56,4	55
2018	16,7	83,3	12	55,8	44,2	43	47,3	52,7	55
2019	40,0	60,0	15	61,4	38,6	44	55,9	44,1	59
2020	40,0	60,0	15	59,1	40,9	44	54,2	45,8	59
2021	40,0	60,0	15	63,6	36,4	44	57,6	42,4	59
2022	40,0	60,0	15	63,4	36,6	41	57,1	42,9	56
2023	46,7	53,3	15	63,6	36,4	44	59,3	40,7	59
2024	46,7	53,3	15	63,6	36,4	44	59,3	40,7	59

Source: authors' elaborations based on Istat administrative data

Between 2019 and 2024 - years in which the number of manager positions remained fixed at 71- women have approached the glass ceiling, though without breaking through it. Representation rose by 9 percentage points among second-level administrative managers and by 2 points among first-level administrators, while declining by nearly 7 points among technical service directors (see Table 5).

Table 5 – *Management position by type and gender at 31 December (percentage composition).*

Positions	2019		2024		W. Var %
	W.	M.	W.	M.	
Director General	0,0	2,9	0,0	3,3	0,0
Level 1 Administrators	2,8	5,7	4,9	3,3	2,1
Level 2 Administrators	5,6	17,1	14,6	6,7	9,1
General Technical Director	16,7	25,7	17,1	26,7	0,4
Non General Technical Administrators	75,0	48,6	68,3	53,3	-6,7
Total	100	100	100	100	

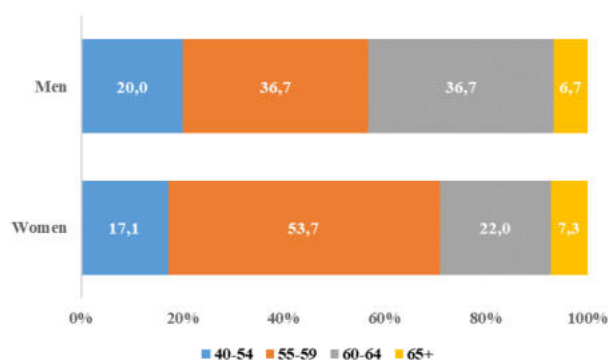
Source: authors' elaborations based on Istat administrative data

Finally, the difficulty of women in advancing in organizational hierarchies is also highlighted by their age. In 2024, the Institute's leadership class is far from young (only 1 of 71 executives is under 44 years of age) but women are older than men.

Analysis by age group shows that 83% of women are over 55 years old, compared with 80% of men (see Figure 1).

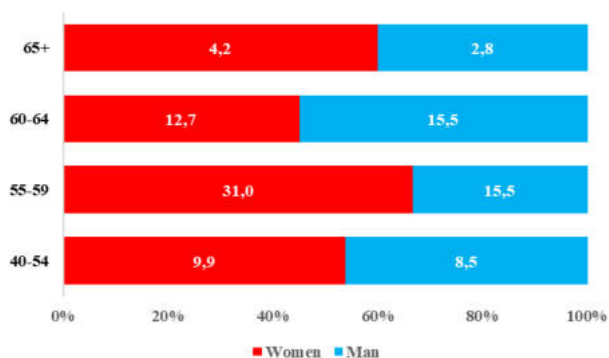
The distribution of the 71 management positions by age group and gender reveals that 31% are held by women aged 55 to 59, 18% by men over the age of 60 and 17% by women over the age of 60 (see Figure 2).

Figure 1 – Istat Managers by age group and gender. Year 2024 (percentage value).



Source: authors' elaborations based on Istat administrative data

Figure 2 – Istat Managerial position by age group and gender. Year 2024 (percentage value).



Source: authors' elaborations based on Istat administrative data

Finally, greater seniority does not necessarily translate into higher pay. According to the 2023 report by Istat's Unified Guarantee Committee (CUG), gender-based pay differences persist. Female managers earned a slightly lower average net salary than men (€ 74.832 vs. € 75.561) amounting to a gap of -0.97%. Conversely, among non-

general managers, women earned on average € 52.096,40 compared to € 50.051,10 for men - a positive wage differential of 3.93% in favor of women⁴.

However, it should be noted that the remuneration of first and second level administrators and that of technical directors is determined by the Institute's Council in accordance with the provisions of the current national collective labor agreement for the "Education and Research" management area, in relation to the organizational complexity and functions assigned to each management structure. This determination is made through a system of weighing the functions of each structure, at the end of which an economic value is assigned to the various management positions. It is important to note that these decisions are typically made in conjunction with the institution's reorganization processes. The determination of remuneration is an independent process from the need to fill a vacant management position. Conversely, is determined by the aggregate sum of the salary scale stipulated in the national collective labor agreement for personnel in the "Education and Research" sector. This calculation incorporates the level and profile of the position and is complemented by the allowance stipulated in Article 22 of Presidential Decree No. 171/1991⁵.

In practice, therefore, there is no gender gap at the regulatory level. This disparity manifests in subsequent discretionary choices, as evidenced by data demonstrating that the most lucrative positions are assigned with greater frequency to male managers.

4. Conclusion

Istat stands out as a virtuous example for having maintained a significant female presence in managerial roles over time and for exhibiting a gender pay gap lower than the national average. Nonetheless, in order to increase the level of responsibility and decision-making power assigned to women, concrete measures are needed to mitigate the cultural and family-based conditions that still fuel these inequalities.

In this regard, the adoption of agile work models, diversity and inclusion training programs, and mentoring initiatives at Istat are highly relevant. Although these measures were initially designed to enhance the overall well-being of the workforce, they may, in the near future, prove to be particularly beneficial for women in

⁴A review of data from all branches of the public sector reveals a consistent pattern: male employees consistently receive higher average daily incomes than their female counterparts. This phenomenon is particularly pronounced in academic institutions, where men often receive salaries that are more than 20 percent higher than those of their female counterparts (Inps, 2025).

⁵ Salary details for managerial positions are published on Istat website under "Transparent Administration - Holders of Management Positions".

leadership roles. Indeed, for women, agile work—which is characterized by high flexibility in time management—can facilitate a better balance between professional and personal responsibilities, thus making leadership roles more accessible. At the same time, targeted training can support women in developing the skills needed and in building support networks that foster their advancement into leadership positions.

References

- CUG ISTAT, 2024. *Relazione sulla condizione del personale*, https://portalecug.gov.it/format-2/relazione-cug-istituto-nazionale-di-statistica-ISTAT-2024?utm_source=chatgpt.com
- EUROPEAN INSTITUTE FOR GENDER EQUALITY. 2024. *Women and Men in Decision Making Methodological report* Luxembourg: Publications Office of the European Union.
- FEDI A., COLOMBO L., BERTOLA L. ROLLERO C. 2017. Donne e carriera tra stereotipi di genere e conciliazione lavoro-famiglia. Un'analisi psico-sociale, *Sociologia del Lavoro*, No. 148, 2017, pp. 113-133.
- INPS. 2025. *Rendiconto di genere 2024*. Roma. INPS.
- ISTAT. 2022. *Censimento permanente delle Istituzioni pubbliche: risultati preliminari anno 2022*. Rome.
- ISTAT. 2024a. *Strutture dirigenziali dell'Istituto nazionale di statistica*. Rome.
- ISTAT. 2024b. *Regolamento del personale*. Rome.
- ISTAT. 2024c. *Regolamento di organizzazione dell'ISTAT*. Rome.
- ISTAT. 2024d. *Statuto dell'Istituto nazionale di statistica*. Rome.
- ISTAT-CNEL. 2025. *Il lavoro delle donne tra ostacoli e opportunità*, Rome.
- KUTEESA K.N. 2024. Redefining leadership: the role of gender in shaping organizational culture, *Comprehensive Research and Reviews in Multidisciplinary Studies*, vol.2, <https://crrjournals.com/crrms/content/redefining-leadership-role-gender-shaping-organizational-culture>.
- LUISS BUSINESS SCHOOL, 2016. *L'impatto delle donne nei board e nei top management team sulla performance d'impresa*, <https://businessschool.luiss.it/news/limpatto-delle-donne-nei-board-e-nei-top-management-teams-sulla-performance-dimpresa/>.

THE IMPACT OF THE “ASSEGNO UNICO E UNIVERSALE” REFORM ON FAMILY WELFARE¹

Paolo Consolini, Mariagloria Narilli, Angela Pepe

Abstract. The recent reform of Italy’s family support system, which introduced the “*Assegno Unico e Universale*” in March 2022, marks a turning point in the country’s family policy. The reform aimed to provide a more inclusive and equitable approach to supporting families. This study draws on longitudinal data from IT-SILC to analyse changes in the pool of beneficiaries in the years surrounding the reform. It also offers an overview of the reform effects using both descriptive statistics and model-based empirical analysis.

1. Introduction

As many authors have highlighted, Italy has long implemented weak, fragmented, categorical, and ultimately ineffective family policies compared to other European countries. These policies have failed to mitigate demographic decline or to adequately address social, generational, and gender disparities (Rosina and Luppi, 2022). This paper investigates the redistributive effects of the recent reform of Italy’s family support system (L.D. n. 46/2021 and D.lgs. n. 230/2021), which introduced the “*Assegno Unico e Universale*” (AUU). Prior to the reform, the system relied on two main instruments: tax deductions for dependent children, available only to those with sufficient tax liability, and the “*Assegno per il Nucleo Familiare*” (ANF), which was primarily reserved for employees. This design excluded certain professional categories, such as self-employed workers and the long-term unemployed. Moreover, it failed to guarantee full and adequate benefit for the poorest families, who often had incomes too low to benefit from tax deductions due to tax non-liability. The implementation of the AUU marked a significant shift in both the design and coverage of family policies, by extending benefits to previously excluded households and simplifying access to support.

The paper begins with a historical overview of family support policies in Italy. It then presents the data and describes the main characteristics of households receiving

¹ The views expressed in this article are solely those of the authors. Although the paper is the outcome of a collaborative effort, individual contributions are attributed as follows: Sections 2, 3 and 5 were authored by P. Consolini, Section 4 by M. Narilli and Sections 6 and 7 by A. Pepe.

the ANF and the AUU, along with the structural changes in the target population over time. Finally, the analysis focuses on the distributional effects of the reform and its impact on poverty risk, using both descriptive statistics and causal models.

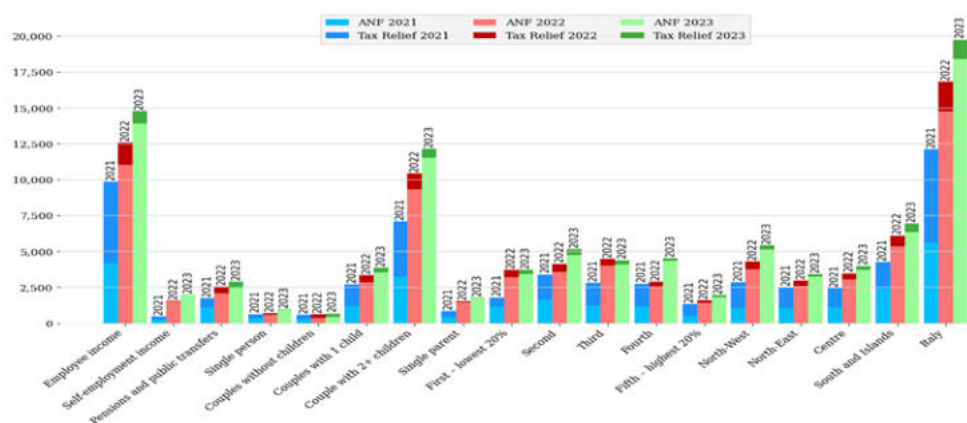
2. Backgrounds

The origins of family support policies in Italy date back to 1934, introduced within trade union agreements to reduce working hours and support employment. Initially limited to industrial workers with at least two dependent children, the scheme aimed to offset income losses and promote vertical equity (Di Biase, 2010). By 1935, it was extended to families with one-child, and by 1937 to all dependent workers regardless of income or job rank. That same year, benefits became proportional to the number of children, reflecting demographic goals. In 1940, eligibility expanded to include spouses and dependent parents. The Italian National Institute of Social Security (INPS) managed the allowances from the beginning, but in 1940 funding shifted exclusively to employers through the creation of the “Single Fund for Family Allowances” (CUAF), featuring sector-specific accounts and inter-sectoral balancing. Over time, eligibility broadened: in 1967 to self-employed agricultural workers (state-funded), and in 1983 to low-income families with children under 18 through means-tested supplementary allowances, reaffirming vertical equity. The ANF, as known today, was established in 1988, replacing prior schemes. It provides cash transfers to dependent workers and retirees below income thresholds, adjusted annually. Eligibility includes those temporarily unemployed receiving income support (e.g., unemployment, wage supplementation, sickness benefits). Since 1998, it also covers INPS Separate Scheme members who lack other mandatory coverage and are not pensioners. The ANF amount depends on household composition and decreases as income rises, provided at least 70% of income comes from employment or related benefits. Between 2000 and 2010, family support shifted toward tax relief for low-to-middle-income households with dependents. However, raising the non-taxable threshold reduced the impact for low earners due to tax incapacity. In response, reform proposals aimed to overcome both this limitation and the categorical nature of ANF. Notably, the concept of selective universalism, integrating tax deductions and ANF into a single benefit varying by need gained traction (Baldini *et al.*, 2004). This approach, assessed through an improved means test (ISEE), shaped the 2021 Family Act and led to AUU.

3. Dataset Description and First evidence

This study draws on data from the EU-SILC (European Union Statistics on Income and Living Conditions), focusing on the period 2022–24, with income reference years 2021–23, covering the phases before, during, and after the implementation of the Family Act. EU-SILC is a minimum 4-year panel survey conducted across European countries, targeting individuals and households residing in the country and living in private dwellings (EUROSTAT, 2022). In the Italian version (IT-SILC), respondents are interviewed annually over a six-year period. For the purposes of this research, the analysis focuses on individuals and households observed continuously over the three-year period considered. The final sample consists of 11,982 households that participated in the survey and maintained the same reference person throughout the panel, corresponding to a total of 23,130 individuals. Using a longitudinal component could introduce attrition bias that, following Eurostat suggestions, can be mitigated by means of longitudinal weights. Unlike previous studies based exclusively on microsimulation models (Cossu *et al.* 2021; Pacifico, 2021), this analysis, drawing on estimates from the IT-SILC longitudinal sample, combining survey data with administrative records from INPS (AUU and ANF) and tax registers CU, 730, and PF (dependent-related tax deductions).

Figure 1 – Amounts of family social and fiscal benefits. Years 2021- 2023.



Values in millions of euros. Quintiles (First, Second,..., Fifth) divide the population into five equal groups (20% each) based on their equivalised disposable income.

Source: Authors' elaboration on longitudinal IT-SILC data.

The comparative analysis shows that in the initial two-year period (2021 compared to 2022), total resources allocated to households – combining benefits and

tax relief – amounted to €12.1 billion and €16.8 billion, respectively (39% YoY increase). This figure rose to €19.7 billion in 2023, marking a further YoY growth of 17.4% compared to 2022 (Figure 1). During this transition, households whose primary income source is self-employment, as well as those with children, experienced the greatest gains particularly in the North-West, where households benefited more than those in other regions. The analysis also highlights a sharp decline in the relative weight of tax relief compared to the overall set of family support policies.

4. The AUU Reform: Beneficiary Profiles and Effects on Household Budgets

In 2021, 19% of all households received ANF. In 2022, with the introduction of AUU, beneficiary households increased to 28.2% (+48.9%) (Table 1). In 2023, when AUU was fully in force, the share of beneficiaries was 26.9%, increasing in comparison to 2021. The rise was due to the introduction of the AUU: most households that previously received the ANF have shifted to receiving the AUU and new households become eligible for the new benefit. As a result, in both post-reform years, the share of ANF beneficiaries decreased to 4.9% in 2022 (-74.1% compared to 2021) and to 3.0% in 2023 (-84.4% compared to 2021).

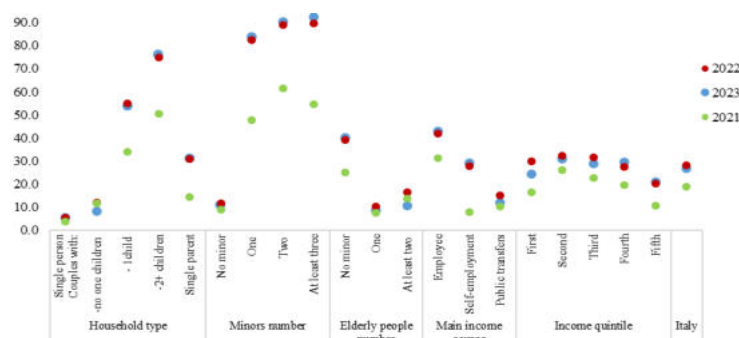
Table 1 - *Beneficiary households and incidence on total family social benefits (TFSBI) by type of measure. Years 2021-2023.*

Type of benefit	2021		2022		2023	
	Households	TFSBI	Households	TFSBI	Households	TFSBI
Family allowance (ANF)	19.0	100.0	15.1	11.0	4.0	97.0
- only ANF	19.0	100.0	4.9	3.6	3.0	1.9
Universal Child Benefit (AUU)	-	-	23.3	89.0	24.0	97.0
- only AUU	-	-	13.1	40.0	22.9	91.4
ANF and AUU	-	-	10.2	56.4	1.1	6.7
Total	19.0	100.0	28.2	100.0	26.9	100.0

Percentage values.

Source: Authors' elaboration on longitudinal IT-SILC data.

The evolution of the family social benefits (ANF and/or AUU) rate over the three-year period examined highlights its impact on the composition of the beneficiary families. Since 2022, couples with children receiving benefits have increased (Figure 2). In particular, the incidence for couples with at least two children increases by about 26 percentage points from 2021 (50.4%) to 2023 (76.2%). Where at least two minors are present, the incidence exceeds 92% in 2023.

Figure 2 –Family social benefits rate by household characteristics. Years 2021-2023.

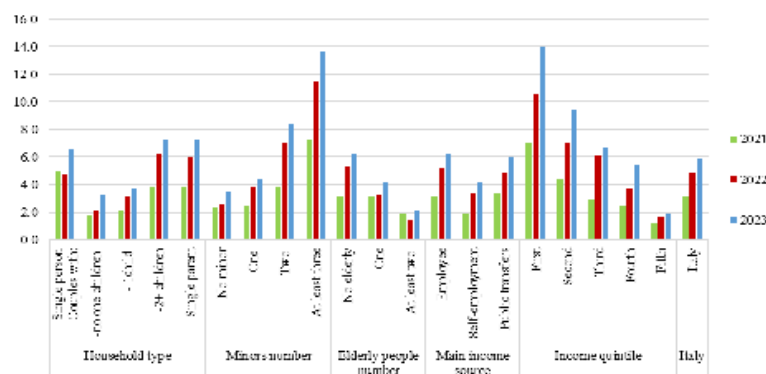
Percentage values per 100 households with same characteristics.

Source: Authors' elaboration on IT-SILC longitudinal data.

The AUU universal nature is particularly evident when a family's main income source is self-employment. Among these families, which in the past were rarely reached by social support measures, the share of beneficiaries grows significantly (from 8% in 2021 to 29.1% in 2023). Conversely, the increase is less marked among households whose main income source is dependent employment (31.1% in 2021 and 42.8% in 2023). The introduction of the AUU expands the pool of beneficiaries, especially among first-quintile households, the most vulnerable segment characterized by higher employment instability. In 2023, the share of beneficiaries was 24.3% compared to 16.5% in 2021 when only the ANF, reserved for employees, was in force. In the fourth and fifth quintiles, the share of beneficiaries grows by about 10 percentage points between 2021 and 2023, driven by the AUU greater inclusivity. The implementation of the AUU has led to an increase in the incidence of social transfers (ANF and/or AUU) on household net income², rising from 3.1% in 2021 to 5.9% in 2023 (Figure 3). The redistributive impact of the new benefit is particularly marked for single-parent households and couples with two or more children. The highest incidence is observed in households with at least three minors, peaking at 13.6% in 2023, compared to 7.2% in 2021 and 11.5% in 2022. Furthermore, for households whose primary source of income is self-employment, the incidence in 2023 (4.2%) is more than double that of 2021 (1.9%), yet remains below the 6.2% of households whose main source is dependent employment (3.1% in 2021). The incidence of family allowance benefits is evident in the first quintile (7.0% in 2021, 10.6% in 2022 and 14.0% in 2023) and in the second quintile (4.4% in 2021, 7.0% in 2022 and 9.4% in 2023) showing the aim of the new measure in addressing economic vulnerability.

² Household net income has been considered excluding imputed rent and in-kind components, in accordance with the harmonized income definition adopted at the European level.

Figure 3 - Share of Family social benefits on net income by household characteristics. Years 2021-2023.

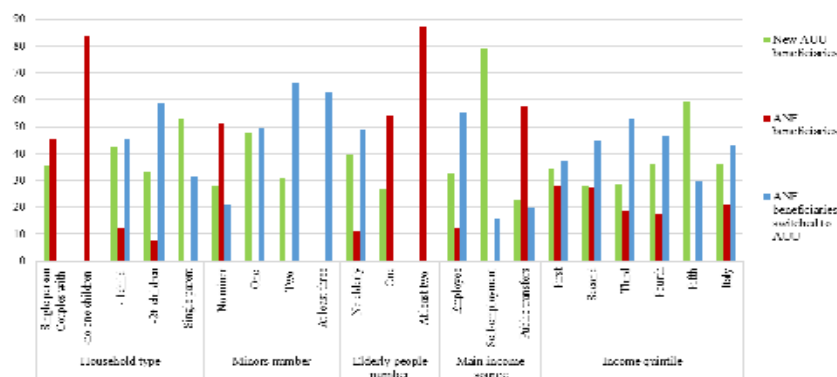


Percentage values.

Source: Authors' elaboration on IT-SILC longitudinal data.

Focusing on the transitions of households between different social benefits in 2021 and 2023, among families receiving the AUU in 2023, 13% have already benefited from ANF in 2021 and 10.9% were new AUU beneficiaries³. Moreover, 6.4% of all the households received ANF at least one time: 3.3% only in 2021, 2.8% in both years. The characteristics of beneficiaries once again highlights the more inclusive nature of the AUU compared to the ANF (Figure 4).

Figure 4 – Beneficiary households by family social benefits transitions and household characteristics. Years 2021 and 2023.



Percentage values per 100 households with same characteristics.

Source: Authors' elaboration on IT-SILC longitudinal data.

³ Households receiving both measures (ANF and AUU) in 2023 are assigned to the category corresponding to the benefit received most predominantly. New beneficiaries are households receiving AUU in 2023 and nothing in 2021.

Newly eligible families or those shifting from ANF to AUU are mostly couples with at least one child, single-parent families and families with minors. In families with elderly members, ANF access is more common (54.3% with one elderly person, 87.0% with two or more). Among families mainly supported by self-employment, 79.1% are newly eligible, while most families relying on dependent employment transitioned from ANF to AUU (55.0%).

5. Winners and Losers in Italy's AUU Reform

This section examines households with children who underwent the transition from the former family allowance to the AUU, assessing the reform effects based on their distribution across loss, neutral, and gain brackets. Specifically, households are classified according to the difference in annual benefit amounts, both extra-fiscal and total, received in 2022 and 2023 (i.e., during or after the reform), relative to the baseline year 2021 under the previous policy framework.

Table 2 – *Household Gain/Loss Distribution by Class and Benefit Type (2022-23 vs '21).*

Gain and Loss Categories	Only Benefits (2022 vs 2021) %	Only Benefits (2023 vs 2021) %	All Measures (2022 vs 2021) %	All Measures (2023 vs 2021) %
Loss > € 2,000	1.2	1.0	3.5	3.2
Loss (€1,000 - €2,000)	1.6	2.0	12.5	11.9
Loss (€250 - €1,000)	5.4	4.1	12.2	12.4
Near balance (± €250)	9.2	8.5	16.0	13.9
Gain (€250 - €1,000)	24.7	17.1	19.7	16.5
Gain (1,000€ - €2,000)	28.8	27.4	20.3	18.0
Gain > € 2,000	29.1	39.9	18.8	24.1

Source: Authors' elaboration on IT-SILC- longitudinal data

The results indicate that, when the reform effects is assessed solely based on social benefits, a more optimistic picture emerges, with a small share of households (8.2% in 2022 and 7.1% in 2023) incurring a monetary loss of at least €250 per year (Table 2). However, when the full set of measures – both fiscal and social protection – is considered, a more pessimistic outcome appears. A substantial share of households experienced losses exceeding €250 in 2022 and 2023, with 27.8% and 27.1% of households, respectively, incurring such losses. The comparison between the baseline scenario (current policy) and the alternative scenario (without ANF/AUU transfers over the next two years) shows substantial changes in key poverty indicators: the poverty rate (H), the poverty gap ratio (IGR), and the Gini coefficient. In the absence of ANF/AUU transfers, poverty indicators, both the rate and the gap (IGR), increase compared to the baseline, with the gap between the two

scenarios widening from 2021 to 2023 (Table 3). Additionally, the removal of ANF/AUU transfers results in progressively higher Gini coefficients in the alternative scenario, indicating growing inequality over the period considered.

Table 3 – *Impact of ANF/AUU Removal on Poverty and Inequality Indicators (2021-23).*

Scenario	H ^(a) 2021	IGR ^(b) 2021	Gini 2021	H ^(a) 2022	IGR ^(b) 2022	Gini 2022	H ^(a) 2023	IGR ^(b) 2023	Gini 2023
Baseline	20.39	0.333	0.329	19.47	0.306	0.313	18.77	0.325	0.316
(-)ANF/AUU	21.36	0.335	0.330	21.12	0.333	0.320	21.51	0.354	0.325

(a) H=Head count ratio; (b) IGR=Income Gap Ratio

Source: Authors' elaboration on IT-SILC longitudinal data

6. Empirical Issues and Econometric Strategy

The findings from the descriptive analyses provide an initial interpretation of the redistributive dynamics potentially generated by the introduction of the universal allowance, highlighting variations in the levels of economic support for families and beneficiary profiles. However, to strengthen the interpretation of the reform's effects through model-based empirical analysis, the analysis was supplemented with statistical models capable of capturing both poverty dynamics and the net impact of the measure on the family support system. The analysis is structured in two distinct phases. The first in-depth examination focuses on poverty mobility in 2023 compared to 2021. To this end, a logistic regression model was estimated, where the dependent variable is the probability of being at risk of poverty among individuals who were not in the previous two-year period. This strategy allows us to explore the association between the reform and changes in economic vulnerability, while controlling for a broad set of covariates. The econometric specification is:

$$\text{logit}(p) = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 \text{BENEFIT} + \beta_2 X_1 + \beta_3 X_2 + \dots + \beta_8 X_7 + u_i$$

where p indicates the probability that an individual enters the condition of poverty compared to the previous two years during which they were not in such a condition. The *BENEFIT* variable reflects the type of family benefit received between the two observed years (2023 and 2021). This variable has four categories: No benefit received (reference category), New AUU beneficiaries, Beneficiaries ANF switched to AUU, and ANF beneficiaries (see note 3). The explanatory variables $X_1, \dots, X_7$ were selected from those identified in the literature as key determinants of poverty mobility dynamics. In addition to individual and family characteristics (e.g., age, gender, marital status, household composition, number of children) and socio-economic factors (e.g., education level, household labour market participation, and

health status), the literature (Bane and Ellwood, 1986; Giraldo *et al*, 2007; Polin and Raitano, 2014) highlights two types of events occurring during the observation period that are particularly relevant for predicting poverty transitions: family formation events (e.g., divorce, separation, or changes in household composition) and labour market events (e.g., increases or decreases in the number of employed adults within the household or in the number of working hours). Individual and household characteristics were measured at the baseline year (2023). Using the stepwise selection method, the control variables included in the analysis are: household composition changes, variation in the number of income earners, presence of minors and elderly members, gender and age of the individual, and the educational attainment of the household's main income

Secondly, a Difference-in-Differences (DiD) model was employed to estimate the reform's impact on monetary transfers linked to family burdens. DiD is a widely used methodology to measure the impact of a "treatment", such as the introduction of a public policy, on a group receiving it (treated group), compared with a control group not exposed to the treatment (Imbens and Jeffrey, 2009). Both groups are observed before and after the treatment introduction, allowing for the estimation of a differential change. The econometric specification is:

$$y_{it} = \beta_1 + \beta_2 Treated(AUU \text{ beneficiaries}) + \beta_3 Post(2023) + \beta_4 Treated(AUU \text{ beneficiaries}) * Post(2023) + \gamma X_{it} + \varepsilon_{it}$$

To analyse the reform's effect on household economic conditions, two specifications of the DiD model were adopted: one measures the effect on the total amount of transfers for family burdens (both social and fiscal), and the other focuses only on fiscal transfers. Control variables include both the squared of the household net income, expressed in thousands, and the number of minor children.

7. Estimation Results: AUU Reform, Poverty Risk, and Family Transfers

The Table 4 presents the results of the logistic regression, where the effects of independent variables are expressed in odds ratio, allowing the estimation of the relative impact of each factor on the probability of being at risk of poverty. The new AUU beneficiaries appear to be least likely to fall into economic vulnerability, followed by those transitioning from ANF to AUU. Conversely, ANF beneficiaries exhibit higher odds of entering poverty. As for the control variables, the results align with literature findings: a decrease in the number of income earners in the household, an increase in household size, and the presence of minors are all factors associated with a higher risk of poverty. Higher education levels serve as a protective factor, substantially reducing the probability of economic distress.

Table 4 – Probability that a person became at risk of poverty. Odds ratio.

Parameter	Analysis of MLE			Odds Ratio Estimate		
	Estimate	Standard Error	P-value	Point Estimate	95% Wald Confidence Limit	
Intercept	-2.3448	0.1489	<.0001	-	-	-
ANF	0.5347	0.1326	<.0001	1.707	1.316	2.213
ANF switched to AUU	-0.6572	0.1618	<.0001	0.518	0.377	0.712
New AUU	-0.7713	0.1676	<.0001	0.462	0.333	0.642
Δ household size	-0.8255	0.1019	<.0001	0.438	0.359	0.535
Δ earners number	1.7042	0.0884	<.0001	5.497	4.623	6.536
At least high school	-1.0217	0.0867	<.0001	0.360	0.304	0.427
Female	0.1704	0.0825	0.0389	1.186	1.009	1.394
Age	-0.00452	0.00259	0.0811	0.995	0.990	1.001
Minors	0.3988	0.1455	0.0061	1.490	1.120	1.982
Elderly	-1.2088	0.1260	<.0001	0.299	0.233	0.382

Source: Authors' elaboration on IT-SILC longitudinal data.

Table 5 – Difference in Difference model.

VARIABLES	(1) Social and Fiscal Benefits	(2) Social and Fiscal Benefits	(3) Tax Relief	(4) Tax Relief
Post (2023)	-0.0675*** (0.00342)	-0.0621*** (0.00348)	-0.0621*** (0.00348)	-0.0512*** (0.00261)
Treated (AUU)	1.429*** (0.0380)	0.748*** (0.0494)	0.780*** (0.0226)	0.679*** (0.0251)
Post (2023) X Treated (AUU)	1.291*** (0.0458)	1.363*** (0.0465)	-0.736*** (0.0205)	-0.727*** (0.0201)
One minor		0.178*** (0.0431)		0.0332* (0.0186)
Two minors		1.379*** (0.0711)		0.215*** (0.0266)
Three or more minors		3.511*** (0.262)		0.400*** (0.0803)
Squared Net Income		-7.01e-09*** (1.81e-09)		2.47e-10 (3.29e-10)
Constant	0.161*** (0.00453)	0.155*** (0.00552)	0.128*** (0.00379)	0.125*** (0.00379)
Observations	23,964	23,964	23,964	23,964
R-squared	0.450	0.553	0.223	0.235
Adj. R-squared	0.450	0.553	0.223	0.235

Robust standard errors clustered by household in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Authors' elaboration on IT-SILC longitudinal data.

8. Conclusion and Policy Implications

The introduction of the AUU represents a significant institutional change in Italy's family support system, aiming to establish a more universal, equitable, and accessible framework in comparison to the previous family support measures. By replacing instruments such as the ANF and tax deductions, the reform expanded coverage, especially among previously excluded groups such as the self-employed and low-income families.

The analysis, based on longitudinal IT-SILC data, indicates a marked increase in families receiving support, particularly among vulnerable groups. The AUU also appears to have increased the incidence of transfers relative to household income, strengthening its role—at least in the short term—as a key instrument for households with children, especially those in the lower income deciles. However, shifting from a mixed system of fiscal and social measures to a single cash benefit entailed trade-offs: over one-quarter of households with children saw their total benefit (fiscal and social) decrease by more than €250 annually. The econometric models suggest that the AUU is associated with a lower probability of entering poverty for both new recipients and those transitioning from the ANF, alongside an average increase in annual family transfers of around €1,350.

Overall, the AUU appears to have steered Italy's family policy in the direction of greater universality and inclusion. Nevertheless, trade-offs between simplification, equity, and fiscal neutrality remain, and may have introduced new disparities or reinforced existing ones. To ensure the benefit remains adequate and equitable in the long run, continuous evaluation and policy fine-tuning will be necessary. Finally, as Saraceno (2022) points out, monetary support for children alone is insufficient; it must be part of a broader system of services facilitating women's work-family reconciliation. A promising direction for future research will be to assess the demographic and fiscal sustainability of the AUU over the long term, especially in light of Italy's evolving socio-economic context.

References

- BALDINI M., BOSI M., MATTEUZZI M. 2004. Sostegno alle responsabilità familiari e contrasto della povertà: ipotesi di riforma, *Rivista delle Politiche Sociali*, No.2, pp. 147-166.
- BANE M.J., ELLWOOD D.T 1986. Slipping into and out of Poverty: the Dynamics of Spells, *Journal of Human Resources*, Vol. 21, No. 1, pp. 1-23.
- DI BIASE R. 2010. Gli assegni familiari in Italia: Effetti redistributivi, *La Rivista delle Politiche Sociali*, No. 1, pp. 259-292.

- COSSU P., DI MARCO M., TANDA P., VIOLANTE A. 2021. La riforma dei trasferimenti monetari per la famiglia in Italia: l'assegno unico per i figli, *Economia & Lavoro*, Vol. 55, No. 2, pp. 87-103.
- EUROSTAT. 2022. *Methodological guidelines and description of EU-SILC target variables, 2022 Operation*. Luxembourg: Eurostat.
- GIRALDO A., RETTORE E., TRIVELLATO U. 2007. Gli episodi di povertà causano ulteriori episodi di povertà? Evidenze dal panel sui bilanci delle famiglie della Banca d'Italia. In BRANDOLINI A., SARACENO C. *Povertà e benessere. Una geografia delle disuguaglianze in Italia*. Bologna: Il Mulino, pp. 237-257.
- IMBENS G.W., JEFFREY M.W. 2009. Recent developments in the econometrics of program evaluation, *Journal of economic literature*, Vol. 47, No. 1, pp. 5-86.
- PACIFICO D. 2021. Assegno unico per i figli: molti guadagnano, pochi perdono, in *Lavoce.info*, <https://lavoce.info/archives/91310/>
- POLIN V., RAITANO M. 2014. Poverty transitions and trigger events across EU groups of countries: Evidence from EU-SILC, *Journal of Social Policy*, Vol. 43, No. 4, pp. 745-772.
- SARACENO C. 2022. L'assegno unico universale; che cosa cambia nel sostegno economico alle famiglie con figli. *Politiche sociali*, No.1, pp.135-140.
- ROSINA A., LUPPI F. 2022. L'assegno unico e universale: alla ricerca della giusta misura tra equità e sostegno alla natalità, *Rivista delle Politiche Sociali*, No.1, pp. 161-178.

OPTIMIZING STRATIFICATION WITH DATA-DRIVEN APPROACH: A CASE STUDY

Ilaria Bombelli, Giorgia Sacco

Abstract. The stratified sampling design is helpful in official statistics to guarantee the accuracy and efficiency of survey estimates. The choice of suitable stratification variables and the subsequent determination of the strata are two of the most important steps in this procedure. When the stratification variables are continuous, to create the strata, these variables must be converted into categorical variables that identify classes.

The quality of the stratification can be greatly impacted by the division of these continuous variables, specifically the choice of intervals or class boundaries. Class intervals are sometimes predetermined based on established procedures or past knowledge. In some cases, however, the researcher must determine the best partitions into classes based on the population's characteristics and the survey's goals. Choosing such partitions can be a hard task.

The R package `SamplingStrata` provides useful assistance in situations when the researcher has the flexibility to define the stratum. This tool is based on a genetic algorithm and provides a data-driven approach for determining the best stratification boundaries, thereby maximizing sampling design efficiency while satisfying precision requirements.

In this study, we present an application of the aforementioned package on a household survey dataset. We illustrate the advantages of utilizing the package to guide the stratification process, especially when working with continuous auxiliary variables. The findings demonstrate how, compared to conventional techniques based on arbitrary or fixed class definitions, data-driven stratification can result in more efficient sample allocations.

1. Introduction

Stratified sampling is one of the most widely used sampling strategies, particularly in official statistics. The population is divided into distinct groups, known as strata. It is desirable for these to be internally homogeneous and externally heterogeneous to optimize the efficiency of the design and to have accurate estimates. To create such strata, available information from population-level auxiliary variables is exploited to improve the precision of survey estimates while keeping data collection costs under control. However, the performance of this approach is highly dependent on how the strata are defined. This is particularly

crucial when the auxiliary variables involved are continuous in nature, and determining how to discretize them effectively becomes a methodological challenge.

In institutional surveys, strata based on continuous variables are often constructed using a priori defined class intervals, whose thresholds are often defined through expert heuristic rules or by administrative cut-offs. While rather simple to implement operationally, a fixed class definition for continuous variables may fail to capture the underlying distributional characteristics of the data. In addition, strata may result to be suboptimal and potentially inefficient since they could lead to obtain a final allocation of a rather high sample size in order to achieve the precision level goals set (Sarndal *et al.*, 2003).

As an alternative to a priori defined class intervals, a data-driven approach to find the cutoff values to determine the classes can be adopted. In the literature, several proposals have been discussed. Khan *et al.* (2008) introduced a dynamic programming method to determine the optimal strata boundaries that minimize the overall variance under Neyman allocation. Subsequently, Khan and Sharma (2015) used nonlinear mathematical programming to jointly optimize both the boundaries and the sample sizes between strata. In the field of integer linear programming, Wright (2014) introduced exact allocation algorithms in the context of stratified sampling that incorporate integral constraints and layer-specific bounds. We propose to address this challenge by using the `SamplingStrata` package in R (Barcaroli, 2014). This package uses a genetic algorithm to search for optimal cut-off points in the continuous auxiliary variables to minimize the sample size and achieve the set precision levels. The algorithm integrates this with the Bethel-Chromy allocation procedure, ensuring efficient sample distribution across strata under linear modelling assumptions.

To evaluate the effectiveness of this approach, we compared two stratification strategies: one that defines standard strata by discretizing the continuous variable a priori and the other that uses the boundaries obtained through a data-driven approach implemented in the `SamplingStrata` procedure. The effectiveness of the proposed method is evaluated both in terms of the coefficients of variation obtained for the same sample size and in terms of the sample size required to achieve a predefined precision target.

The paper is structured as follows. Section 2 presents the methodological framework and algorithms used. Section 3 illustrates the application of the case study on household survey data in both the standard procedure and the data-driven approach. Section 4 summarizes the main results of this work.

2. Methodology

To determine both the optimal population stratification and the corresponding allocation, subject to predefined precision constraints, `SamplingStrata` package in R (Barcaroli, 2014; Barcaroli *et al.*, 2020), provides a flexible tool in this framework. Indeed, its flexibility lies in the fact that it allows for management of the stratification determination when both categorical and continuous variables are used.

We recall that when choosing auxiliary variables for stratification, the researcher should focus on variables highly correlated with the target variable to improve the performance, both in terms of reducing the coefficient of variation in the domains of interest and in terms of reducing the sample size.

For this reason, when a continuous variable is a target variable, we can also use it as an auxiliary variable for stratification. This scenario represents the ideal use case since there is a perfect correlation between the auxiliary variable and the target variable (Lavallée, 1988).

In real-world surveys, both categorical and continuous variables are considered as stratification variables. To stratify using both categorical and continuous variables, when a-priori classes of the continuous variable are not provided, a data-driven approach can help. We need to define the domains by cross-classifying the categorical variables, and then for each domain, we need to discretize the continuous variable. Then, the final stratification is the combination of the domains and the cuts of the continuous variable found for each domain. In this way, we are able to construct a stratification framework that reflects the complexity of a design often encountered in real-world surveys (Särndal *et al.*, 2003).

To implement this strategy, we use the `SamplingStrata` R package. The first step in the procedure is to construct a sampling frame using the `buildFrameDF()` function. Using this function, each unit in the population is associated with a unique identifier, auxiliary variables, and domain membership. Then, within each domain, stratification is driven by the continuous variable that needs to be discretized.

To determine the number of classes into which to divide the continuous variable within each domain, the `KmeansSolution2()` function is applied. This function uses the k-means algorithm to provide insight into the possible optimal number of final classes and to provide an initial solution for the optimization phase. Next, the `optimStrata()` function is applied with the method set to “continuous” (specific for continuous-type variables). This function applies a genetic algorithm to find the optimal combination of cut points in the continuous variable. Each candidate solution corresponds to a specific stratification that is evaluated through a fitness function that estimates the total sample size required to satisfy the coefficient of variation (CV) constraints and chooses the combination of cuts that minimizes the

required sample size. In addition, the function also calculates the sample allocation between strata using Bethel's algorithm (Bethel, 1989).

3. Application

To test the data-driven approach to determine the stratification, we use the population dataset provided by the R2BEAT package¹, filtered on individuals aged over 14, which contains demographic and economic information on 2050016 population units. It's worth mentioning that this dataset is a synthetic dataset that mimics a real population dataset. For each individual, identified by an ID (id_ind), we have information about his/her residence (region/province/municipality), the ID of the family he/she belongs to, his/her gender, his/her age in aggregated form (class of age), his/her level of education, his/her income, and three flags indicating whether or not he/she is employed, unemployed, inactive (1: yes, 0: no). In Table 1 a complete description of the available variables is provided.

Table 1 – *Variables' descriptions.*

Variable	Description	Type
id_ind	Identifier of individual	Categorical (2050016 categories)
reg	Region of residence	Categorical (3 categories)
prov	Province of residence	Categorical (6 categories)
mun	Municipality of residence	Categorical (513 categories)
id_fam	Identifier of individual's family	Categorical (961457 categories)
gender	Gender of individual	Categorical (2 categories)
Cleta	age class: 14-24; 24-34; 34-44; 44-54; 54-64; 64-74; 74+	Categorical (7 categories)
Titstu	Level of Education	Categorical (5 categories)
Income	Income of the individuals	Numeric
Employed	Flag indicating individual is employed	Categorical (2 categories)
Unemployed	Flag indicating individual is unemployed	Categorical (2 categories)
Inactive	Flag indicating individual is inactive	Categorical (2 categories)

We suppose we want to implement a sampling survey aiming at measuring the population income, and the estimates are given at the following domains of

¹ <https://github.com/barcaroli/R2BEAT/tree/master/data>, dataset pop.RData

estimates: DOM1: national level; DOM2: province; DOM3: age class; DOM4: province crossed with age class. To design a sample, we opt for a stratified sampling design and we choose as stratification variables age class (Cleta), province (prov), and income, as we believe they can be correlated with the target variable.

Following a standard approach, the continuous variable is manually discretized as a new categorical variable (clred, which stands for class of income), with 6 categories: 0-4999, 5000-9999, 10000-19999, 20000-29999, 30000-99999, 100000+.

The final stratification is given by crossing the categories of province, age class, and income class, for a total of 252 strata.

To determine the final allocation in stratified sampling designs, several methods are available. Assume that n units are to be allocated among H strata, with n_h units allocated among each stratum $n_h, h \in \{1, \dots, H\}$. Clearly, $\sum_{h=1}^H n_h = n$. The allocation of units inside strata can be uniform, proportional, and optimal. The uniform allocation allows allocating the same constant number of units in each stratum; proportional allocation allows allocating more units in strata which have a higher dimension; finally, optimal allocation allows allocating more units in strata which have a higher dimension and are characterized by a higher variability of the target variable (s). The optimal allocation with one target variable and one domain has been introduced by Tschuprow (1923) and Neyman (1934); its extension to the multivariate framework is thanks to Bethel (1989); finally, Falorsi *et al.* (1998) developed the optimal allocation in a multivariate, multi-domain framework. Ballin and Barcaroli (2013) developed a methodology for the joint determination of the best stratification and best allocation in a multivariate and multi-domain framework.

Given the aforementioned strata, the optimal allocation of units in a multidomain and multivariate framework has been determined with the function `beat.1st` of the `R2BEAT` R package (Barcaroli *et al.*, 2023). The final sample consists of $n = 10000$ units.

Conversely, following a data-driven approach, we use the `SamplingStrata` R package to make the stratification. We decided to make the package discretize the variable income, for each combination of the categories of province (prov) and age class (cleta) (i.e., a total of 42 combinations). In detail, we use equal precision constraints in all domains (42 combinations), set to 0.01, and the algorithm is configured with 50 iterations, with parallel computation enabled to improve efficiency.

Among the outputs, one describes for each combination of province's and age class' categories, the boundaries of the cuts of the income variable, the stratum label, the number of population units falling in the stratum, and the number of sampling units allocated in the stratum. Table 2 shows the aforementioned output of the first six strata for the domain `prov:1_cleta:(14,24]`.

Table 2 – Summary of 6 strata of Domain “prov:1_cleta:(14,24]” Stratification.

Domain	Stratum	Population (Nstr)	Allocation (SOLUZ)	Lower Income	Upper Income
prov:1_cleta:(14,24]	1	18859	61	0.000	4572.43
prov:1_cleta:(14,24]	2	7584	13	4573.130	7018.21
prov:1_cleta:(14,24]	3	12070	42	7019.220	12087.49
prov:1_cleta:(14,24]	4	3438	5	12089.390	14050.20
prov:1_cleta:(14,24]	5	6664	27	14052.290	19909.03
prov:1_cleta:(14,24]	6	4853	33	19911.350	30002.83

The two approaches to stratification are discussed in terms of results evaluation, focusing on both the estimates’ precision and the final sample size.

4. Results evaluation

The first analysis carried out to compare results obtained by the standard approach and the data-driven approach to stratification is devoted to the Coefficient of Variations (CV), which are a measure of estimates’ errors. They are used to measure the precision of the estimates and are obtained by computing the ratio between the standard deviation of the estimates to the mean; obviously, the lower the coefficient of variation, the more precise the estimate; viceversa, the higher the coefficient of variation, the less precise the estimate. Therefore, we compute for each estimate domain the expected coefficient of variation of the income. This is done both for the stratification and allocation obtained with a standard approach and for the stratification and allocation obtained with a data-driven approach.

To make results comparable, we adjust the resulting allocation from the data-driven approach to stratification to make the final sample size equal to the one obtained from the resulting allocation corresponding to the standard approach to stratification ($n=10000$): the adjustment is made proportionally within each stratum and preserves the optimality of the solution (Bethel, 1989).

Figure 1 shows a radar plot reporting the expected coefficient of variation of every category of all the domains of interest for the allocations obtained with both a standard approach to stratification and a data-driven (proposed) approach to stratification. As it can be easily seen, the proposed approach leads to lower CVs in every domain than the ones obtained with a standard approach. Table 3 summarizes the results of the radar plot, by reporting for every target domain, the maximum level of expected coefficient of variations obtained with both the standard and data-driven (proposed) approach. From the table, it is possible to appreciate that the proposed approach performed better than the standard one.

Figure 1 – CV for each domain category. Comparison between standard and proposed stratification with fixed final sample size.

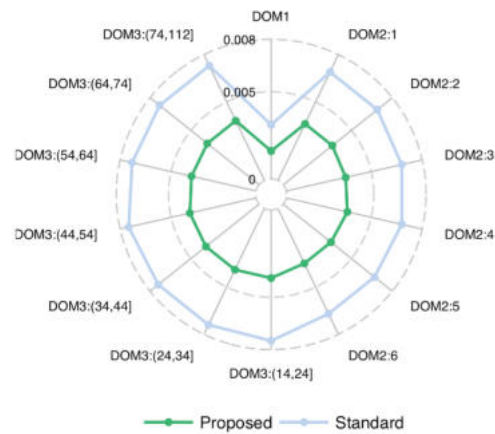
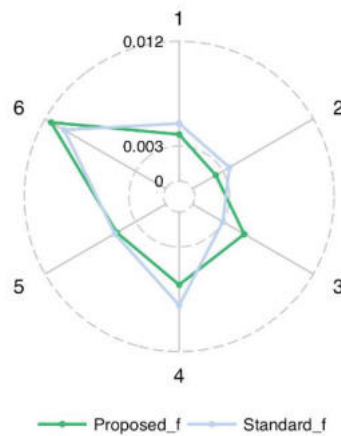


Table 3 – Max CV (%) for each domain. Comparison between standard and proposed stratification with fixed final sample size.

Domain	Max CV (%) standard allocation	Max CV (%) proposed allocation
DOM1	0.31	0.16
DOM2	0.69	0.36
DOM3	0.75	0.39
DOM4	1.62	0.65

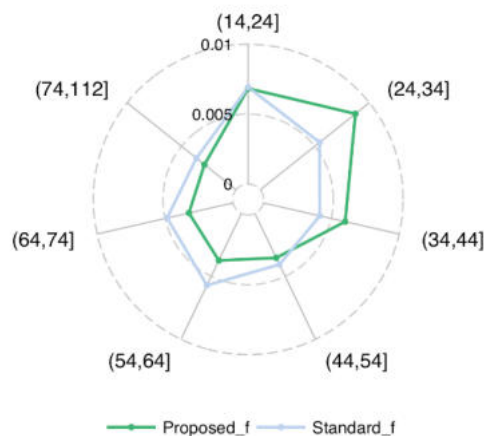
Given that the final sample size is the same in both approaches ($n=10000$), we also investigate the allocation separately in each domain. The radar plot represented in Figure 2 shows the sampling fraction in each domain category of province (DOM2). Only in province 3 and 6, the sampling fractions of the proposed approach are higher than the standard one; however, they are balanced by the lower sampling fractions in the other categories of the domain, and the larger amount of sampling units in these categories of the domain leads to a lower level of CV.

Figure 2 – Sampling fraction for each domain category of DOM2 (province). Comparison between standard and proposed stratification with fixed final sample size.



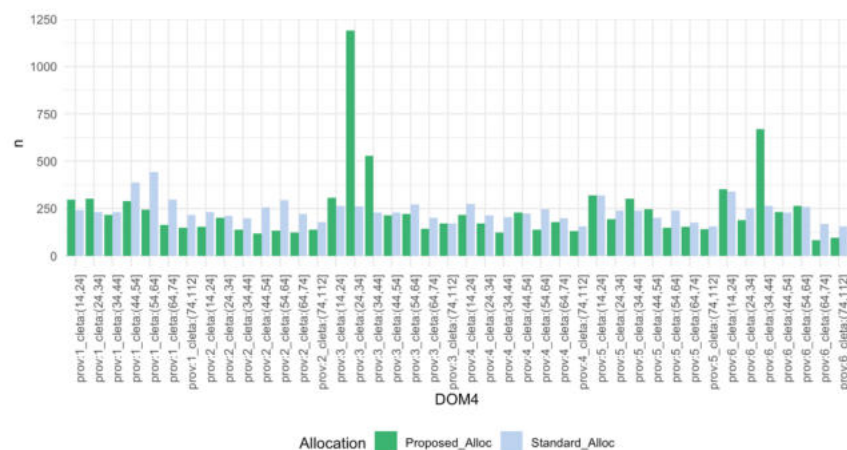
The radar plot represented in Figure 3 shows the sampling fraction in each domain category of age class (DOM3). Only in age classes (24, 34] and (34, 44] the sampling fractions of the proposed approach are higher than the standard one: however, they are counterbalanced by the other categories' smaller sampling fractions, and the higher number of sampling units in these categories results in a lower CV.

Figure 3 – Sampling fraction for each domain category of DOM3 (age class). Comparison between standard and proposed stratification with fixed final sample size.



Finally, the bar plot displayed in Figure 4 shows the comparison between allocations in each domain category of domain province crossed with age class (DOM4). It is possible to notice that the proposed approach allows to obtain an allocation lower than the one obtained with a standard approach in most of the domain categories. However, we notice that the proposed allocation is strongly higher than the standard allocation in domains prov:3_cleta:(24,34], prov:3_cleta:(34,44], prov:6_cleta:(34,44]. Results are coherent with the sampling fractions showed in the previous radar plots (Figure 2 and Figure 3).

Figure 4 – Final allocation for each domain category of DOM4 (province crossed with age class). Comparison between standard and proposed stratification with fixed final sample size.



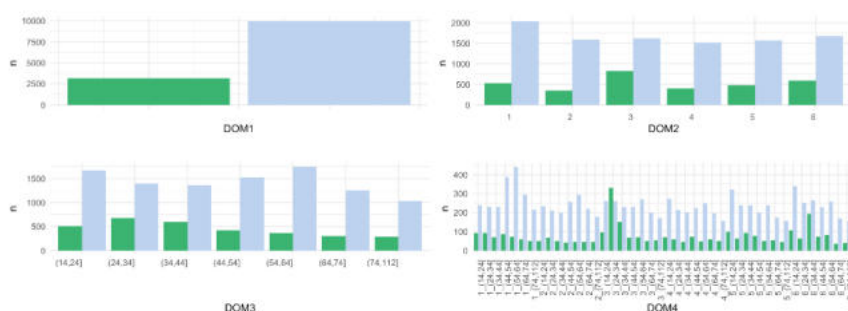
Therefore, we can conclude that in terms of estimates' precision, with the same final sample size, the proposed approach allows for obtaining more precise estimates, with coefficient of variations lower than the one obtained with the standard approach in all the domains of interest.

We implemented another analysis on the comparison of the results. So far, we have shown that, by keeping the final sample size fixed, the estimates are better in terms of CV. We now decide to test whether, keeping the CV fixed equal to that of the standard approach, the proposal still preserves its better performance in terms of final sample size. Fixing the CV, we run the data-driven proposed approach to determine the stratification and the allocation. The final allocation with the proposed approach consists of 3162 sampling units. Therefore, we can conclude that the

proposal preserves its good performance also in terms of sample size. Indeed, a lower sample size allows for a reduction in the overall survey cost.

The overall sample size obtained with the proposed approach (3162) is significantly lower than the one obtained with the standard approach (10000), and we can also appreciate it separately by domains. As it is highlighted in Figure 5, the final proposed allocation is always significantly lower than the standard one in all the categories of the domains of interest. The only exception is province 3, age class (24, 34], where the proposed allocation is slightly above.

Figure 5 – Final allocation for each domain category of DOM1 (national level), DOM2 (province), DOM3 (age class), DOM4 (age class crossed with province). Comparison between standard and proposed stratification with fixed CV.



5. Conclusions

When dealing with a stratified sampling design, two main aspects must be considered: first, the choice of the stratification variables; then, the way numerical stratification variables are divided into classes.

In this paper, we showed how it is possible to adopt a data-driven approach to help the researcher in the definition of the classes using the `SamplingStrata` R package.

It is important to underline that the package is primarily designed for use with real-world data. The synthetic dataset we used in the application closely resembles real-world data, with around 2 million records; results suggest that the package can handle large datasets efficiently. To further speed up computation, the `parallel=TRUE` option can be used for parallel processing, reducing execution time.

In terms of package functions, most parameters need to be defined by the researcher arbitrarily, depending on the specific problem (e.g., population frame, error constraints, domains, target variables, auxiliary variables). However, some

parameters require further tuning, such as the number of iterations and the number of strata. The package documentation provides default values and suggests using a k-means algorithm to initialize these parameters.

The proposal turns out to be helpful once we compare its performance with that obtained with standard classes definition, i.e. classes defined a priori. The performance is measured both in terms of expected coefficient of variations, by keeping the final sample size fixed, and in terms of final sample size, by keeping the coefficient of variations fixed. In both cases, the performance of the proposed approach is significantly better than the standard approach: the coefficient of variations are halved and the final sample size is reduced by about 70%, from 10000 to 3162 sampling units.

References

- BARCAROLI G., BALLIN M., ODENDAAL H., PAGLIUCA D., WILLIGHAGEN E., ZARDETTO D. 2020. *Sampling Strata: optimal stratification of sampling frames for multipurpose sampling surveys*, R package.
- BARCAROLI G. 2014. SamplingStrata: An R package for the optimization of stratified sampling. *Journal of Statistical Software*, Vol. 61, pp. 1–24.
- BARCAROLI G., FASULO A., GUANDALINI A., TERRIBILI M. D. 2023. Two Stage Sampling Design and Sample Selection with the R Package R2BEAT. *The R Journal*, Vol. 15, No. 3, pp. 191–213.
- BETHEL J. 1989. Sample allocation in multivariate surveys. *Survey methodology* Vol. 15, No. 1, pp. 47–57.
- COCHRAN W. G. 1977. *Sampling techniques*. John Wiley & Sons.
- FALORSI P. D., BALLIN M., DE VITIIS C., SCEPI G. 1998. Principi e metodi del software generalizzato per la definizione del disegno di campionamento nelle indagini sulle imprese condotte dall'ISTAT. *Statistica Applicata*, Vol. 10, No. 2, pp. 235–257.
- KHAN M.G.M. NIRAJ N. NURAIN A. 2008. Determining the optimum strata boundary points using dynamic programming. *Survey methodology*. Vol. 34, pp. 205–214.
- KHAN M. G., SHARMA S. 2015. Determining optimum strata boundaries and optimum allocation in stratified sampling. *Aligarh Journal of Statistics*, Vol. 35, pp. 23–40.
- LAVALLÉE P. 1988. Two-way optimal stratification using dynamic programming. *Proc. Sect. Surv. Res. Methods*, pp. 646–651.

- NEYMAN J. 1934. On the two different aspects of the representative method: the method of stratified sampling and the method of purposive selection. *Journal of the Royal Statistical Society*, Vol. 97, No. 4, pp. 558–625.
- SÄRNDAL C. E., SWENSSON B., WRETMAN, J. 2003. *Model assisted survey sampling*. Springer Science & Business Media.
- TSCHUPROW A. A. 1923. On the mathematical expectation of the moments of frequency distributions in the case of correlated observations. *Metron*, Vol. 2, pp. 646–683.
- WRIGHT T. 2014. A simple method of exact optimal sample allocation under stratification with any mixed constraint patterns. *Statistics*, Vol. 7.

AN EXPERIMENTAL APPROACH TO MAPPING EXPOSURE IN CONTAMINATED SITES¹

Daniela Vacca, Enrico Olla, Giovanna Pala,
Stefano Tersigni, Luigi Minerba

Abstract. The management of Sites of National Interest (SIN) in Italy represents a major environmental, health, and social challenge, as these areas often face severe socio-economic problems and a high risk of social inequality. This paper proposes an experimental approach to map population exposure in contaminated areas, operating on two territorial levels: sub-municipal, through the aggregation of Istat enumeration areas, and supra-municipal, through clusters of municipalities, in order to represent different levels of pollutant exposure. By integrating GIS-based proximity analysis with census and environmental data, the approach allows exploration of spatial gradients of potential exposure beyond administrative boundaries. Applied to the Sulcis–Iglesiente–Guspinese SIN (Sardinia), it aims to support complex environmental and social issues, highlighting areas that may be more vulnerable. It is conceived as a replicable tool to support evidence-based governance at multiple territorial levels.

1. Introduction and literature review

The management of contaminated sites and the assessment of their environmental and social impacts represent a global challenge. Research on environmental justice, initially developed in the United States, has shown that exposure to contaminants is unevenly distributed among social groups, with the most severe impacts on vulnerable communities characterized by lower education levels, reduced income, or minority status (Bullard, 2000; Brulle and Pellow, 2006; Mohai and Saha, 2006). These studies introduced the concept of environmental inequality as a key consideration for planning remediation and mitigation policies.

At both European and national levels, epidemiological and risk assessment studies have documented similar dynamics. The European Environment Agency (2018) and the World Health Organization (WHO, 2010) emphasize the importance of integrating environmental and socio-demographic data to identify the populations most exposed. In Italy, the SENTIERI project provides systematic evidence on mortality and morbidity in proximity to Sites of National Interest (SIN, see §2),

¹ The paper has been jointly written by all the authors but §1 and §5 to Daniela Vacca, §2 to Stefano Tersigni, §3 to Luigi Minerba, §4.2 and §4.3 to Enrico Olla, §4.1 and §4.4 to Giovanna Pala, §6 to all authors.

highlighting particularly severe impacts on socially disadvantaged communities (Pirastu *et al.*, 2013; SENTIERI VI Working Group, 2023). In recent studies additionally highlight the relationship between environmental degradation and socio-territorial vulnerability, underlining the need for integrated approaches to spatial planning and contaminated site governance (Pasetto, 2022; Scognamiglio, 2023).

From a methodological perspective, the study relies on spatial analysis methods, using Geographic Information Systems (GIS) to integrate Istat census data and apply distance-based spatial models to estimate territorial risk and identify potentially exposed populations in contaminated sites (ATSDR, 2005). Specifically, proximity and buffer analyses are employed to represent spatial gradients of potential exposure, assuming that pollutant concentrations decrease with increasing distance from contamination sources (Anderton *et al.*, 1994; Chakraborty *et al.*, 2011).

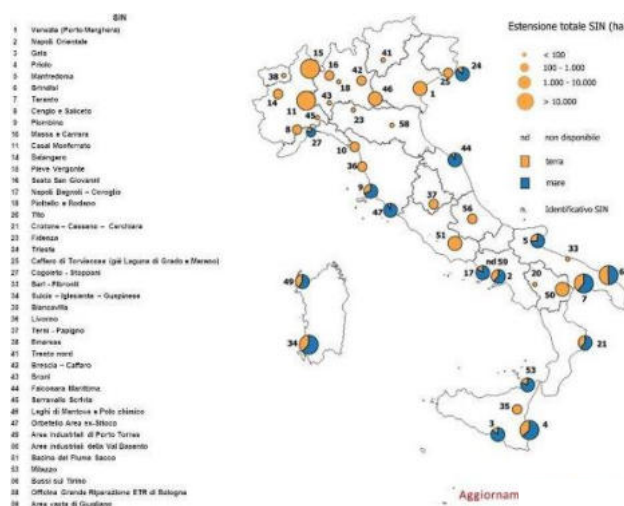
The two most common approaches to quantifying exposure are *spatial coincidence*, which identifies the exposure area to environmental risk with the boundaries of the territorial units where pollution sources are located and buffer analysis (Chakraborty and Armstrong, 2001; Mohai and Saha, 2006) which defines concentric zones around the source. Both approaches assume that proximity to the source corresponds to higher exposure (Anderton *et al.*, 1994; Chakraborty *et al.*, 2011).

This study applies these methods across two territorial levels with the aim of identifying the influence areas of contamination sources and grading the risk of affected territories; the sub-municipal level which allows high-resolution mapping in areas close to contamination sources, and the supra-municipal level which aggregates municipalities into statistically robust units, supporting local governance, planning, and comparisons across different sites.

2. Sites of National Interest (SIN): characteristics, risks and governance

Sites of National Interest (SIN) are officially designated areas recognized for their high levels of environmental contamination and the associated risks to human health and ecosystems (Figure 1). SINS are characterized by complex contamination profiles affecting multiple environmental matrices—soil, groundwater, surface water, and air—which interact to generate cumulative risk processes (Briggs, 2003; Landrigan *et al.*, 2018).

Contamination in these territories primarily stems from past and/or ongoing human activities, including industrial, mining, port and maritime activities, and waste disposal operations, often persisting over long periods. The situation is further exacerbated by delayed remediation, insufficient environmental controls, and inadequate land-use planning (Comba *et al.*, 2014; ISPRA, 2024).

Figure 1 – Italian Sites of National Interest (SIN).

Source: Ministry of Environment and Energy Security

The main sources of contamination include former metallurgical and petrochemical plants, mining districts, decommissioned industrial zones, and poorly managed or illegal landfills. Such activities have produced complex exposure scenarios affecting both environmental quality and public health.

Scientific literature identifies three main analytical dimensions of SINs for assessment: (i) multi-matrix contamination, where pollutants interact across different environmental components (Briggs, 2003; Landrigan *et al.*, 2018); (ii) documented health impacts, supported by epidemiological and mortality evidence (Comba *et al.*, 2014; SENTIERI VI Working Group, 2023); (iii) socio-territorial inequalities, stemming from processes of marginalization and unequal exposure (Bullard, 2000; Mohai and Saha, 2006).

From an institutional perspective, the coordination of SIN management is assigned by Italian law² to the Ministry of Environment and Energy Security (MASE), in collaboration with the Ministry of Health. Management decisions follow integrated criteria combining environmental and health risk assessments (ISPRA, 2024). The primary policy goal is the sustainable remediation and reuse of contaminated areas. However, high costs, technical complexity, and long implementation times continue to challenge remediation efforts, underlining the need for robust analytical tools to support planning and governance.

² Legislative Decree n. 152 of 3 April 2006, the so-called “Consolidated Environmental Act”.

In line with European policy directions, the European Commission (2022) emphasizes integrated, multisectoral, and participatory governance approaches for contaminated site management, incorporating ecological, social, and health dimensions. This perspective aligns with the environmental justice literature, highlighting that SIN management should focus not only on physical remediation but also on reducing territorial and social inequalities.

The Sulcis–Iglesiente–Guspinese SIN provides a paradigmatic example of such complex contamination profiles and socio-environmental challenges, as discussed in the following section.

3. The case study

The Sulcis–Iglesiente–Guspinese SIN, located in South-western Sardinia, exemplifies the intersection between historical industrialisation³, socio-economic fragility, and environmental risk (Figure 2). The coexistence of legacy mining and metallurgical activities with more recent petrochemical complexes illustrates how cumulative industrial legacies can amplify territorial vulnerability. Long-term demographic decline, population ageing, and limited economic diversification further reduce the area's adaptive capacity.

For over a century, the territory has been subjected to intensive mining and industrial operations that have produced widespread multi-source contamination across environmental matrices such as soil, groundwater, surface water, and air. The persistence of heavy metals, hydrocarbons and other industrial pollutants reflects the complexity of cumulative risk processes that continue to affect both ecosystems and human health (Comba *et al.*, 2014).

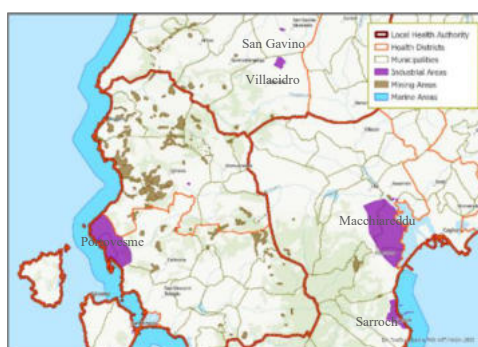
Environmental degradation is closely mirrored by adverse health outcomes, including excess mortality and higher hospitalisation rates for cancer, respiratory, and cardiovascular diseases, consistent with chronic exposure to industrial contaminants (SENTIERI VI Working Group, 2023). Combined with socio-economic vulnerability, these patterns point to a cumulative condition of environmental and social fragility.

The Sulcis–Iglesiente–Guspinese SIN also serves as a pilot site within the One Health Citizen Science (OHCS), initiative promoted by the Italian Ministry of Health. The project integrates environmental and health data to apply the One Health

³ In particular, the Portovesme industrial complex, historically linked to non-ferrous metal processing, exemplifies persistent soil and groundwater contamination, sometimes accompanied by polycyclic aromatic hydrocarbons (PAHs) and fluorides. Other sites, including Sarroch and Macchiareddu, dominated respectively by petrochemical and chemical production, show contamination associated with hydrocarbons and organochlorine compounds (BTEX, dichloroethane). Additional areas, such as Portoscuso, San Gavino Monreale, and Villacidro, illustrate the diffuse and multi-source nature of contamination across the territory.

approach to contaminated sites, strengthening monitoring and prevention strategies while fostering interdisciplinary and participatory models of environmental governance. This pilot context provides an ideal setting for testing the dual-level analytical approach proposed in this study.

Figure 2 – *Sulcis-Iglesiente-Guspinese SIN.*



Source: our elaboration on MASE and Istat data

4. Methods

4.1 Methodological design

This methodological framework is applied to the Sulcis–Iglesiente–Guspinese SIN, providing a concrete example of how sub-municipal and supra-municipal territorial level can capture environmental exposure.

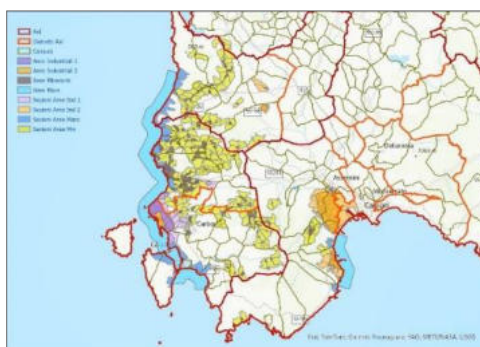
Building on the methodological considerations outlined in Section 1, the study adopts a two-tier territorial framework to assess exposure and vulnerability in contaminated sites. While spatial coincidence and buffer analysis define exposure metrics, the sub-municipal and supra-municipal levels represent complementary dimensions tailored for SINs.

The sub-municipal level allows high-resolution mapping of areas near contamination sources, supporting identification of potentially exposed populations and delineation of high-risk zones. The supra-municipal level aggregates municipalities into statistically coherent units, facilitating the integration of demographic, environmental, and epidemiological data to support broader planning and governance. By combining these two levels, the framework provides a two-tiered perspective on environmental vulnerability, capturing local specificity while linking it to wider socio-territorial dynamics. This approach is designed to be transferable to other SINs, allowing comparative analyses across different contaminated contexts (Chakraborty *et al.*, 2011).

4.2 GIS-based spatial modelling

Geographic Information Systems (GIS) provided the analytical environment for integrating and visualising spatial data from heterogeneous sources. ArcGIS software was used to model the potential influence zones around contaminated sites through the creation of distance-based buffers. This spatial modelling follows the distance-decay principle, according to which pollutant concentrations tend to decrease with increasing distance from the source (Zandbergen and Chakraborty, 2006).

Figure 3 – *SIN Sulcis Iglesiente Guspinese* - overlay of Istat enumeration areas.



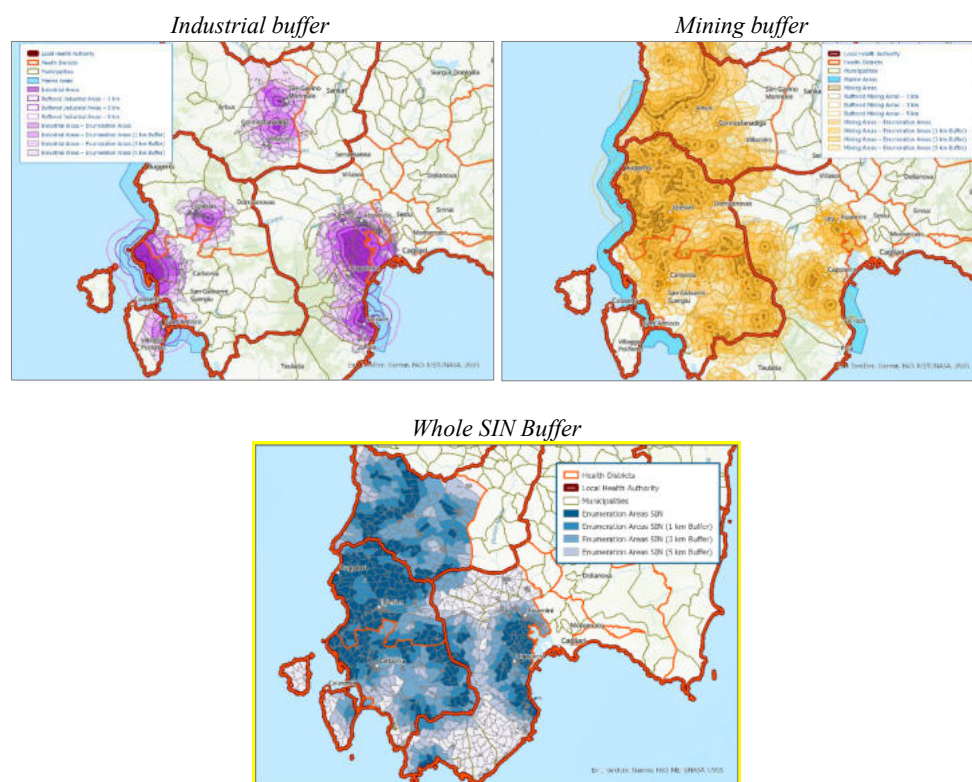
Source: our elaboration on MASE and Istat data

Boundaries of contaminated areas, provided by the Ministry of Environment and Energy Security (MASE), were intersected with 2021 Istat enumeration areas to identify local exposure patterns (Figure 3). Resulting polygons were overlaid with administrative boundaries to ensure spatial coherence across governance levels.

The delineation of influence zones provides the spatial foundation for subsequent multi-thematic analyses of exposure and vulnerability, ensuring consistency with epidemiological frameworks and supporting various levels of local governance, including Health Districts (HD) and Local Health Authorities (LHA).

4.3 Sub-municipal analysis

At the sub-municipal level, Istat enumeration areas serve as the basic spatial unit. All sections intersecting the boundaries of the contaminated site (buffer 0) were included. From the boundary of each section, concentric zones with radii of 1 km, 3 km, and 5 km were drawn (APAT, 2004), which allowed additional sections to be included and classified according to potential exposure, assuming a gradual decrease in risk with distance (Figure 4, Table 1).

Figure 4 – Influence buffers of Mining, Industrial, and Whole SIN – Sub-municipal level.

Source: our elaboration on MASE and Istat data

Table 1 - Mining, Industrial and Whole SIN sub-municipal areas by buffer - Year 2021.

	Mining		Industrial		Whole Sin	
buffer	n. en	areas area (km ²)	n. en	areas area (km ²)	n. en	areas area (km ²)
0	339	796,1	167	217,7	503	1.006,7
1	613	548,8	254	125,0	832	606,1
3	1.068	797,1	762	319,0	1.233	885,8
5	641	581,6	582	372,0	591	558,8
9	1.420	1.102,3	2.316	2.792,3	922	769,0
Total	4.081	3.826,0	4.081	3.826,0	4.081	3.826,4

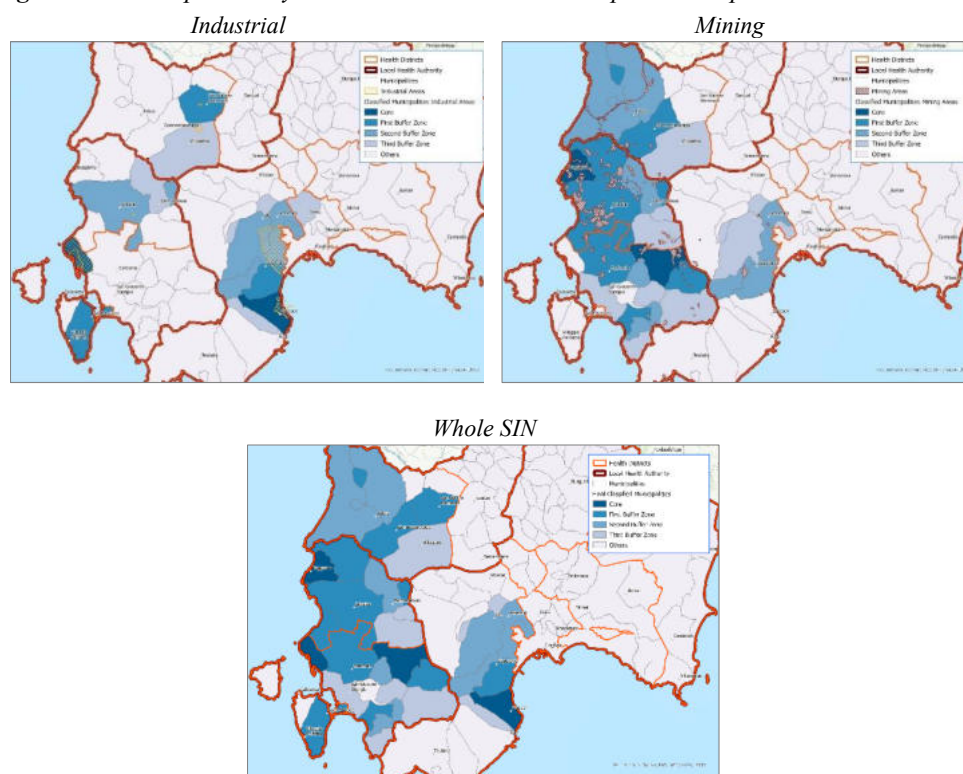
Industrial and mining sites were initially analyzed separately and then combined, assigning each section the highest corresponding risk class. This approach provides a continuous representation of exposure gradients and highlights inhabited areas

most directly affected by contamination. The sub-municipal framework supports detailed population-based exposure assessment and informs local planning and targeted interventions.

4.4 Supra-municipal analysis

At the supra-municipal level, municipalities are aggregated into statistically coherent territorial units based on spatial proximity and the proportion of residents within exposure buffers. This procedure generated five territorial risk bands - Core, Buffer 1 (0–1 km), Buffer 2 (1–3 km), Buffer 3 (3–5 km), and Outer Zone (>5 km) - ensuring statistical robustness and comparability (Figure 5, Table 2).

Figure 5 - Municipalities by environmental risk zone – Supra-municipal level.



Source: our elaboration on MASE and Istat data

Table 2 - Mining Industrial and Whole SIN Municipalities and areas by buffer(a)–Year 2021.

	Mining		Industrial		Whole SIN	
Areas	n. municipalities	area (km ²)	n. municipalities	area (km ²)	n. municipalities	area (km ²)
Core	2	134,2	2	105,9	4	240,1
First buffer zone	7	727,2	3	243,8	10	971,0
Second buffer zone	8	781,1	4	475,2	9	861,4
Third buffer zone	10	733,6	4	331,7	9	624,7
Others	19	1.446,7	33	2.666,3	14	1.125,6
Total	46	3.822,9	46	3.822,9	46	3.822,9

(a) The difference in area compared to Figure 4 is due to different rounding methods used at the municipal and section levels

Together, the two scales of analysis offer a complementary perspective on environmental vulnerability: the sub-municipal level captures the spatial specificity of exposure, while the supra-municipal level translates these insights into actionable knowledge for health management and territorial policy (Chakraborty *et al.*, 2011; SENTIERI VI Working Group, 2023).

5. Preliminary results and discussion

This section presents preliminary findings for the Sulcis Local Health Authority (LHA), a subset of the Sulcis–Iglesiente–Guspinese SIN encompassing three Health Districts (HD): Carbonia, Iglesias, and Isole Minori. The study area includes 1,842 Istat enumeration areas covering 1,342.8 km², with a total population of 119,086 in 2021, nearly half residing in the Carbonia HD (Table 3). Marked spatial heterogeneity emerges across the HDs.

Table 3 – Enumeration areas and population within buffers –Sulcis LHA.

HD Buffer	Carbonia HD				Iglesias HD				Isole minori HD				LHA			
	n.	en_area	area	en_area	n.	en_area	area	en_area	n.	en_area	area	en_area	n.	en_area	area	en_areas
	pop	s	(km ²)	s with pop	pop	s	(km ²)	s with pop	pop	s	(km ²)	s with pop	pop	s	(km ²)	with pop
HD	54.858	923	668,3	548	44.687	693	605,0	333	19.541	226	69,6	126	119.086	1.842	1.343	1.007
0	6.992	146	226,8	68	3.666	187	389,8	50	961	6	3,5	4	11.619	339	620	122
1	15.996	225	137,2	147	22.905	259	132,7	150	4.296	36	9,1	24	43.197	520	279	321
3	18.095	268	218,7	180	12.695	175	55,4	106	5.287	55	26,4	29	36.077	498	301	315
5	10.353	151	85,6	92	5.418	66	27,1	26	130	14	30,6	7	15.901	231	143	125
9	3.422	133	-	61	3	6	-	1	8.867	115	-	62	12.292	254	-	124

Source: our elaboration on MASE and Istat data

Within the Carbonia HD, about one-quarter of enumeration areas lie within one kilometer of a contaminated site, involving roughly 16,000 inhabitants.

In the Iglesias HD, more than half of the population (51.3%) lives within this proximity range, reflecting the historical persistence of mining and metallurgical activities that produced the highest density of contaminated areas in the region. The Isole Minori HD, though smaller, also shows a high proportion of residents in the first buffer zone, accounting for more than half of its total population.

At the supra-municipal scale, the 23 municipalities of the Sulcis LHA were classified into five environmental risk zones (Table 4). The Core zone, corresponding to the areas of highest contamination, hosts around 9,000 residents, while the first buffer includes more than 60% of the LHA population (around 73,000 inhabitants). Population density is therefore highest in areas under territorial pressure, particularly in the Carbonia HD, where industrial and residential functions have historically coexisted.

These results show that industrial legacies continue to shape the spatial overlap between environmental pressure and population concentration. The persistence of this alignment suggests cumulative vulnerability within specific territorial clusters, reinforcing the need for place-based approaches to health surveillance, remediation, and environmental governance.

Table 4 – Municipalities and population by environmental risk zone – Sulcis LHA.

Areas	Carbonia HD			Iglesias HD			Isole minori HD			LHA Sulcis		
	n. municip	area (km ²)	pop	n. municip	area (km ²)	pop	n. municip	area (km ²)	pop	n. municip	area (km ²)	pop
Core	2	124,0	7.974	1	48,0	1.053				3	172,0	9.027
First buffer zone	3	238,0	29.939	3	364,0	32.760	1	87,9	10.756	7	689,9	73.455
Second buffer zone	3	70,0	3.369	1	81,0	5.922				4	151,0	9.291
Third buffer zone	4	262,0	12.556	2	112,0	4.952				6	374,0	17.508
Others	1	31,0	1.020				2	82,0	8.785	3	113,0	9.805
Total	13	725,0	54.858	7	605,0	44.687	3	169,9	19.541	23	1.499,9	119.086

Source: our elaboration on MASE and Istat data

6. Conclusions and perspectives

This study proposes a two-tier territorial framework for assessing population exposure and environmental risk in contaminated sites. By integrating environmental, demographic, and health data at both sub-municipal and supra-municipal levels, the approach provides a conceptual and operational basis for more detailed analyses of exposure gradients and socio-environmental vulnerability. The Sulcis-Iglesiente-Guspinese SIN serves as an initial application of this framework, aimed at testing its spatial coherence and potential usefulness for environmental planning and governance.

Preliminary results highlight spatial and demographic patterns that may reflect the lasting influence of historical industrial activities, but further investigation is

required to validate these patterns through the integration of environmental, health, and socio-economic indicators. The integration of environmental, demographic, and health data within these new territorial divisions enables the construction of more robust and representative indicators, helping to overcome the limitations of formal administrative boundaries.

Future developments will extend the application of this methodology to other SINs to test its robustness and adaptability across different contexts, ultimately supporting more equitable and spatially informed environmental health governance. Overall, the proposed framework offers a replicable approach to integrate environmental, demographic, and health data, strengthening governance and decision-making at multiple territorial levels.

References

- ATSDR (AGENCY FOR TOXIC SUBSTANCES AND DISEASE REGISTRY). 2005. Element 5: Potentially exposed populations. U.S. Department of Health and Human Services.
- ANDERTON D. L., ANDERSON A. B., OAKES J. M., FRASER M. R. 1994. Environmental equity: The demographics of dumping, *Demography*, Vol. 31 No 2, pp. 229-248. <https://doi.org/10.2307/2061884>.
- APAT (Agenzia per la Protezione dell'Ambiente e per i servizi Tecnici). 2004. Analisi del Rischio per la Gerarchizzazione dei siti Inquinati presenti nell'Anagrafe. *Manuale Operativo (1.2)*, Roma.
- BRIGGS D. 2003. Environmental pollution and the global burden of disease, *British Medical Bulletin*, Vol. 68, No. 1, pp. 1–24.
- BRULLE R. J., PELLOW D. N. 2006. Environmental justice: Human health and environmental inequalities, *Annual Review of Public Health*, Vol. 27, pp. 103–124.
- BULLARD R. D. 2000. *Dumping in Dixie: Race, class, and environmental quality*, 3rd ed. Boulder, Routledge.
- CHAKRABORTY J., ARMSTRONG M. P. 2001. Assessing the impact of airborne toxic releases on populations with special needs. *The Professional Geographer*, Vol. 53 No 1, pp. 119-131. <https://doi.org/10.1111/0033-0124.00274>.
- CHAKRABORTY J., MAANTAY J. A., BRENDER J. D. 2011. Disproportionate proximity to environmental health hazards, Methods, models, and measurement, *American Journal of Public Health*, Vol. 101, No. S1, pp. S27-S36.
- COMBA P., RICCI P., IAVARONE I., PIRASTU R., BUZZONI C., FUSCO M., FERRETTI S., FAZZÒ L., PASETTO R., ZONA A., CROCETTI E. 2014. “Cancer incidence in Italian contaminated sites”, *Annali dell'Istituto Superiore di Sanità*, vol. 50, N. 2, pp. 186-191. DOI: 10.4415/ANN_14_02_13.
- EUROPEAN COMMISSION. 2022. Soil Strategy for 2030: Reaping the benefits of healthy soils for people, food, nature and climate. Brussels, European Commission.

- EUROPEAN ENVIRONMENT AGENCY. 2018. Unequal exposure and unequal impacts: Social vulnerability to air pollution, noise and extreme temperatures in Europe. Copenhagen, EEA Report No. 22/2018. DOI: 10.2800/324183.
- ISPRA. The state of remediation of contaminated sites in Italy: third report on regional data, ISPRA Report No. 409/2025, Roma, 2025.
- LANDRIGAN P. J., FULLER R., ACOSTA N. J. R. 2018. The Lancet Commission on pollution and health, *The Lancet*, Vol. 391, No. 10119, pp. 462–512.
- MOHAI P., SAHA R. 2006. Reassessing racial and socioeconomic disparities in environmental justice research, *Demography*, Vol. 43, No. 2, pp. 383–399.
- PASETTO, R., DIFONZO, D., PORCU, R., DE SANTIS, M., ZONA, A. 2022. Environmental health inequalities among municipalities affected by contaminated sites in Italy, *Environmental Justice*, Vol. 15, No. 4, pp. 228-234. DOI: 10.1089/env.2021.0068.
- PIRASTU R., PASETTO R., ZONA A., ANCONA C., IAVARONE I., MARTUZZI M., COMBA P. 2013. The health profile of populations living in contaminated sites: SENTIERI approach, *Journal of Environmental Public Health*, DOI: 10.1155/2013/939267.
- SCOGNAMIGLIO G. 2023. Giustizia ambientale nei siti industriali contaminati: i casi di Napoli Orientale e Bagnoli, in V. Albanese, G. Muti (a cura di), *Oltre la Globalizzazione – Narrazioni / Narratives*, Società di Studi Geografici. Memorie Geografiche, No 23, pp. 519-524.
- SENTIERI VI WORKING GROUP 2023. Epidemiological Study of Residents in National Priority Contaminated Sites. Sixth Report, *Epidemiologia & Prevenzione*, Vol.47. No 1–2 Suppl 1, pp. 375–384.
- WORLD HEALTH ORGANIZATION. 2010. Environmental burden of disease associated with inadequate housing. Copenhagen, WHO Regional Office for Europe.
- ZANDBERGEN P. A., CHAKRABORTY J. 2006. Improving environmental exposure analysis using cumulative distribution functions and individual geocoding, *International Journal of Health Geographics*, Vol. 5, pp. 1–15.

Daniela VACCA, Istat, daniela.vacca@istat.it

Enrico OLLA, Istat, enrico.olla@istat.it

Giovanna PALA, Istat, giovanna.pala@istat.it

Stefano TERSIGNI, Istat, stefano.tersigni@istat.it

Luigi MINERBA, Università degli Studi di Cagliari, luigi.minerba@unica.it

RESILIENCE IN ITALIAN LLMAS: THE ROLE OF SPECIALIZATION AND DIVERSIFICATION PATTERNS IN TWO RECENT CRISES

Sheila A. Chapman, Vito Pipitone

Abstract. This paper investigates the resilience of local economic systems (LLMAs) in Italy over 2008 to 2022 distinguishing between two resistance periods (2008–13 and 2019–20) and two recoveries (2013–19 and 2020–22). The main focus is on the role of diversification patterns, to check whether –and to what extent– related/unrelated variety is important in determining local performance. We estimate a spatial model and include a number of control variables. Results show that relatedness is important both for resistance and for recovery; unrelated variety is less important. We also find significant spatial spillovers only for recovery, with ambiguous effects over time. Results confirm the country’s general de-industrialization trend, coupled with growing importance for services, in particular for the less knowledge-intensive ones. While the South recovers better than the rest of the country, we tentatively explain this fact in terms of the role played by traditional services.

1. Introduction

When faced by the same exogenous shock, some regions react well and quickly; others lag behind. What lies behind this different behaviour? Which features are most important in determining local response? These questions have gained momentum in recent times, following the 2008 financial crisis, the subsequent sovereign debt crisis (2011-12) and the Covid-19 pandemic of 2020-21¹.

While the literature provides no universally accepted definition of resilience, a common approach follows an evolutionary perspective and focusses on an area’s capability to restore, or improve, its pre-crisis performance, eventually adapting to new conditions (evolutionary, or adaptive, resilience)². In this sense, it is possible to distinguish between an area’s ability to: (i) withstand a shock in the short-run (resistance); (ii) restore previous paths and/or develop new ones in the longer term (recovery) (Martin, 2012; Martin and Sunley, 2015).

¹ The two shocks were quite different in nature. The 2008-13 Great Crisis, that evolved into the sovereign debt crisis, had both real and financial effects, causing the longest and deepest recession of peacetime. Its exogenous/endogenous character is still debated. The 2019-20 pandemic was short-lived and entirely exogenous. At least in part these differences may shape different local reactions.

² The other two definitions are engineering and ecological resilience. The first assumes that systems have an underlying long-run equilibrium path (à la Solow); it measures resilience in terms of the rapidity with which an economy restores it. The second one allows economies to evolve towards new paths (à la Schumpeter), depending on the magnitude of the shock. In this sense it is closer to the adaptive definition. See Martin and Sunley (2015).

Traditionally, the differences in regions' response to shocks are associated with the local production structure (the "industry mix"), often in connection with other features (Lagravinese, 2015). More recently, specialization and diversification have been enriched by the notion of "variety", with a focus on the combinability of existing knowledge and skills across local activities. This allows actors to deepen/expand existing abilities, ultimately developing new trajectories. Put differently, innovation arises essentially as a combination of pre-existing local features; it proceeds incrementally branching from the sectors/technologies in which a territory has a competitive advantage. In this sense, innovative performance is largely related to the existing economic domain. The literature stipulates that diversified local economies with an adequate array of differentiated, but complementary, activities ("related variety") are apt to resist sector-specific shocks relatively well. They are able to reallocate labour and resources across sectors (industrial portfolio effect) and stand to benefit from consolidated ties, routines and procedures, which act as shock absorbers. By allowing the cross-fertilization across different but complementary activities, related variety may also promote recovery in the short run.

In other cases, innovation stems from a re-combination of technologies that mixes a firm's knowledge with that belonging to the context within which it operates. As firms draw from the externalities that are embedded locally, they generate truly innovative paths. Thus it is this type of diversified economic systems ("unrelated variety") that allows to develop new, high value-added activities that raise productivity, competitiveness and ultimately move the local economy towards new development paths. As diversification evolves towards more advanced activities and eventually moves from *niche* creation to adoption, the local system achieves recovery in the longer run^{3,4}.

With reference to Local Labor Market Areas (LLMAs)⁵ in Italy, this paper explores the features that shape the local response to an exogenous shock; in particular, it aims at investigating the role of the local production structure, of variety and of diversification patterns in promoting resistance and/or recovery. It explicitly accounts for space by estimating a spatial model that measures spatial spillovers across units. Control variables are also introduced to check for other features that may affect resilience. The paper is organized as follows: par. 2 describes the data,

³ Boschma, 2015. In some case it is suggested instead that, by relying strongly on market forces, unrelated diversification may offer less resistance. See Lazzaretti *et al.*, 2022.

⁴ The distinction between resistance and recovery, however, is not mechanical: in any moment the existing local features shape an area's future structural change possibilities, marking the interrelatedness between the two ideas. It follows that resilience is a process that has its roots in a region's production structure and in the complementarities that arise between it and the local knowledge bases. See Boschma, 2015

⁵ LLMAs are self-contained units that are defined by commuting patterns; they are independent from administrative boundaries.

the model and the variables taken in consideration. Par. 3 provides a brief descriptive picture; par. 4 reports the results of the spatial regression analysis. Par.5 concludes.

2. Data, methodology and variables

The empirical study takes LLMA as units of analysis and focuses on resilience and recovery in four key periods: two crises (2008–13 and 2019–20) and two recoveries (2013–19 and 2020–22). Data come from the ASIA Business Register of the Italian National Institute of Statistics (ISTAT) and cover active enterprises in industry, commerce, and services from 2007 to 2022. Firm-level data is aggregated by the 610 LLMA identified by ISTAT in 2018.

As in much of the literature, we measure our dependent variable, resilience, with reference to employment⁶. Alternative measures consider value added (or GDP) (Armenise and Benassi, 2022) and/or productivity indicators (Boschma and Iammarino, 2009). However, Martin (2012) argues that employment is preferable when tracing local resilience. Di Caro (2015) adds that employment series in Italy are more articulated at a regional level; moreover, they avoid deflation.

As in Martini and Platania (2019), both resistance (y_{res}) and recovery (y_{rec}) indexes are modified to account for LLMA.

$$y_{res} = \frac{(\Delta EMP_{llma}/EMP_{llma}) - (\Delta EMP_{nat}/EMP_{nat})}{|\Delta EMP_{nat}/EMP_{nat}|} \quad (1)$$

$$y_{rec} = \frac{(\Delta EMP_{llma}/EMP_{llma})}{(\Delta EMP_{nat}/EMP_{nat})} \quad (2)$$

where $(\Delta EMP_{llma}/EMP_{llma})$ and $(\Delta EMP_{nat}/EMP_{nat})$ are the percentage changes in employment respectively in the LLMA and in the country over a given period, measured as the difference between the first and last year of each period⁷.

The main explanatory variables, related and unrelated variety, are measured through modified versions of Thiel's entropy index, calculated on employment at different levels of sectoral aggregation⁸. Related variety (RV) records diversification at the 5-digit Ateco level within 2-digit sectors. Unrelated variety (UV) registers variety between 2-digit Ateco sectors.

$$RV_{llma} = \sum_{g=1}^G \frac{EMP_{g llma}}{EMP_{llma}} \sum_{s \in g} \left(\frac{EMP_{s llma}}{EMP_{llma}} / \frac{EMP_{g llma}}{EMP_{llma}} \right) \log_2 \left(\frac{EMP_{s llma}}{EMP_{llma}} / \frac{EMP_{g llma}}{EMP_{llma}} \right)^{-1} \quad (3)$$

⁶ See, among others, Di Caro (2015), Martin *et al.* (2016), Sedita *et al.* (2017), Cainelli *et al.* (2019)..

⁷ That is, respectively, 2013 vs. 2008; 2019 vs. 2013; 2020 vs. 2019 and 2022 vs. 2020.

⁸ Following Frenken *et al.* (2007) this measure is adopted, among others, by Boschma and Iammarino (2009), Sedita *et al.* (2017), Cainelli *et al.* (2019), Chen *et al.* (2024).

$$UV_{llma} = \sum_{g=1}^G \frac{EMP_{g llma}}{EMP_{llma}} \log_2 \left(\frac{EMP_{g llma}}{EMP_{llma}} \right)^{-1} \quad (4)$$

where $s = 1 \dots n$ is the 5-digit sector belonging to 2-digit sector g , with $g = 1 \dots G$.

Besides considering differentiation patterns, we control for a number of other variables. Thus, the population density (the average number of inhabitants above 15 years per square metres) reflects local demand for goods and services and local supply in the labour market. It also proxies the externalities that are linked to urbanization, as densely populated areas often house higher education institutions, big firms and organizations, which are likely to lead the local economy to react better to a crisis⁹. Along the same lines the density of firms (the number of firms over the population) may affect resilience by acting as a shock absorber¹⁰ by offering relocation opportunities (industry portfolio effect).

With reference to the peculiar features of Italy's production system, we control also for the share of employment in small firms (below 2mn Euros turnover per year; median values reported by the ASIA Business Register, ISTAT). As pointed out by Frenken *et al.* (2007) this also provides information on the level of local competition. In the case of Italy, we expect that larger firms, being more dependent on external factors, are more exposed to crises, while smaller ones could be more sheltered. Other controls include the share of employment respectively in manufacturing firms, low technology ones (LOT) and in less knowledge-intensive services (LKIS). These variables are meant to capture the role of sectoral specialisation; we expect the manufacturing sector to be more hard hit by crises and services to react better¹¹. Finally, we introduce a dummy to identify LLMA located in the South or in the two main islands (the *Mezzogiorno*) to check for differences with respect to the more industrialised, market-oriented Centre-North. By the same token, Altitude (defined as the average elevation of firms' location in the LLMA) is used as a proxy that captures the degree of local isolation from external factors.

3. Descriptive statistics

A preliminary view of the territorial pattern of resistance/recovery is shown in Figs. 1a and 1b; the distribution of relatedness/unrelatedness indexes in initial year 2008 is reported in Fig. 2. Fig.1a suggests a rather evident spatial pattern of resistance, especially in 2019-20. At least in part, this may reflect temporary restrictions on layoffs and job retention schemes. These policies, while implemented

⁹ See Frenken *et al.* (2007), Faggian *et al.* (2018), Sedita *et al.* (2017), Cainelli *et al.* (2019) Chen *et al.* (2024).

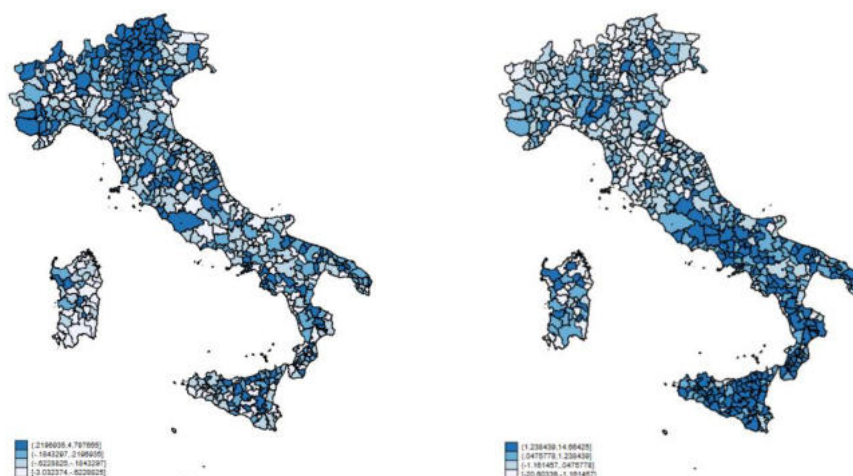
¹⁰ The opposite occurs in case of a sector-specific shock hitting less diversified LLMA. In this case firm density acts as a shock diffuser (Boschma, 2015).

¹¹ Di Caro (2015).

nationwide, produced uneven effects across sectors, affecting employment dynamics differently¹². However, the spatial pattern fades in recovery (Fig. 1b).

Fig.2 instead shows that relatedness/ unrelatedness distribute according to a rather clear-cut North-South divide, with RV being mostly higher in southern LLMA and lower in central and northern ones. On the contrary, UV is low in the South and high in the Centre-North¹³. This uneven spatial distribution points to different diversification paths: while in the *Mezzogiorno* diversification occurs mainly within existing specialization patterns, in the Centre-North it is driven more by new paths. Figs. 1a and 1b also point to a connection between resistance and recovery, implying that the LLMA that resist better are also those that recover faster. This appears evident especially in the two earlier periods¹⁴.

Figure 1a – Resistance patterns in Italian LLMA (2008-13 and 2019-20).



Source: our elaboration

Finally, the general picture outlined by Figs.1 and 2 seemingly runs counter the literature's indications in at least two respects. First, in 2008-13 it is the (more unrelated) Centre-North that resists better than the (more related) *Mezzogiorno*, somewhat disclaiming the suggestion that consolidated ties and routines, spillovers and the like act as shock absorbers¹⁵. Second, unrelatedness, which should encourage

¹² For instance, although national in scope, sector-specific policies in favour of construction or tourism could have created asymmetries against the more manufacturing-oriented Centre-North. An alternative view could focus on manufacturing alone, or consider a longer time span.

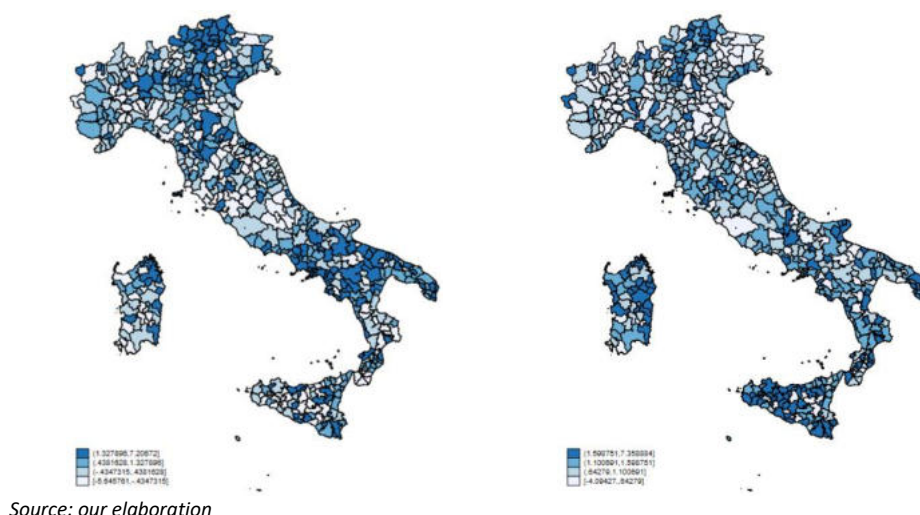
¹³ Fig. 2 shows the distribution in 2008. Over time the divide, if any, strengthens.

¹⁴ This finding is in line with that by Faggian *et al.* (2018) who describe a low resistance/low recovery pattern prevailing mostly in southern LLMA over 2007-11. We find correlation coefficients around 0.6 throughout the whole period (falling marginally only during the Covid-19 crisis).

¹⁵ The *Mezzogiorno* resists well in 2019-20, when it could be argued that exogenous factors were at play, due to the peculiar nature and territorial distribution of the Covid-19 pandemic in Italy.

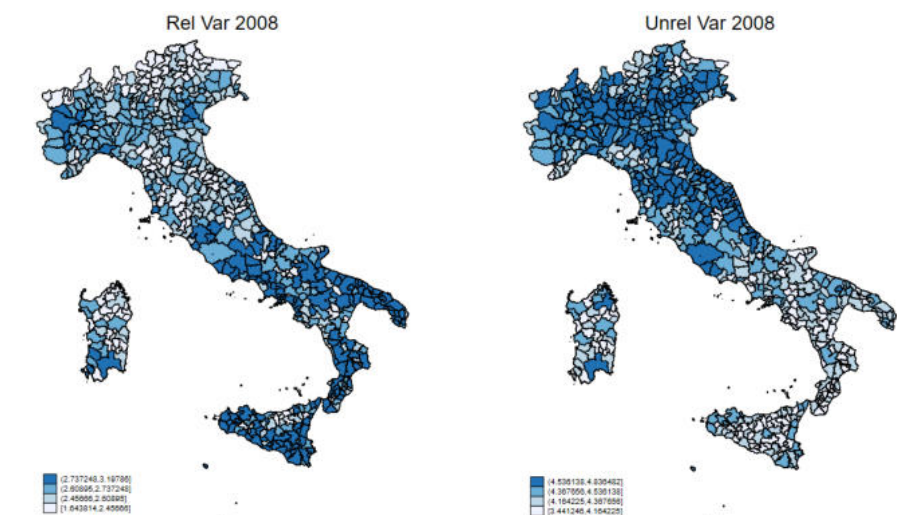
recovery inasmuch as it offers a wider portfolio of advanced, dynamic activities, associates rather weakly with it both in 2013-19, and (even less) in 2020-22.

Figure 1b – *Recovery patterns in Italian LLMA's (2013-19 and 2020-22).*



Source: our elaboration

Figure 2 – *Related and Unrelated Variety (2008).*



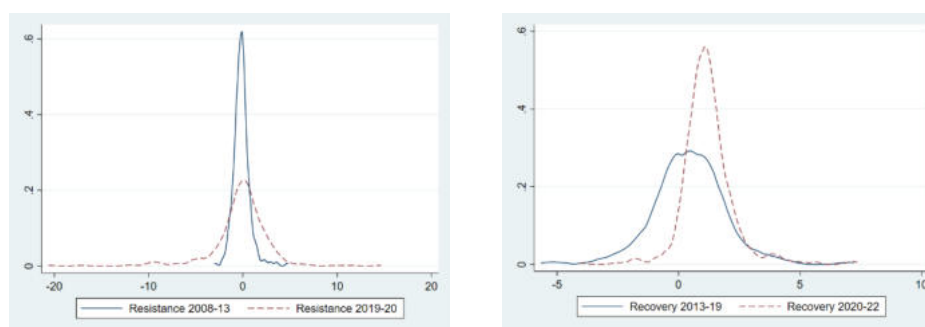
Source: our elaboration

Further detail is added by Fig. 3 that shows the kernel density of LLMA's' resistance/recovery indexes for the two crises under consideration¹⁶. While in 2008-

¹⁶ The kernel density distribution estimates the probability density function of a continuous variable to represent its distribution. A tight, peaked kernel indicates a cluster around the mean. A flatter, wider,

13 LLMA resist according to a homogeneous pattern (amounting to layoffs/freezing of new hiring), the pandemic produces strongly asymmetric effects, as some sectors (tourism, retail commerce) are hard hit and others (logistics, digital services) are boosted. In recovery this pattern is inverted: while in 2020-22 reactions are evidently clustered¹⁷, it is interesting to note the dispersed response of 2013-19, when some LLMA scale down employment and other raise it. This underlines the importance of other factors -the industry mix, firms' characteristics and strategies in driving recovery. These elements are the object of the following econometric analysis.

Figure. 3 – Kernel density.



4. Estimates and results

The presence of global spatial dependence in resilience patterns is tested through Moran's I statistic. For each time-period the index records high values that grow over time: these move from 0.29 (2008-13) to 0.45 (2013-19), to 0.61 (in the pandemic) and fall only slightly in 2020-22, reaching 0.58¹⁸. This means that LLMA that resist/recover better (or badly) tend to cluster together.

The strong overall spatial correlation suggests that standard econometric models, which are based on the independence of each geographical unit, would yield biased results. Spatial models, that explicitly account for units located in space and allow for externalities and spillovers, should be considered instead¹⁹.

The Spatial Durbin model (SDM) provides a flexible framework that encompasses most spatial models. It may be described as follows:

$$y = \beta_1 X + \beta_2 WX + \rho Wy + \varepsilon \quad (5)$$

one shows more heterogeneous values. Our estimations are based on the Epanechnikov kernel with bandwidth selected according to Silverman's rule.

¹⁷ This could be linked to nation-wide extraordinary regulations (subsidies, transfers) addressing all firms and all sectors.

¹⁸ All coefficients are highly significant.

¹⁹ See, among others, Cainelli *et al.* (2019) and Chen *et al.* (2024).

where y is the resistance/recovery index for each LLMA; X is a $N \times K$ matrix of independent variables (N is the number of LLMA; K that of independent variables); W is a $N \times N$ non negative (spectral normalized) spatial contiguity weights matrix (where element $w_{ij}=1$ if units i and j share a border; else $w_{ij}=0$); Wy is the spatial lag of y ; WX is the spatial lag of X ; ε is a $N \times 1$ vector of errors with zero mean and σ^2 variance; β_1 , β_2 and ρ are the response parameters to be estimated.

The SDM nests most spatial analysis models. Setting $\beta_2 = 0$ yields the spatial autoregressive model (SAR), which allows spatial dependence in the dependent variable of neighbouring units, but not in their covariates. Imposing the restriction that $\rho = 0$ leads to the spatially lagged X regression model (SLX), which assumes independence across the dependent variables but includes the characteristics of neighboring regions. When both parameters are set to zero, the model reduces to a standard non-spatial regression (OLS). Given the big cross-sectional dimension of the panel (610 units), statistical testing allows to select models in an easy and reliable way. We therefore choose to compare the SDM, the SAR and the SLX models through Likelihood Ratio (LR) tests²⁰. Results suggest that the SAR specification is preferred for resistance periods while the SDM applies best to recovery.

Table 1 shows the estimated of model (5) for each period. Related variety shows a positive, significant impact on resistance, acting as a shock absorber both in 2008-13 and in 2019-20. It also acts as a recovery-promoter only in 2013-19 – not after the Covid-19 crisis. This confirms, and extends over time, previous results reached for Italy's LLMA (Sedita et al., 2016, and Cainelli et al., 2019) and NUTS3 provinces (Boschma and Iammarino, 2009). The interpretation of this result is straightforward: a more inter-related local economy offers a wider range of opportunities. It allows firms to reallocate skills and technologies, exchange knowledge and adjust to shocks.

Instead, unrelated diversification is mostly irrelevant for resilience. Variable UV shows a positive and significant coefficient only for resistance in pandemic-ridden 2019-20, when LLMA offering a wide portfolio of activities benefit from shock absorbing effects. Again, this is generally confirmed by the literature²¹.

²⁰ Results –available upon request- are not reported for the sake of brevity. Le Sage (2015) argues in favour of Bayesian techniques for model selection. This method has the advantage of integrating model uncertainty but requires prior assumptions that lie beyond the scope of the present study. We leave the issue for future research.

²¹ However, exceptions do exist: Boschma and Iammarino (2009) find that unrelatedness leads to growth (and hence to resilience) in NUTS3 provinces only in terms of value added, and not for employment. For US units Chen et al. (2024) find that UV acts as shock absorbers, promoting resilience.

Table 1 – *Spatial Model Estimates: Resistance (2008-13; 2019-20) and Recovery (2013-19; 2020-22).*

	RES 2008-13	REC 2013-19	RES 2019-20	REC 2020-22
Rel Var	0.500*** (0.143)	0.697*** (0.197)	1.231*** (0.375)	0.226 (0.156)
Unrel_Var	-0.0777 (0.121)	-0.0892 (0.171)	0.639** (0.323)	-0.0787 (0.145)
Population density	0.127 (0.153)	-0.268 (0.313)	0.00199 (0.441)	0.110 (0.205)
Firm density	-0.00456* (0.00255)	0.00811** (0.00393)	-0.0197** (0.00774)	0.00625* (0.00327)
% Small firms	8.828** (3.847)	25.79*** (6.004)	-1.595 (9.921)	-5.286 (4.660)
% Manuf. firms	-6.132*** (1.857)	-7.930*** (2.715)	-2.451 (5.686)	1.247 (2.443)
% LOT manuf.	6.209*** (2.009)	6.548** (3.009)	-1.650 (6.610)	-1.982 (2.901)
% LKIS	1.949* (1.008)	5.014*** (1.448)	-23.12*** (2.597)	7.167*** (1.045)
Mezzogiorno	-0.186* (0.105)	0.687*** (0.150)	0.126 (0.333)	1.176*** (0.166)
Altitude	0.000730*** (0.000152)	-8.14e-05 (0.000190)	0.00214*** (0.000416)	2.60e-05 (0.000193)
W_y	0.275 (0.199)	0.572*** (0.0957)	-0.103 (0.131)	-0.661*** (0.146)
e.y	-0.0736 (0.239)	-0.611*** (0.156)	0.309** (0.135)	0.610*** (0.0986)
W_x (pop. density)		1.662*** (0.536)		0.105 (0.458)
W_x (firm density)		-0.00399 (0.00255)		0.00656** (0.00294)
Constant	-0.919 (0.648)	-2.987*** (0.925)	0.671 (1.766)	-1.332* (0.752)
Observations	610	610	610	610
(Pseudo) R-squared	0.106	0.2479	0.460	0.276

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Analyzing the control variables shows that, contrary to previous findings, population density is not important²², while firm density is. The latter shows a positive and significant coefficient in recovery (although values are low), and a negative one in resistance, when possibly many marginal firms exit the market.

²² Boschma and Iammarino (2009) find the same result for NUTS3 provinces in 1995-2003.

A strong share of employment in small firms has a big and important effect on resilience in the first two periods, but is irrelevant in the following ones. The same occurs for the share of manufacturing, which shows a (big) negative effect in 2008-13 and until 2019; later it not significant. We interpret this as a reflection of the country's general de-industrialization process. Also the coefficients relative to LOT manufacturing firms – the traditional backbone of Italian industry – are positive and significant only in the first two periods. This contrasts previous results for which high shares of LOT manufacturing associate with low resilience (Compagnucci *et al.*, 2022). Coming to services, LKIS increasingly promote resilience (not in 2019-20), acting as shock absorbers and growth promoters. Again, this runs counter existing results, that find negative effects of LKIS for resilience.

As far as the North-South dimension is concerned, location in the *Mezzogiorno* rather unexpectedly associates positively and significantly with recovery; moreover, the coefficient grows over time. This is an interesting result; it confirms national statistics that record higher value added, employment and productivity growth in the region from the mid-'Nineties on²³. Contrary to the literature's indications, we find that location in the sheltered, less diversified, *Mezzogiorno* has either a negative or an irrelevant impact on resistance. Finally, LLMAAs located in high-altitude areas benefit from a modest, but significant, buffering effect in resistance. We explain this by assuming that these units probably identify more stable, self-contained systems with a strong public sector, leading to lower exposure to external shocks.

Coming to spatial effects, these matter only for recovery, but give ambiguous results. By activating positive spillovers on demand and on labour markets in neighbouring LLMAAs, they promote recovery during 2013-19 but hamper it in 2020-22. In the latter case spatial effects seemingly amount to competition effects across LLMAAs, leading to resource diversion, labour drain and firm relocation (see Chen *et al.*, 2024). We find that also population and firm density show positive and significant spatial effects in recovery: that of population counts most in 2013-19 and that of firms in 2000-20.

As a robustness check, we estimate model (5) using a second-level normalized contiguity weights matrix (with weight reflecting also the neighbours of each unit's neighbours). As a robustness check, we estimate model (5) using a second-level normalized contiguity weights matrix (with weight reflecting also the neighbours of each unit's neighbours). The main results of our estimations remain unchanged.

²³ See Barca (2006), Boschma and Iammarino (2009) and Lazzaretti *et al.* (2022). Over 2007-22 the *Mezzogiorno* records higher growth of net firm creation in services than the North, (4.1% against 3.3%). Manufacturing firms instead fall less in the South (-11.5% with respect to -12.5%).

5. Conclusion

This paper analyses the resilience patterns of Italian LLMAAs over two recent, wide-sweeping, shocks: the Great Recession and the COVID-19 pandemic. For both episodes, it distinguishes between resistance and recovery performance.

We estimate a model that allows for spatial dependence. Results highlight a number of points. First, we find that LLMAAs' resilience changes over time: what appears important in the earlier periods often becomes less effective in later ones; also, not always resistance and recovery are affected by the same variables.

The main focus is on the impact of diversification patterns. In this domain we find that relatedness significantly promotes resilience, both in terms of resistance and of recovery; instead unrelated variety appears less important. We also find that the behaviour of neighbouring LLMAAs has spatial effects mostly in recovery, producing negative spillovers in 2013-19 and positive ones in 2020-22.

Although the two crises are different in nature, the Great Recession deepening pre-existing local weaknesses while the 2019-20 pandemic possibly concealing them due to State intervention, we find a number of common results for the two episodes. First, the country's general de-industrialization trend is confirmed, coupled with the growing importance of services. We show that what matters for resilience is specialization in traditional, less knowledge-intensive sectors, such as food and beverages, accommodation, call centres and the like. We also show that firms in the *Mezzogiorno* recover better than those located elsewhere in the country. This represents a still largely unexplored phenomenon that, as such, claims further investigation. We tentatively link the good performance of southern LLMAAs to the growing importance of traditional low-knowledge services.

References

- ASSO P.F., NEROZZI S., PIPITONE V. 2021. Italy's North-South Divide Yet Again: Some New Evidence from Firms, Sectors and Territories. *Rivista Internazionale di Scienze Sociali*, Vol. 2, pp. 91-124.
- BARCA F., 2006. *L'Italia frenata*. Donzelli Editore.
- BOSCHMA R., 2015. Proximity and Innovation: A Critical Assessment, *Regional Studies*, Vol. 39, No. 19, pp. 61-74.
- BOSCHMA R., IAMMARINO S. 2009. Related Variety, Trade Linkages and Regional Growth in Italy. *Economic Geography*, Vol.85, No. 3, pp. 289-311.
- CAINELLI G., GANAU R., MODICA M., 2019. Does related variety affect regional resilience? New evidence from Italy. *The Annals of Regional Science*, Vol. 63, No.3, pp. 657-80.

- CHAPMAN S., PIPITONE V. 2023. The productivity of Italian firms: a spatial analysis. *Rivista Italiana di Economia Demografia e Statistica*, Vol. LXXVII, No. 4, pp. 145-56.
- CHAPMAN S., PIPITONE V. 2022. Total Factor Productivity in Italian Manufacturing: Does Location Matter? *Rivista Italiana di Economia, Statistica ed Economia*, Vol. LXXVI, No. 3, pp. 155-66.
- CHEN J., XIAOJING L., YUANYUAN Z., 2023. Shock absorber and shock diffuser: the multiple roles of industrial diversity in shaping regional economic resilience after the Great Recession, *The Annals of Regional Science*, Vol. 72, No.2, pp. 1015-45.
- COMPAGNUCCI F., GENTILI A., VALENTINI E., GALLEGATI M., 2022. Asymmetric response to shocks: the role of structural change on resilience of the Euro area regions, *Applied Economics*, Vol. 54, No. 37, pp. 4324-55.
- DI CARO P. 2015. Recessions, recoveries and regional resilience: evidence on Italy, *Cambridge Journal of Regions, Economy and Society*, Vol. 8, No. 2, pp. 393-410.
- FAGGIAN A., GEMMITI R., JAQUET T., SANTINI I. 2018. Regional economic resilience: the experience of the Italian local labor systems, *The Annals of Regional Science*, Vol. 60, No. 2, pp. 393-410.
- FRENKEN K., VAN OORT F., VERBURG T. 2007. Related variety, unrelated variety and regional economic growth, *Regional Studies*, Vol. 5, No. 41, pp.685-97.
- LAGRAVINESE R. 2015. Economic crisis and rising gaps North-South: Evidence from the Italian regions, *Cambridge Journal of Regions, Economy and Society*, Vol. 8, No. 2, pp. 331-42.
- LAZZERETTI L., OLIVA S., INNOCENTI N. 2022. Unfolding Smart Specialisation for Regional Economic Resilience: the role of Industrial Structure, *Investigaciones Regionales*, Vol. 3, No. 54, pp. 5-25.
- LESAGE J. 2015. Software for Bayesian cross section and panel spatial model comparison, *Journal of Geographical Systems*, Vol. 17, No. 4, pp. 297-310.
- MARTIN R., 2012. Regional economic Resilience, Hysteresis and Recessionary Shocks, *Journal of Economic Geography*, Vol. 12, No.1, pp.1-32.
- MARTIN R., SUNLEY P. 2015. On the Notion of Regional Economic Resilience: Conceptualization and Explanation, *Journal of Economic Geography*, Vol. 15, No.1, pp.1-42.
- SEDLITA S.R., DE NONI I., PILOTTI L. 2017. Out of the crisis: an empirical investigation of place-specific determinants of economic resilience, *European Planning Studies*, Vol. 25, No. 2, pp. 155-80.

Sheila A. CHAPMAN, LUMSA University, chapman@lumsa.it

Vito PIPITONE, CNR-ISMed Palermo & LUMSA University, vito.pipitone@cnr.it

AUTOMATED TICKET CLASSIFICATION FOR TRAINING ISTAT'S PUC CHATBOT¹

Samanta Pietropaoli, Gabriella Fazzi

Abstract. The increasing volume of user requests handled by ISTAT's contact center for supporting participants in official statistical survey has underscored the need for automated solutions to optimise ticket classification and reduce reliance on manual processing.

This study presents the development and evaluation of a supervised classification system that leverages Natural Language Processing (NLP) techniques to enhance the accuracy, efficiency and scalability of request management within a public administration context.

The proposed framework integrates a TF-IDF-based text representation with synthetic oversampling (SMOTE) and three supervised learning algorithms: Random Forest, LightGBM, and Multilayer Perceptron. The methodology also incorporates a tailored preprocessing pipeline—covering tokenisation, lemmatisation, stopword removal, and anonymisation of personal information—to ensure data quality and privacy compliance.

The classification system was designed to support the training phase of ISTAT's PUC chatbot, which will provide first-level assistance to citizens and establishments involved in statistical surveys. By generating high-quality labelled data, this approach aims to improve chatbot intent recognition and facilitate self-service interactions for survey respondents.

Model performance was evaluated using standard classification metrics, including accuracy and both weighted and macro-averaged F1 scores.

Among the tested configurations, LightGBM demonstrated the most balanced and robust performance. The results confirm the effectiveness of integrating machine learning and NLP into institutional workflows. Future work will explore the integration of the classifier into the generative architecture of Salesforce Agentforce, contributing to the evolution of intelligent support systems in citizen-facing public services.

1. Introduction

In recent years, the increasing demand for efficient and timely customer support has driven public institutions to explore innovative technological solutions. For the Italian National Institute of Statistics (ISTAT), this need is particularly pressing due to the vast volume of interactions with both citizens and businesses participating in official statistical surveys. Managing these requests manually is time-consuming and

¹ This article reflects only the opinions of the authors. This paper is the result of the joint work of the authors. S. Pietropaoli has written Sects 2, 3, 4, 5; G. Fazzi has written Sects. 1, 6;

prone to inconsistency, particularly when incoming messages vary in format, communication channels and language use.

To address these challenges, ISTAT is developing a first-level support chatbot within the framework of the "Punto Unico di Contatto" (PUC)², a unified omni-channel interface that allows external users to interact with the Institute in a standardised and integrated manner. The deployment of the chatbot is a key element within a broader digital strategy aimed at enhancing user experience, increasing operational efficiency, and reducing dependency on human operators for handling common and routine requests.

A chatbot is a virtual agent trained using specific machine learning algorithms to interpret and respond to user requests in a standardised and automated manner. Designed to simulate human-like conversations, it offers consistent assistance across a predefined set of tasks and queries.

The chatbot is trained on a set of *intents* that represent the various types of user queries—such as password recovery procedures, deadline requests, or survey clarification—which it must recognise in order to determine the appropriate response path. Accurate and comprehensive classification of past tickets is essential for generating high-quality labelled data that reflect real-world user needs. To address this, a robust classification pipeline that leverages advanced NLP techniques and supervised machine learning was developed. The goal is to automatically assign categories to the support tickets while simultaneously enhancing the quality of chatbot training data and improving the overall accuracy and efficiency of request management.

2. Context

The increasing relevance of Artificial Intelligence (AI) in the public sector is reflected in numerous research and innovation programs promoted at both European and national levels. For example, the AI4PublicPolicy project (Horizon 2020 - GA No. 101004480) developed a cloud-based platform to support policy development through AI technologies, including NLP and chatbots, with a strong emphasis on transparency and citizen feedback (European Commission, 2024). In particular, the Italian pilot led by the City of Genoa (Marceddu et al., 2024) closely aligns with this research's objective of automating the classification and analysis of helpdesk tickets using NLP models. Similarly, INPS—Italian National Social Security Institute—has placed AI at the heart of its digital transformation strategy (2022–2024). Key

² The PUC platform was launched in July 2024 and aims to centralise and harmonise interactions between ISTAT and its users by providing a single access point for information requests, survey participation support, and collaboration on statistical activities.

initiatives include AI-powered chatbots, automated contact center routing, classification of certified emails (PEC), and experiments with generative AI based on institutional knowledge bases (INPS, 2024). These efforts highlight the growing operational maturity of AI within Italian public administration. As a key actor in the implementation of the National Recovery and Resilience Plan (PNRR)³—especially under Mission 1, focused on digitalisation—INPS exemplifies how AI can enhance the quality and efficiency of citizen services.

The present research shares important parallels with these initiatives, particularly in its use of NLP for classifying user-generated content. It adopts a modular and experimental approach, focusing on fine-tuning pre-trained transformer models on domain-specific data, with special attention to data quality, linguistic challenges, and model explainability.

Such initiatives aim to drive digital transformation, increase efficiency in public service delivery, and promote citizen-centric governance through AI, data analytics, and cloud computing. While they mostly address large-scale service and policy transformation, this research contributes by adapting transformer-based NLP models to improve internal workflows at ISTAT.

These technological advancements also provide the broader context for the growing adoption of conversational agents in public administration. Among these, chatbots are increasingly adopted in public service delivery (European Commission, 2020), and are currently the most prominent form of AI applications in the public sector (Van Noordt & Misuraca, 2022). Typically adopted as a complementary service channel, chatbots are reshaping both information delivery and citizen interaction in public agencies (Vassilakopoulou et al., 2022). These systems are also recognised as tools for creating public value (Aoki, 2020), with implications for administrative processes, service quality, and the relationships between citizens and public institutions (Twizeyimana & Andersson, 2019). In this perspective, the ISTAT chatbot represents not only a technological advancement, but also a potential shift in how statistical services are accessed and perceived by users. Its long-term success depends not only on its initial design, but also on its ability to learn, adapt, and respond effectively to evolving user needs.

By automating the classification of helpdesk tickets, this research transforms cutting-edge AI and NLP methodologies into operational tools that support the PNRR's vision of a modern, efficient, and citizen-oriented public administration.

³ The PNRR is Italy's program for using the European Union's Next Generation EU funds, with the aim of revitalizing the economy after the COVID-19 pandemic and promoting sustainable and inclusive growth.

3. Data and preprocessing

3.1. Dataset and classification taxonomy

This research addresses the automation of the classification process by analysing over 24,000 historical support tickets, collected between June 2024—the launch date of the PUC platform—and February 2025, and categorised into 29 predefined classes. These tickets originate primarily from transcripts of phone calls handled by contact center operators and from email communications submitted by survey participants, specifically related to the activities of ISTAT’s Data Collection Directorate. Most of these messages are written in Italian and show substantial variation in length, structure, and formality. To support the classification task, each ticket was pre-associated with a code⁴ corresponding to one of 29 subcategories defined within a hierarchical, scenario-based taxonomy developed for the chatbot project.

Scenarios represent the overarching topical areas used to organise user inquiries and were established through a classification system specifically designed for this initiative. Initially informed by a 2020 experiment conducted in ISTAT on automated ticket classification⁵, the structure was refined through in-depth analysis of frequently asked questions from various household and business surveys.

A multidisciplinary team reviewed and categorised these FAQs, leading to a hierarchical classification structure that distinguishes seven main scenario groups (labelled A to G), each grouping user requests by thematic domain and further divided into subcategories. These scenario groups are:

- A – Access and Navigation: Includes issues related to login credentials, website usability, and access to the data collection portals (A1–A10).
- B – Regulatory Aspects: Covers questions concerning mandatory response obligations, sanctions, privacy policies, and the legal framework for participation (B1–B8).
- C – Sample Composition and Variations: Encompasses requests about sample inclusion or exclusion, as well as participant status changes such as relocations, deaths, or business closures (C1–C8).

⁴ The initial categorization of support tickets was generated during routine contact center operations. First-level operators handled cases by consulting a centralised Knowledge System—integrating FAQs and supporting documentation produced and maintained by Istat domain experts according to standardised procedures—and by accessing Istat’s data acquisition back-office systems. As a result, ticket categorisation reflects shared operational practices and standardised information sources rather than an annotation scheme explicitly designed for machine learning purposes.

⁵ For further information, see Bianchi et al., 2022.

- D – Interview Bookings: Refers to scheduling or rescheduling appointments with interviewers for CATI or CAPI surveys (D1).
- E – Assessment and Dispute Reports: Involves disputes or clarifications related to official notices, sanctions, or non-compliance assessments (E1).
- F – Questionnaire and Survey Information: Includes a broad set of queries about survey content, response deadlines, participation procedures, and technical aspects of questionnaire completion and submission (F1–F17).
- G – Communication with ISTAT: Covers inquiries about previous unanswered requests, official reminders, or clarification of institutional communications (G1–G4).
- H – Other: Reserved for tickets that do not fall into any of the predefined categories.

While the original taxonomy included 51 subcategories (as indicated in parentheses), it was streamlined to 29 for chatbot training purposes, maintaining the seven high-level scenarios. This restructuring preserved both the breadth of the thematic coverage and the clarity required for automated classification, while ensuring mutual exclusivity among classes.

3.2. Text Pre-processing

To prepare the textual data for the supervised classification, a comprehensive and modular preprocessing pipeline was designed to ensure data quality, linguistic consistency, and full compliance with privacy regulations (e.g., GDPR). This phase was crucial to reduce data sparsity, eliminate noise, and prevent the model from inadvertently learning patterns based on sensitive information. The pre-processing steps, implemented using Python 3.11 and the SpaCy NLP library⁶ (version 3.7), included the following components:

- Empty message removal: All records with missing values, null content, or messages composed solely of non-informative text (e.g., greetings or placeholders) were systematically excluded. This step was essential to minimize noise in the training data and avoid bias introduced by semantically empty inputs.
- Tokenization and lemmatization: Texts were segmented into individual tokens—the smallest units into which text is divided, which may range from words to subword components—using SpaCy’s language model for Italian (`it_core_news_lg`). Each token was lemmatised to its canonical form to normalise lexical. These operations facilitate lexical generalisation and reduce

⁶ SpaCy stands out for its support of over 70 languages through dedicated pipelines, many of which integrate advanced technologies such as BERT-based language models and multitask learning.

feature dimensionality, improving model robustness and generalisation, especially in low-resource or imbalanced class scenarios (Manning et al., 2010).

- Lowercasing: All tokens were converted to lowercase to treat words with identical but different casing as the same feature. This normalisation step prevents the artificial inflation of the vocabulary.
- Stopword removal: Standard Italian stopwords were removed using SpaCy's predefined list, which was supplemented with a custom lexicon of domain-specific terms and email-specific expressions. This included formal salutations, closings, and a curated list of recurring boilerplate phrases (e.g. legal disclaimers, environmental notices) and personal disclaimers, which were deemed semantically uninformative and irrelevant for the classification task.
- PII filtering: Personally identifiable information (PII)—including names, email addresses, telephone numbers, fiscal codes, and dates/time references—was detected and removed using a hybrid approach combining regular expressions and custom rule-based patterns in SpaCy. This process ensured full compliance with privacy standards and prevents the classifier from learning spurious associations based on sensitive identifiers. A similar rule-based strategy, successfully applied to Hungarian electronic health records, has demonstrated the effectiveness of NLP techniques for automated de-identification in domain-specific contexts (Berzi et al., 2023).

These pre-processing steps played a key role in reducing feature sparsity and noise, while standardising linguistic patterns across tickets and minimising the impact of irrelevant or sensitive information on model training. Such procedures are fundamental to improve computational efficiency and classification accuracy, especially when handling informal or semi-structured text typical of email-based communications (Méndez et al., 2005).

4. Methodology

The classification of support tickets was framed as a supervised multi-class problem, in which each message was assigned to one of 29 predefined categories. This approach follows established practices in text classification and relies on a pipeline integrating feature extraction, model training, and evaluation based on multiple metrics.

To convert the unstructured textual data into a machine-readable format, the input was vectorised using the Term Frequency–Inverse Document Frequency (TF-IDF) technique (Salton & Buckley, 1988), configured to extract both unigrams and

bigrams. This allowed the model to account for individual word relevance as well as short lexical patterns observed in user communications. Tokens appearing in fewer than five documents were excluded to reduce noise and improve generalisation. A major challenge in this task was the strong class imbalance across ticket categories⁷. To mitigate this, all categories with fewer than 205 instances were merged into a single residual class (labelled X), thereby enhancing statistical robustness and improving model stability.

The dataset was then partitioned using an 80/20 stratified train–test split, with class labels numerically encoded. For oversampling, the Synthetic Minority Oversampling Technique (SMOTE) was applied to the training set to increase the representation of minority classes (Fernández et al., 2018). To limit oversampling noise, the number of nearest neighbours was dynamically adjusted based on the smallest class size (Chen et al., 2024). Three classification models were evaluated using the same pre-processing pipeline and TF-IDF feature set to ensure comparability. While the input representation and data split remained constant, the classifier architecture varied across model configurations. Evaluation metrics included overall accuracy, as well as class-level precision and recall, along with both weighted and macro-averaged⁸ versions of precision, recall, and F1 scores⁹.

The first setup employed a Random Forest (RF) classifier with 200 decision trees and a maximum depth of 50, balancing model complexity and overfitting risk. RF models aggregate predictions from multiple trees trained on random subsets of data, introducing stochasticity that reduces variance and enhances generalisation (Géron, 2019). This architecture is particularly suitable for capturing non-linear relationships and is widely recognised as a robust baseline for classification tasks (Breiman, 2001). The second setup retained the same pipeline architecture but replaced the classifier with light gradient boosting machine (LightGBM), a framework optimised for speed and memory efficiency in high-dimensional contexts such as text classification. The model was configured with 200 estimators and a maximum tree depth of 40, offering a trade-off between performance and generalisation. As in the RF model configuration, TF-IDF features—including both unigrams and bigrams—were used, and SMOTE was applied to address class imbalance. LightGBM’s histogram-based learning algorithm enabled faster training and better handling of

⁷ Some categories were significantly underrepresented in the original dataset, making it difficult for the classifier to learn consistent patterns. This included, for example, category A4 (“server malfunctions, slow system, supported browser, smartphone form filling”), F1 (“survey calendar”), and F11 (“form blocking, issues submitting the questionnaire”).

⁸ While weighted metrics account for class imbalance by giving more weight to frequent classes, macro-averaged metrics treat all classes equally, offering a better measure of the model’s ability to generalise across minority categories.

⁹ For a comprehensive description of these metrics, see Géron A., 2022.

sparse input, making it a strong candidate for large-scale, multi-class classification tasks (Ke et al., 2017). The third setup explored a neural network-based approach using a Multilayer Perceptron (MLP) classifier. The architecture consisted of a single hidden layer with 50 neurons and was trained for a maximum of 200 iterations, with early stopping enabled to prevent overfitting when no further improvement was observed on the validation set. As in the previous setups, the input was based on TF-IDF features. However, to improve convergence and reduce the dimensionality of the feature space, the vectorizer was slightly modified to extract only unigrams and to exclude tokens appearing in fewer than 10 documents. SMOTE was again applied to rebalance the training data. While the MLP offered a more flexible modelling structure, its performance was more sensitive to feature sparsity and class imbalance, particularly for underrepresented categories (Haykin, 1994).

5. Results

The outcomes of the three classification setups are presented and compared in Table 1. The evaluation focused on the models' ability to handle the imbalanced multi-class nature of the dataset, highlighting their respective performance across both frequent and underrepresented categories. Among the tested configurations, LightGBM yielded the best overall performance. It achieved the highest scores across all evaluation metrics, including accuracy (0.65), weighted precision, recall, and F1-score (all 0.65), along with the best macro-F1 score (0.52), indicating greater robustness in handling both frequent and rare classes. While weighted metrics account for class imbalance by giving more weight to frequent classes, macro-averaged metrics treat all classes equally, offering a better measure of the model's ability to generalise across minority categories. These results confirm LightGBM's suitability for high-dimensional, sparse classification tasks and its effectiveness in managing imbalanced data distributions.

The Random Forest classifier achieved slightly higher weighted precision (0.67) compared to LightGBM, suggesting a tendency to produce more confident positive predictions. However, this came at the cost of lower recall (0.61), which negatively impacted the overall balance of the model's performance ($F1 = 0.63$; macro-F1 = 0.50). This behaviour reflects a more conservative classification pattern, where relevant instances—particularly in minority classes—are more likely to be missed.

The MLP classifier, while conceptually more flexible due to its neural architecture, underperformed in comparison to the ensemble-based models. It yielded the lowest accuracy (0.57), as well as the lowest weighted and macro-averaged F1-scores (0.58 and 0.44, respectively). These results suggest that the MLP was more sensitive to the sparsity and imbalance of the input data. Despite

preprocessing efforts to limit rare features and improve convergence, they struggled to generalise effectively, especially on underrepresented categories.

Table 1 – Performance metrics of the classification models on the multi-class ticket dataset.

Model	Accuracy	Precision		Recall		F1	
		Macro	Weighted	Macro	Weighted	Macro	Weighted
Random Forest	0.61	0.49	0.67	0.54	0.61	0.50	0.63
LightGBM	0.65	0.52	0.65	0.53	0.65	0.52	0.65
MLPClassifier	0.57	0.42	0.60	0.47	0.57	0.44	0.58

Source: elaboration on support tickets from ISTAT’s PUC platform (June 2024 - February 2025).

Figure 1 – Heatmap of class-wise F1-scores for Random Forest, LightGBM, and MLP classifiers on the dataset.

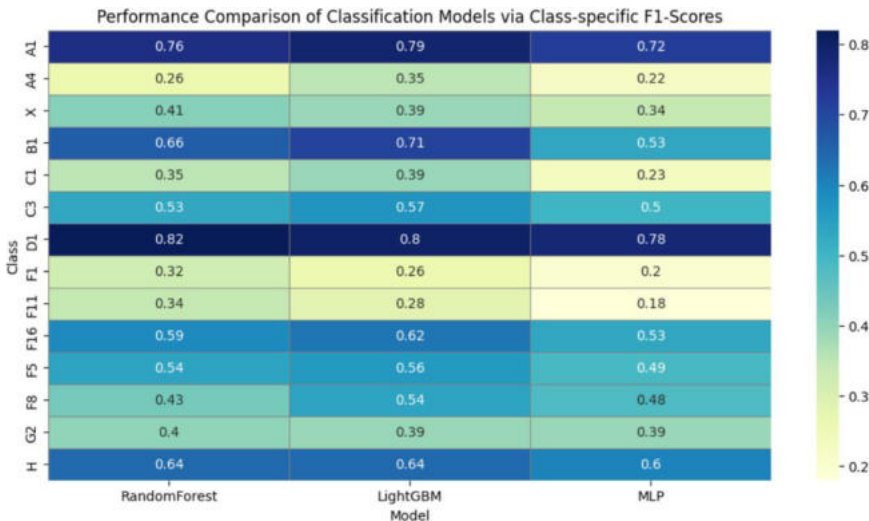


Figure 1 further illustrates these findings by reporting the F1-score achieved by each model for every target class. The most represented classes, such as A1 and D1, achieved high F1-scores across all models (above 0.7), indicating that the classifiers are able to correctly learn and predict these well-populated categories. Other classes such as F16, F5, and F8 showed moderate F1-scores (around 0.5–0.6), suggesting a fair level of predictive capability. In contrast, some underrepresented or imbalanced classes, including A4, F1, F11, and G2, exhibited significantly lower F1-scores (often below 0.4), highlighting the difficulty of all models in handling these categories. This result suggests that, despite the use of SMOTE with $k\_neighbors=5$, oversampling may not be fully effective for classes with very few examples or

complex feature distributions. Furthermore, LightGBM demonstrated improved performance over Random Forest for certain minority classes, such as B1 and C3, reflecting its stronger ability to capture class-specific patterns in the data. Conversely, the MLP classifier tended to underperform, particularly on less frequent classes—likely due to limited generalisation capacity or the need for further tuning or more complex architectures.

A qualitative inspection of misclassified instances revealed that most errors occurred between semantically adjacent categories within the same high-level scenario. Confusion was frequent between regulatory-related classes (e.g., B1 and B5) and questionnaire-related categories with overlapping procedural content (e.g., F5 and F8), indicating that misclassifications reflect genuine ambiguity in user language rather than randomness. Some failure cases involved very short or underspecified messages, such as brief requests lacking explicit references to the issue (e.g., “I need clarification about the survey”), difficult to disambiguate even for human operators. Other tickets contained multiple intents within a single message, leading the classifier to prioritise the most frequent or lexically salient category. These findings highlight intrinsic limitations of single-label classification in real-world support data and suggest that future work could explore multi-label approaches or the inclusion of contextual metadata to better capture user intent.

6. Conclusions and future perspectives

The experimental results confirmed the feasibility and effectiveness of using NLP and supervised learning techniques to automatically classify user support tickets in a public administration context. Among the tested models, LightGBM showed the most balanced and reliable performance, making it suitable for integration into real-world chatbot training pipelines.

Initially, development and testing were conducted using Einstein Bot, an AI solution embedded in Salesforce. This chatbot relied on NLP and ML technologies to analyse conversations, interpret user intent, and generate accurate responses through a supervised classification model.

During the project, ISTAT transitioned to a new conversational platform—Agentforce—representing a significant technological shift. Unlike traditional chatbots based on pre-defined decision trees, Agentforce is a generative agent capable of understanding natural language, reasoning through conversation, and dynamically selecting actions using both structured and unstructured sources.

Within this architecture, the classification model can enrich the Agent’s knowledge base by assigning semantic labels to user requests, improving context interpretation, enhancing response relevance, and supporting real-time decision-

making. However, some categories remain underrepresented or are associated with brief and ambiguous messages. These limitations can be mitigated by expanding the training dataset with additional contextual signals, historical behaviour, and newly collected tickets, which will enable finer-grained classification and a more detailed taxonomy.

Future work will focus on integrating the classification module into Agentforce and evaluating its impact on end-to-end chatbot performance. Ensuring that the system learns from high-quality, verified content is essential to reduce the risk of reproducing inaccurate responses.

This work demonstrates how AI-driven automation can enhance digital public services, providing a replicable model for intelligent support systems in data-intensive institutional environments. Within Agentforce, the classifier serves as an upstream semantic enrichment component: probabilistic intent labels guide response generation and knowledge retrieval, improving response consistency and reducing hallucination risks while posing challenges related to latency, confidence calibration, and taxonomy alignment.

References

- AOKI N. 2020. An experimental study of public trust in AI chatbots in the public sector. *Government information quarterly*, Vol .37, No.4.
- BERZI A., BERÉNYI E., KÉPES Z., ANTAL B., VARGA Á. G., EMRI M. 2025. NLP-based removal of personally identifiable information from Hungarian electronic health records. *Frontiers in Artificial Intelligence*, Vol. 8, 1585260.
- BIANCHI G., BELLINI G., BOSSO P., PAPA P. 2022. A machine learning based help-desk approach for units involved in official surveys. In *Proceedings of UNECE Expert Meeting on Statistical Data Collection 2022*.
- BREIMAN, L. 2001. Random forests. *Machine learning*, Vol. 45, pp. 5-32.
- CHEN, Y., ZOU J., LIU L., HU C. 2024. Improved Oversampling Algorithm for Imbalanced Data Based on K-Nearest Neighbor and Interpolation Process Optimization. *Symmetry*, Vol. 16, No. 3, p. 273.
- EUROPEAN COMMISSION 2020. *AI watch - artificial intelligence in public services*. Technical report.
- EUROPEAN COMMISSION 2024. *Horizon 2020 - Automated, Transparent Citizen-Centric Public Policy Making based on Trusted Artificial Intelligence*. Project web page. <https://cordis.europa.eu/project/id/101004480/results>.
- FERNÁNDEZ A., GARCIA S., HERRERA F., CHAWLA N. V. 2018. SMOTE for learning from imbalanced data: progress and challenges, marking the 15-year anniversary. *Journal of artificial intelligence research*, Vol. 61, pp. 863-905.

- GÉRON A. 2022. *Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow: Concepts, tools, and techniques to build intelligent systems*. O'Reilly Media, Inc.
- HAYKIN S., 1994. *Neural networks: a comprehensive foundation*, Prentice Hall PTR.
- INPS 2024. *Linee guida sull'implementazione di sistemi di Intelligenza Artificiale in INPS*. Direttiva del Direttore Generale n. 8 del 8 aprile 2024. Allegati circolare 14541.
- KE G., MENG Q., FINLEY T., WANG T., CHEN W., MA YE Q., LIU T. Y. 2017. Lightgbm: A highly efficient gradient boosting decision tree. *Advances in neural information processing systems*, Vol. 30.
- MANNING C. D., RAGHAVAN P., SCHÜTZE H. 2010. An introduction to information retrieval. In Mogotsi, I. C. (Ed.), *Information retrieval*, Cambridge University Press, pp. 192-195.
- MARCEDDU A., Miccoli, M., Amicone, A., Marangoni, L., Risso, A. 2024. Artificial Intelligence for Urban Safety: A Case Study for reducing road accident in Genoa. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Vol. 48, pp. 131-138.
- MENDEZ J. R., IGLESIAS E. L., FDEZ-RIVEROLA F., DÍAZ F., CORCHADO J. M. 2005. Tokenising, stemming and stopword removal on anti-spam filtering domain. In: Marín, R., Onaindía, E., Bugarín, A., Santos, J. (Eds) *Current Topics in Artificial Intelligence*. CAEPIA 2005. Lecture Notes in Computer Science, Vol 4177. Springer, Berlin, Heidelberg.
- SALTON G., BUCKLEY C. 1988. Term-weighting approaches in automatic text retrieval. *Information processing & management*, Vol.24, No. 5, pp. 513-523.
- TWIZEYIMANA J.D., ANDERSSON A. 2019. The public value of E-Government—A literature review. *Government information quarterly*, Vol. 36, No. 2.
- VAN NOORDT C., MISURACA G. 2022. Artificial intelligence for the public sector: results of landscaping the use of AI in government across the European Union. *Government information quarterly*, Vol. 39, No. 3.
- VASSILAKOPOULOU P., HAUG A., SALVESEN L. M., PAPPAS I. O. 2023. Developing human/AI interactions for chat-based customer services: lessons learned from the Norwegian government. *European journal of information systems*, Vol. 32, No. 1, pp. 10-22.

THE PRELIMINARY RECODING PROCEDURE FROM ATECO 2022 TO ATECO 2025

Francesca Alonzi, Annarita Mancini, Caterina Viviano

Abstract. On 1 January 2025, the revised Italian classification of economic activities, Ateco 2025, entered into force. To implement it for both statistical and administrative purposes, an automated procedure recodes enterprises according to the new scheme. This process relies on a mapping and operational correspondence table that automatically resolves one-to-many cases between Ateco 2022 and Ateco 2025. This research work is intended to describe the process of development of the above-mentioned tool including: i) the application of an automatic matching algorithm that compares the text strings headings and inclusion notes of the two classifications Ateco 2022 and Ateco 2025, ii) the analysis of the SEA Survey of Economic Activities results and iii) the involvement of classification experts. Results have shown that, in the absence of any kind of information describing the economic activity at individual level, the developed tool is very useful to make a preliminary large scale recoding of registers and archives of enterprises maintained by various bodies.

1. Introduction

The Italian classification of economic activities is known as Ateco. Deriving from the European NACE, it is adopted by Istat for statistical purposes especially within the business statistics, i.e. for the compilation and dissemination of official statistical data on enterprises. However, it is also used for non-statistical purposes by several administrative bodies such as Chambers of Commerce and tax authorities; the Ateco classification is also widely used by the Government and local agencies, trade associations and other organisations.

The latest version of the Ateco classification, namely Ateco 2025, represents the national version of the European NACE Rev. 2.1 nomenclature. Economic classifications like NACE and its national counterparts, such as Ateco in Italy, play a fundamental role in organising statistical information. In order to depict the real world of enterprises in a reliable way, such classifications must adapt over time to structural economic changes and emerging technologies. The transition from the previous version, Ateco 2022, to the newest Ateco 2025, reflecting the updated NACE version, has introduced new challenges in ensuring the continuity and comparability of economic data.

Into force since January 1, 2025, Ateco 2025 started to be implemented by Istat and other organisations since April 1, 2025. Known as ‘the implementation date’, April 1, 2025 is therefore not a regulatory constraint for other administrations but a choice deliberately agreed upon by Istat, Chambers of Commerce and tax authorities to undertake in a coordinated way the numerous tasks necessary to guarantee the complete transition to the new classification within their own registers and informative systems. In order to assist such a complex operation, Istat jointly with the Italian Chambers of Commerce have developed an operational correspondence table to massively and automatically reclassify enterprises in statistical and administrative registers according to the new Ateco code.

As stated by Alonzi *et al.* (2024), from a theoretical perspective, correspondence tables provide the most relevant framework for supporting recoding activities. However, in the absence of detailed information on economic activities at the individual level — whether from statistical surveys or administrative sources — several methods can be developed to assign new codes on a group basis. The method based on a single code can only be applied to one-to-one (1:1) or many-to-one (N:1) changes from the old to the new classification; that is, using simple correspondences, a classification at the lowest aggregation level is directly recoded to the revised classification. In these cases, the corresponding new code is the only eligible option. In all other cases, further methods are needed. To this aim, the new tool developed by Istat was specifically designed to answer the following research question: *Which methods can be used to recode enterprises involved in one-to-many links from the former classification to the new one without detailed information on the specific activities of each enterprise?* To the best of our knowledge, the developed tool is one of a kind and offers a range of potential applications. Moreover, unlike a standard technical report, it is provided in a user-friendly format that can be integrated into any program or information system with minimal adjustments.

The content of this work is divided into five sections. Apart from the first section that is devoted to the introduction, the second one is intended to provide a background on the Ateco classification. All data and methods used in this study are presented in the third section while the major results are described in the fourth section. Finally, the last section contains the main conclusive remarks on the issues dealt with in this study presenting and critically evaluating the output.

2. Background

2.1. The structure and contents of the Ateco classification

Ateco is a hierarchical classification system aligned with the European NACE at the first four levels, and extended to additional levels (fifth and sixth) to provide a

more detailed representation of the national context. Structurally, it consists of codes and headings (categories in the broad sense). Each Ateco code represents an economic activity that is shortly described by its heading. In this way, Ateco codes, together with their headings, provide a standardised definition of all economic activities carried out by enterprises, enabling the grouping of enterprises with similar characteristics for statistical, administrative, fiscal, and other purposes. Figure 1 illustrates an example of Ateco codes as well as of the relationship between NACE and Ateco classifications.

Figure 1 – *The structure of the Ateco classification: an example.*

NACE – European classification		
Section	C	Manufacturing
Division	30	Manufacture of other transport equipment
Group	30.9	Manufacture of transport equipment n.e.c.
Class	30.91	Manufacture of motorcycles
Category	30.91.1	Manufacture of motorcycles, other than parts and accessories
Subcategory	30.91.11	Manufacture of engines for motorcycles
	30.91.12	Manufacture of motorcycles, other than engines
	30.91.2	Manufacture of parts and accessories for motorcycles
	30.91.20	Manufacture of parts and accessories for motorcycles

Nevertheless, while a short title may be sufficient to describe simple and common economic activities (e.g., growing of rice), it generally does not meet the clarity standards required for a statistical classification. For this reason, the structure (codes and headings) of the Ateco classification are enriched by definitional descriptions (explanatory notes) that provide supporting information about the classification codes and headings. They are statements which clearly define the category or they may assist users in determining the boundaries of the category. Explanatory notes may explain the content by giving examples of inclusions and exclusions or provide rules or guidelines for how to use that category. Explanatory notes are optional but are usually included in the classification when further definition of categories is required.

2.2. The theoretical correspondence table between Ateco 2022 and Ateco 2025

A correspondence provides a link between different versions of a classification or between different classifications. A correspondence details how a category in one classification relates, or links, to the new/other classification (Hancock, 2013).

To facilitate the full implementation of the new classification within statistical, administrative or other types of processes, correspondence relationships between the new Ateco 2025 classification and its previous version (Ateco 2022) have also been made available. The correspondence relationships are presented in the form of a table, known as correspondence, conversion or mapping table, in which each Ateco 2025 code is linked with at least one Ateco 2022 code (Alonzi and Viviano, 2025). This is therefore a theoretical mapping; for instance, when an old category splits into several categories in the new classification, all possible links are provided. Thus, the correspondence table is designed to support the recoding of enterprises (and other statistical units) when transitioning between the previous and the new classification.

A total of 6,678 correspondence relationships were identified across the various hierarchical levels of the Ateco classification. Each correspondence relationship defines a link between a pair of Ateco codes: one Ateco 2025 code and one Ateco 2022 code. Table 1 presents the theoretical correspondence links between Ateco 2022 and Ateco 2025 across hierarchical levels, along with the number of codes in each classification at each level.

Table 1 – Theoretical correspondence links between Ateco 2022 and Ateco 2025

Hierarchical level	No. of Ateco 2022 codes	No. of Ateco 2025 codes	Correspondence links
1 Section	21	22	80
2 Division	88	87	251
3 Group	272	287	566
4 Class	615	651	1,171
5 Category	920	920	1,883
6 Subcategory	1,241	1,290	2,727
Total	3,157	3,257	6,678

The correspondence links are of different types:

- 1:1 (one-to-one): one Ateco 2022 corresponds to only one Ateco 2025, and vice versa;
- N:1 (many-to-one): many Ateco 2022 codes merging into a single Ateco 2025 code;
- 1:M (one-to-many): one Ateco 2022 code splitting into several Ateco 2025 codes;

- N:M (many-to-many): many Ateco 2022 codes linked to many Ateco 2025 within complex structural changes.

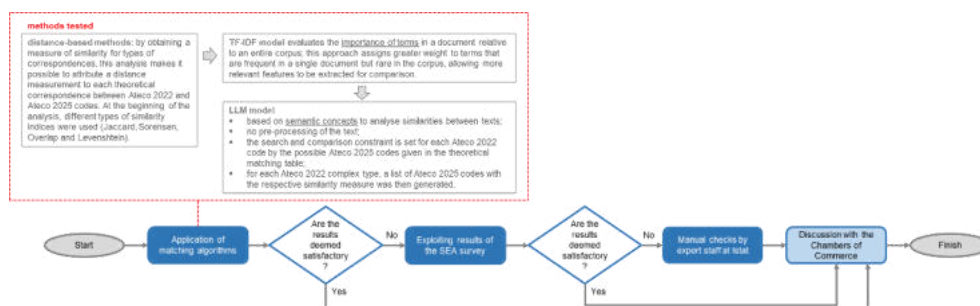
One-to-one and many-to-one cases can be seen as simple matches: in such cases, an automatic recoding of Ateco 2022 codes can be applied straightforward. However, the most frequent types of relationships (representing more than 70 percent of all correspondences) are of many-to-many type, which, along with one-to-many relationships, is considered complex for reclassification purposes. In these cases, the recoding is possible only if specific information is available, i.e. information describing the economic activity carried out by the statistical unit (information at the micro level). Especially in the early phase of recoding, this step is impractical for direct operational use when ambiguous correspondences exist, no specific information is available or when there is the need to have a tool to recode a large number of units in a short time.

3. Developing the operational correspondence table: methods

The theoretical correspondence table can be easily applied to 1:1 links or to complex links when information at the micro level, i.e. referring to each single unit, is available. In order to solve in an automatic way the cases of complex matches transforming them in simple matches (1:1), Istat developed an operational correspondence table, which assigns a single predominant Ateco 2025 code to each Ateco 2022 code, ensuring consistency for automated reclassification across large statistical and administrative registries. The logic underlying the operational table is to associate each Ateco 2022 code with a single, most representative, Ateco 2025 code among those proposed by the theoretical correspondence table. The choice of the Ateco 2025 code to be uniquely associated to the starting Ateco 2022 is the result of an integrated methodology combining in cascade the following three components (Alonzi *et al.*, 2025).

1. Using an automatic matching algorithm that compares headings and inclusion notes (text strings) of the two classifications, Ateco 2022 and Ateco 2025. This algorithm assigns a similarity measure to each of the M possible Ateco 2025 linked to each Ateco 2022 code, resulting from the comparison of the words into which the set of strings (headings and explanatory notes) is broken down.
2. Using the results of the Survey of Economic Activities (SEA) — also known as Ateco survey — to support automatic unsatisfactory choices based on similarity scores resulted from the above algorithm.
3. Applying manual checks when results are still unsatisfactory.

Figure 2 illustrates the main steps of the methodology.

Figure 2 – The methodology: main steps.

3.1. The automatic matching algorithm to compare headings and inclusion notes of Ateco 2022 and Ateco 2025

The innovative aspect of this procedure lies in its use of automatic matching methods based on textual analysis¹, designed to simplify a complex task that would be excessively burdensome if performed manually. The initial aim of the algorithm was to associate each Ateco 2022 code with all Ateco 2025 codes exhibiting similar informational content, based on an analysis of the headings and explanatory notes of both classifications. Each identified pair was assigned a similarity score, guiding the selection toward the pair with the highest score while respecting the constraints of the theoretical correspondence table² (Rajaraman and Ullman, 2011).

Several methods were tested to determine the most appropriate similarity measure between the strings of the two classifications. The processing phase was carried out using the Python programming language. At first, a pre-processing of the initial data was necessary, which involved two main steps: i) removal of irrelevant words (stop words): terms not meaningful for content analysis; ii) conversion of words to their lexical root (stemming), to reduce them to their base forms.

Each Ateco 2025 code deemed similar to the source code was associated with a similarity indicator (or score). Different types of similarity indices were tested, for example Jaccard, Sorensen, Overlap and Levenshtein (Cohen *et al.*, 2003; Levenshtein, 1966). However, these distance-based methods presented some critical issues. It was found that the words used in the descriptions of Ateco 2025 did not always match

¹ This step of the study received valuable support from Istat's Directorate for Methodology and Statistical Process Design.

² At first the analysis undertaken by Istat focused on 5-digit codes because, for statistical purposes, these are the codes subject to reclassification. But then the analyses were extended to all hierarchical levels of the Ateco respecting the same hierarchical level of the starting code.

those in Ateco 2022, making the previously mentioned similarity indexes ineffective. Furthermore, there have been cases in which the highest level of similarity was associated with a pair not present in the theoretical correspondence table.

To address this problem, a TF-IDF (Term Frequency-Inverse Document Frequency) method was then applied, which assesses the importance of terms in a document relative to the entire corpus. This approach assigns greater weight to terms that are frequent in a single document but rare across the corpus, allowing for the extraction of more relevant features for comparison.

Nevertheless, the TF-IDF method also has some limitations: it does not consider the semantic meaning of words, making it less effective with synonyms or different phrases that express the same concept. Moreover, it assumes independence between terms and focuses solely on frequency, making it difficult to capture the context or relationships between words (Manning *et al.*, 2008).

In a later phase, the activity shifted towards models based on semantic concepts to analyse text similarities. Among the most promising approaches, a deep learning algorithm — a Large Language Model (LLM) — was used (Wolf *et al.*, 2020; Devlin *et al.*, 2019). Its main function was to assign a similarity score between texts capable of better capturing semantics, thereby improving upon previous distance-based methods. In this method, no text pre-processing was carried out, and the scope of search and comparison was defined, for each Ateco 2022 code, by the possible Ateco 2025 codes listed in the theoretical correspondence table. The similarity score ranges from 0 to 1: the higher the value, the greater the likelihood that the match is reliable and accurate. For each complex Ateco 2022 code, a list of corresponding Ateco 2025 codes was generated along with their respective similarity scores.

Although the latter method was considered the most reliable, it still presented some critical issues, as it was not able to map all complex correspondences with a high similarity score. For this reason, the selection of the predominant or most representative Ateco 2025 code was finally based on a combination of the results from this automated tool, with the results of the Ateco survey and the manual checks by Business Register and classification experts.

3.2. *Using the results of the SEA survey and the contribution of classification experts*

Started in April and run until July 31, 2024, Istat has conducted a survey in order to detect the economic activity carried out by enterprises and to use the information collected to reclassify the units registered in the statistical business register (SBR) according to the new Ateco 2025 classification.

To address cases where automatic choices based on similarity scores proved unsatisfactory due to low values, the results of the SEA survey, where available, were taken into account, guiding the selection toward the most frequent empirical

responses. In addition, critical codes and ambiguous matches were carefully analysed by expert staff, who manually reviewed the algorithm's automatic assignments. In particular, the explanatory notes of the two classifications were checked and compared to determine the predominant Ateco 2025.

4. Main results

The operational reclassification table between Ateco 2022 and Ateco 2025 contains 3,157 one-to-one relationships (Table 2), corresponding to the number of codes included in the Ateco 2022 classification; all hierarchical levels have been considered. Each Ateco 2022 codes (source codes) is then linked to only one Ateco 2025 chosen among the M possible Ateco 2025; when the theoretical link is simple (one-to-one or many-to-one), the choice has been straightforward. The chosen code has the same hierarchical level as the source code except for some cases for which it was necessary to choose a code with a higher hierarchical level. In only one case — J Information and communication services — it was not possible to assign any code that is representative of all the thirteen possible choices.

Table 2 – *Operational reclassification table: number of links between Ateco 2022 and Ateco 2025 by type of hierarchical level.*

Hierarchical level	Same hierarchical level	Higher hierarchical level	Total
1 Section	20	1 ⁽¹⁾	21
2 Division	88	0	88
3 Group	268	4	272
4 Class	594	21	615
5 Category	887	33	920
6 Subcategory	1,113	128	1,241
Total	2,970	187	3,157

⁽¹⁾ J Information and communication services

The choice of a higher hierarchical level arises from the difficulty in choosing the most representative code among Ateco 2025 codes at the same hierarchical level as Ateco 2022, due to the original activities being distributed among new codes. In such cases, it was necessary to select a code from a higher hierarchical level because it includes all the activities covered by the more detailed lower-level codes. It is the case, for example, of Ateco 2025 code 47.1 — Non-specialised retail sale — that is being repeated several times as a representative code also for several lower-hierarchy Ateco 2022 codes (Table 3).

Table 3 – *Example of the operational table when the chosen representative code 47.1 'Non-specialised retail sale' occurs several times.*

Ateco 2022 code	Ateco 2022 heading	No. of theoretical matches	Type of correspond.	Representative Ateco 2025 code
47.1	Retail sale in non-specialised stores	2	N-M	47.1
47.8	Retail sale via stalls and markets	6	N-M	47.1
47.9	Retail trade not in stores, stalls or markets	27	N-M	47.1
47.91	Retail sale via mail order houses or via Internet	32	N-M	47.1
47.91.1	Retail sale via Internet	74	N-M	47.1
47.91.10	Retail sale via Internet	96	N-M	47.1
47.91.2	Retail sale via television	72	N-M	47.1
47.91.20	Retail sale via television	94	N-M	47.1
47.91.3	Retail sale via mail order houses, radio, telephone	73	N-M	47.1
47.91.30	Retail sale via mail order houses, radio, telephone	95	N-M	47.1
47.99	Other retail sale not in stores, stalls or markets	54	N-M	47.1
47.99.1	Retail sale through door-to-door sale agents	95	N-M	47.1
47.99.10	Retail sale through door-to-door sale agents	118	N-M	47.1
47.99.2	Retail sale through vending machines	22	N-M	47.1
47.99.20	Retail sale through vending machines	25	N-M	47.1

The advantages of such a table are clear, as its use enables large-scale automation of conversion operations. However, some critical issues also arise that deserve attention. By design, the selection of a single code, although considered the most

representative, is suitable in most cases, offering an effective and standardised solution. Nonetheless, it tends to sacrifice heterogeneity, failing to represent the specificities of economic activities considered less frequent or representative, which may have been split from the original Ateco code. It is therefore worth noting that some Ateco 2025 codes are never selected as representative codes, while other codes are chosen many times (Table 4). Moreover, the adoption of a representative code showing a lower hierarchical level than the one required by the recoding operations (e.g. in the SBR the Ateco code is implemented at 5 digits), necessitates the development of supplementary methods for completing the code to the required digits.

Table 4 – *Operational reclassification table: number of Ateco 2025 chosen repeatedly and not represented.*

Hierarchical level	No. of Ateco 2025 codes chosen repeatedly	No. Ateco 2025 codes not represented	Total
1 Section	20	2	22
2 Division	86	1	87
3 Group	260	27	287
4 Class	564	87	651
5 Category	804	116	920
6 Subcategory	979	311	1,290
Total	2,713	544	3,257

As expected, the percentage of Ateco 2025 codes never chosen increases as the granularity of the classification structure increases: it reaches a 24 percent rate of codes never chosen at lowest level (hierarchy 6). Anyway, there is no doubt about the potential offered by the operational reclassification table, which makes it possible to “squeeze” complex correspondences into simple relationships.

5. Conclusions

Implementing a new classification of economic activities poses several challenges, particularly when it introduces new categories that statistical and administrative registers lack sufficient information to recode units at the micro level. This research work presented the development of an operational correspondence table between Ateco 2022 and Ateco 2025 to solve in an automatic way and at macro level the cases of one-to-many splits by identifying only one Ateco 2025 (the

‘predominant’ or ‘most representative’) among M Ateco 2025 associated to the starting Ateco 2022. Above all, it is the result of an automatic matching algorithm that compares headings and inclusion notes (text strings) of the two classifications, Ateco 2022 and Ateco 2025, and assigns a similarity measure. Such a tool has several advantages. The main advantage is its scalability and ability to transform complex matches into simple 1:1 matches thus enabling rapid and standardised recoding. In fact, it is useful for massive recoding operations of economic units representing a quick and standardised solution when information at the micro level is not available. This is exactly the case of both statistical and administrative registers that have applied this tool in the early phase of recoding.

The operational correspondence table has been used not only by its developers (Istat and the Italian Chambers of Commerce) but also by other administrative bodies, making it a significant step forward in the modernisation of statistical and administrative practices and a best practice in inter-institutional cooperation within the public administration. However, users should be aware of this tool’s limitations: possible information loss, especially for underrepresented activities; non-selection of some Ateco 2025 codes, leading to sectoral underestimation (e.g. intermediation service activities); reduced granularity from higher-level coding; and potential statistical error due to the adoption of probabilistic methods and practical choices.

All the above considered, the current implementation of this tool marks a first step in the recoding activities of enterprises. Over time, direct updates from enterprises themselves will refine the classification. Future improvements may involve retraining models, incorporating business feedback, and adapting the operational table to emerging economic realities. Anyway, the Ateco 2025 recoding process demonstrates the potential of combining machine learning with expert insight. The hybrid method presented in this research work offers a practical, scalable solution for updating economic classifications, though continuous refinement will be essential for its long-term success.

Acknowledgements

The authors would like to thank their Istat colleagues Alessandra Fiori, Giulio Massacci and Arianna Speranza for their valuable support in the developing of the operational correspondence table providing technical solutions and undertaking manual checks. We would also like to extend special thanks to all colleagues working for the Italian Chambers of Commerce who have heavily contributed to the development of the first draft of the table and then reviewed its final version before the official dissemination.

References

- ALONZI F., CONSALVI M., VIVIANO C. 2024. *A Comprehensive Strategy for Implementing NACE Rev. 2.1 in the Italian Statistical Business Register*. Meeting of the Group of Experts on Business Registers Organised by UNECE
<https://unece.org/statistics/events/meeting-group-experts-business-registers-0>
- ALONZI F., MANCINI A., SPERANZA A., VIVIANO C. 2025. *La tabella operativa di riclassificazione da ATECO 2007 aggiornamento 2022 a ATECO 2025*.
<https://www.istat.it/classificazione/ateco-2025/>
- ALONZI F., VIVIANO C. 2025. *Le relazioni di corrispondenza tra le classificazioni delle attività economiche ATECO 2025 e ATECO 2007 aggiornamento 2022*.
<https://www.istat.it/classificazione/documenti-ateco/>
- COHEN W. W., RAVIKUMAR P., & FIENBERG S. E. 2003. *A Comparison of String Distance Metrics for Name-Matching Task* Proceedings of the IJCAI-2003 Workshop on Information Integration on the Web (IIWeb-03)
- DEVLIN J., ET AL. 2019 *BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding* NAACL <https://arxiv.org/abs/1810.04805>
- HANCOCK A. 2013. *Best Practice Guidelines for Developing International Statistical Classifications*
https://unstats.un.org/unsd/classifications/bestpractices/Best_practice_Nov_2013.pdf
- LEVENSHTEIN V. I. 1966. *Binary codes capable of correcting deletions, insertions, and reversals*. Soviet Physics Doklady
- MANNING G., RAGHAVAN P. , SCHÜTZE H, 2008 *Introduction to Information Retrieval*, Cambridge University Press
- RAJARAMAN A., ULLMAN J. D. 2011. *Mining of Massive Datasets* Cambridge University Press
- WOLF T. ET AL. 2020. *Transformers: State-of-the-Art Natural Language Processing* EMNLP

Francesca ALONZI, Istat - Italian National Institute of Statistics, francesca.alonzi@istat.it
 Annarita MANCINI, Istat - Italian National Institute of Statistics, annarita.mancini@istat.it
 Caterina VIVIANO, Istat - Italian National Institute of Statistics, caterina.viviano@istat.it

USE OF ARTIFICIAL INTELLIGENCE IN ISTAT TO IMPROVE THE CUSTOMER EXPERIENCE ¹

Gianpiero Bianchi, Carlo Boselli, Mauro Bruno, Alessio Cardacino,
Cecilia Colasanti, Mario Magarò, Emiliano Montefiori, Francesco Ortame,
Serenella Ravioli, Francesco Rizzo

Abstract. The ongoing digital transformation, the evolution of computational capabilities and the widespread use of artificial intelligence (AI) make information management and intelligence strategies increasingly central themes. Starting from the state of the art, the aim of this paper is to explore how these phenomena are interpreted in Istat, through a project dedicated to the use of AI for the data search in Istat's data warehouse, where official statistical data are published. They include, among others, national accounts, household economic conditions, prices, labour and wages, industry, justice, services, health, education, culture, welfare, daily life, public administrations, environment and energy, and agriculture. The obtained result was to facilitate data searches through the use of an AI-based chatbot. Our goal is to enhance the user experience by assisting users in searching for content already published in the data browser.

Istat, as the official producer of statistics for our country, pays particular attention to the accuracy and quality of the data released. Even if the use of AI is widespread, from a business perspective, it is not yet a mature technology. On the one hand, therefore, the drive for innovation has led us to experiment with this new technology, and Istat is among the first public administrations to offer a similar service. On the other hand, the project, despite being online and validated by the methodological sector, and despite having trained the data only on the Istat domain, has an experimental nature. What we obtained is the first step. We expect to continuously improve our data research by investing in AI.

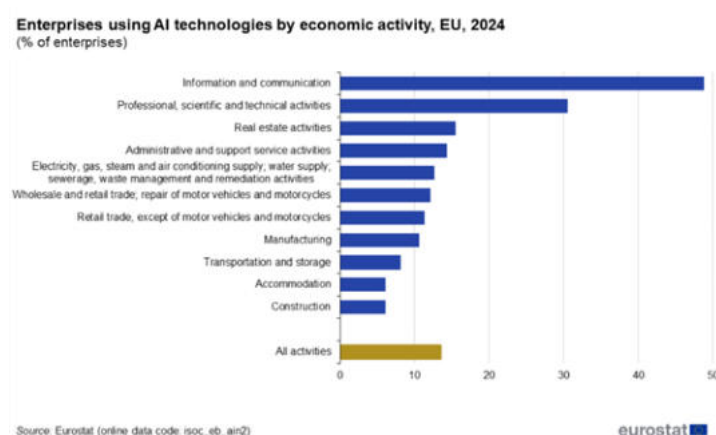
Finally, we want to emphasize the teamwork that underpinned this project. The IT, communication and methodological departments have worked in a truly synergic way, seeking together a point of balance in the complexity, in the attempt to provide a better public service.

¹ Carlo Boselli and Francesco Rizzo gave their contribution as project manager; Serenella Ravioli was responsible for the dissemination part of the project; Gianpiero Bianchi, Mauro Bruno, Francesco Ortame took care of the methodological point of view of the project; Alessio Cardacino, Mario Magarò, Emiliano Montefiori represented the IT side of the work; Cecilia Colasanti was the IT responsible and reviewed this paper.

1. Introduction

The widespread use of artificial intelligence (AI) impacts both the private and the public sectors. By referring to the “Use of artificial intelligence in enterprises”, a recent “Statistics Explained” released by Eurostat², shows that AI is developing quickly in many economic activities (Figure 1).

Figure 1 – Enterprises using AI technologies by economic activity, EU, 2024.

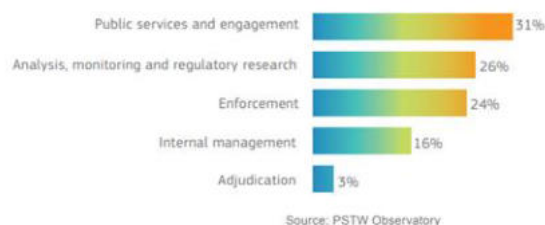


In some economic activities AI is used a lot more than in others. This might indicate that AI is more relevant for certain activities. In 2024, the information and communication sector (with 48.72%) and professional, scientific and technical service activities (with 30.53%) stood out with the highest share of enterprises that used AI.

For the government AI activities in Europe, “AI watch”, the European Commission’s Joint Research Centre (JRC), studies the evolution of this phenomenon, relevant for digital services and products in the public administration, health, transport, and education. In particular, the Public Sector Technology Watch (PSTW) provides valuable insights about AI governance and AI solutions designed to enhance services within the public sector³. As shown in Figure 2, 31% of AI public applications are referred to as “Public services and engagement”.

² https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Use_of_artificial_intelligence_in_enterprises

³ <https://interoperable-europe.ec.europa.eu/sites/default/files/document/2024-04/PSTW%20-%20AI%20and%20blockchain%20in%20the%20European%20Public%20Sector.pdf>

Figure 2 – AI use cases distribution according to Process and Application Type, EU, 2024.

Within the public services and engagement domain, service personalisation emerged as the most prevalent application, accounting for 18%. This also marks the highest application type across the entire repository. Engagement management (5%), service integration (6%), data sharing management (1%) and others (1%) represent less prevalent applications.

Naturally, the National Statistical Offices are involved in the use of AI-driven innovation to improve part of the official statistics production.

The use of an AI-based system for the dissemination of official statistics requires a very high level of commitment to validating the model's results. This is especially true when using generative AI components, which can produce not entirely accurate outcomes and must be employed carefully and sparingly. For this reason, there are very few instances of major international institutions that have developed systems or prototypes capable of ensuring adequate levels of reliability. One such example is the project launched by the International Monetary Fund called StatGPT, which is still under development. Similar to the system developed by Istat for IstatData, it uses artificial intelligence models applied to different SDMX data nodes or repositories used by international and national organizations to identify relevant datasets.

Narrowing the field to Istat, several AI-based projects have been started.

This paper aims to explore the AI-IstatData project, which focuses on leveraging artificial intelligence to enhance data search capabilities within Istat's data warehouse, where official statistics are published.

2. The Istat's corporate data warehouse

IstatData is the corporate data warehouse that disseminates the aggregate results of all socio-economic surveys conducted by the Institute. At a strategic level, our data warehouse must serve as the sole dissemination point for official statistical production. Therefore, there is an ongoing process of consolidation and migration of the different Istat web systems towards IstatData.

In recent years, the data warehouse has been enriched with information, and approximately 3,000 multidimensional tables are currently disseminated, for a total of 2 billion aggregate values. These numbers are expected to grow.

Although the information is organized into themes to make the identification of the tables easier, the growth of topics covered has required the identification of innovative technological solutions for data research, for the benefit of researchers, journalists, institutions and more general users. The AI-IstatData project was therefore born with the aim of improving the research tool and the customer experience in customizing the aggregate information available on the Institute's corporate data warehouse through the use of artificial intelligence. Specifically, to enhance semantic search capabilities an AI-based search chatbot was integrated, allowing users to interact with it. Through the same function we have enhanced the use of the user guide. Our goal is to improve the user experience by supporting them in searching for content already published in the data browser. The glossaries and information dictionaries already available on the Istat website will be integrated into the AI system. This enhancement will improve the user interface and chatbot interactions, enabling the AI to also incorporate graphs and maps in response to user queries. Furthermore, in the second phase of the project, it will be possible to maintain the history between the user and the chatbot in order to allow a more effective "dialogue".

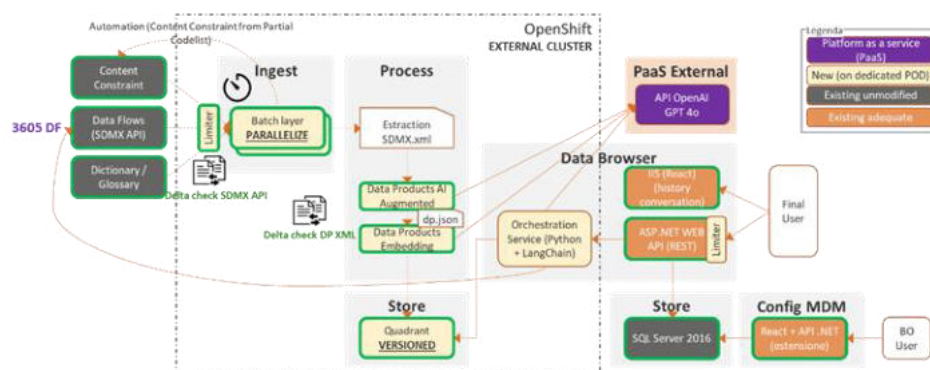
The main advantages can be summarized as follows:

- It allows searches in simple and commonly used words, using natural language (greater ease of use);
- It makes communication smoother through integrated suggestions;
- It explains why data sets are selected by the system and how they are connected to the question (greater transparency). In this way, the user trust can be maintained high.

This chatbot not only improves the search, but also the use of tools like graphic viewers and maps.

2.1. The IT point of view

IstatData is based on the open-source tools "Data Browser" and "Meta & Data Manager" developed by Istat and on the international data transfer standard, recognized by the International Standard Organization, SDMX (Statistical Data and Metadata eXchange) for the exchange and sharing of statistical data and metadata. For those who need to use these data for other developments, the platform also makes machine-to-machine access available via a specific API (Figure 3).

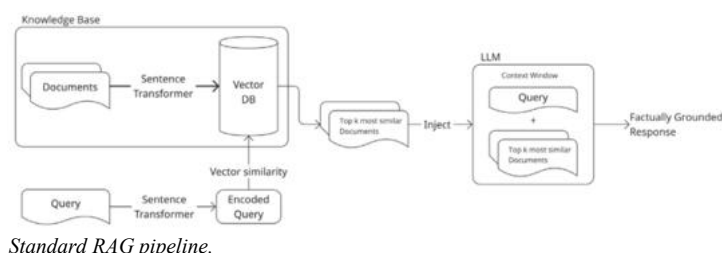
Figure 3 – IT architecture.

In addition to the use of AI, which represents a great innovation, the IT architecture is also based on cutting-edge technical standard.

2.2. The methodological point of view

Istat, as the official producer of statistics for the country, pays particular attention to the accuracy and quality of the data released. Even if AI is widely used, it is a constantly evolving technology. On the one hand, therefore, the drive for innovation has made us invest in AI (we are among the first PAs to offer a similar service); on the other hand, while the project is now live and has been methodologically validated, using exclusively Istat-sourced data, it retains an experimental character.

System Overview - The chatbot implements a retrieval-augmented generation (RAG) pipeline (Lewis et al., 2020). When a user submits a query, a GPT-4o classifier first assesses whether the query pertains to a dataset search. If not, the system displays a polite clarification or redirection. Otherwise, it proceeds to retrieve candidate datasets.

Figure 4 – Scheme of a RAG system.

Standard RAG pipeline.

Figure 4 shows the structure of a standard RAG pipeline. The knowledge base is the set of vectors representing the pool of texts we want to extract. In this case, the knowledge base comprises the complete set of Istat public datasets, each represented by multiple sentence-level dense embedding vectors and a sparse vector representing keywords for exact matching. Texts are transformed into vectors using sentence-level embedding models, specifically, OpenAI's *text-embedding* models. The whole set of vectors is stored in a vector database. Next, a natural language query is embedded using the same embedding model, and its embedding vector is compared to the vectors in the database to extract the most similar measuring vector similarity. This step aims to extract datasets that are semantically similar to the text in the user's query. After the most similar vectors are extracted, they are mapped back to the original datasets, creating a list of candidate datasets. This is list of result displayed in the user interface. This list and the user's query are injected into a lightweight GPT-4o-mini model, which synthesizes a coherent, context-aware, user-friendly response.

Evaluation - There has been a careful evaluation process, particularly towards the relevance of the extracted datasets given user queries, including manual labelling of results with several degrees of relevance.

To test and enhance the search algorithm and its relevance ranking, two distinct types of questions were developed: (1) 340 *specific* questions, each linked to a single correct answer within a strictly relevant dataset, and (2) 516 *generic* questions for which the number of pertinent datasets is broader.

Specific questions were developed by domain experts and data modelers, both familiar with the respective data structures. They formulated these questions by analyzing the contents of specific data structures. Generic questions were developed by domain experts and internal Istat platform users who work closely with end-users and have experience with the types of queries most commonly submitted.

Regarding relevance testing, for the specific questions, it was possible to perform a direct comparison between the search system's results and the predetermined set of correct answers. For the generic questions, however, a manual, point-by-point review of the coherence of the system's top 20 answers for each query was required. This human evaluation was conducted by domain and data warehouse experts, as the number of relevant answers is higher and they can span different thematic areas.

Retrieval Strategy – The retrieval strategy was defined empirically based on the system's performance in the relevance tests (Table 1). Initially, a hybrid—yet non-hierarchical—model combining dense and sparse vector components was used. This approach achieved a 65% objective match rate for specific queries within the top five results. For generic queries, an average of only 57.4% of the top 10 answers were

deemed correct by the domain experts and data warehouse evaluators, with 14% considered non-relevant and a significant 34% being non-relevant and exhibiting clear characteristics of hallucination.

Analysis of the generic responses led to a breakdown into two subsets of comparable size: one derived solely from the dense vector component and the other solely from the sparse vector component. This revealed that the correct answer rate in the first subgroup (dense-only) rose to 81%, while it fell to 17% in the second (sparse-only). Notably, within the sparse-only subset, the rate of hallucinated answers rose to 65%. Furthermore, it was interesting to observe that in the group of answers identified by both the dense and sparse components simultaneously, the share of correct answers rose to 82%, with a noticeable shift of correct results into the top 10 positions.

Given that the answers generated by the sparse component alone were characterized by a substantial rate of hallucinations, the decision was made to adopt a hierarchical model. This model first identifies a preliminary subset of answers using the dense component and then applies a hybrid of both dense and sparse methods within this subset. While other approaches were experimented with, this hierarchical model yielded the most significant increase in correct answers. Specifically, for specific queries, the rate of correct answers in the top 5 results rose to 71% (compared to 65% with the non-hierarchical model). For generic queries, the rate of correct answers within the top 10 results increased to 81%.

Table 1 – Dataset retrieval accuracy for different scenarios.

Scenario	Acc. on specific queries (Presence/Top 5)	Acc. on generic queries (Relevant / Top10)
Dense + Sparse non Hier	0.652	0.574
Dense + Sparse Hier	0.713	0.805

Results ranking.

3. A team effort

Artificial intelligence, like any multifaceted phenomenon, requires different professional skills and sensibilities to be governed. Teamwork and deep synergy among different skills become critical success factors especially for a project that uses AI. The introduction of this chatbot is a good example to show the power of team working. Within Istat, the Departments of communication, IT and statistical

methodology have worked in a synergic way, seeking together a point of balance between innovation and rigor. The strategic goal of improving the user experience led us to choose the project manager in the communication area, where the statistical contents of the data warehouse are managed. On the other hand, it was the work of the IT department that allowed the development and release of the project within the expected time and with the required quality, and thanks to the methodological department the rigor of the results was obtained. Naturally, the Department of Legal Affairs also contributed for the risk analysis and for the disclaimer published on the website.

4. Conclusion

The fact that there aren't many analogous experiences makes this project original and pioneering compared to international institutions similar to ours. Istat's experience can be considered food for thought for other producers of official statistics.

First of all, this AI-based project is based on a platform (IstatData) that has centralized and rationalized the statistical data disseminated. Master data management activity is therefore preliminary to any AI project. Indeed, good data quality is an essential element to ensure the quality of the required results.

Connected to the first, the semantic correctness of the data was an element in which Istat invested heavily before applying AI.

Continuous tuning of the results improves the quality of the responses offered to users.

This is a virtuous and meaningful example in which a public institution, putting together its different souls, is providing a better service to the country.

Acknowledgements

The Authors thank the Istat colleagues Mara Cammarota, Daniela Casale, Cecilia Catalano, Gianluca D'Amato, Catello Di Somma, Gianluca Ferri, Alessandro Ghizzoni, Luigi Malatesta, Fausto Panicali, Manlio Paterniti, Mirko Tassinari, Leonardo Tininini, Michela Troia for their contribution to the implementation of the work.

References

- LEWIS P. PEREZ E., PIKTUS A., PETRONI F., KARPUKHIN V., GOYAL N., ...
, KIELA D. 2020. Retrieval-augmented generation for knowledge-intensive NLP
tasks. In *Proceedings of the 34th International Conference on Neural Information
Processing Systems*, Article No. 793, pp. 9459 – 9474.
- EUROSTAT. 2025. Use of artificial intelligence in enterprises, *Statistics Explained*.
- BRIZUELA A. et al. 2024. *Public Sector Tech Watch. Mapping Innovation in the
EU Public Services*. Luxembourg: Publications Office of the European Union.

Gianpiero BIANCHI, Istat, gianbia@istat.it
Carlo BOSELLI, Istat, cboselli@istat.it
Mauro BRUNO, Istat, mbruno@istat.it
Alessio CARDACINO, Istat, alcardac@istat.it
Cecilia COLASANTI, Istat, cecolasa@istat.it
Mario MAGARO', Istat, magaro@istat.it
Emiliano MONTEFIORI, Istat, montefiori@istat.it
Francesco ORTAME, Istat, francesco.ortame@istat.it
Serenella RAVIOLI, Istat, serenella.ravioli@istat.it
Francesco RIZZO, Istat, rizzo@istat.it

BOOTSTRAP DOUBLE FREQUENCY DICKEY FULLER TEST FOR UNIT ROOTS

Margherita Gerolimetto, Stefano Magrini

Abstract. In this paper we present some advances over the Double Frequency Dickey Fuller test for unit root, recently proposed in literature to capture those situations where the time series might be affected by potential unknown structural breaks, asymmetrically located.

The Double Frequency Dickey Fuller is based on the idea the Fourier approach allows capturing the behavior of a deterministic function form even if it is not periodic, working better than dummy variables, independent of the breaks are instantaneous or smooth and avoiding the problem of selecting the dates and the form of the breaks. For the Double Frequency Dickey Fuller test, it has been developed the asymptotic theory and, via simulations, its finite sample properties have been shown with respect to a variety of processes.

To the best of our knowledge, however, no results have yet been presented to combine this test with using bootstrap methods, in order to possibly improve the finite sample performance. To address this issue, we propose a bootstrap test based on the sieve bootstrap for unit root and intend to conduct an extensive Monte Carlo experiment to evaluate its finite sample performance.

1. Introduction

Traditional unit root tests suffer from a loss of power when structural breaks in the data-generating process are ignored (Perron, 1989). By highlighting this issue, Perron (1989) initiated a new line of research focused on developing unit root tests that are robust to structural breaks or outliers in the data. This presents a significant challenge for applied economists, as the number, duration, and nature of structural breaks are often unknown. Furthermore, efforts to detect the number or location of these breaks may introduce pre-testing bias. Adding to the complexity, structural breaks occurring in a given year may not have an immediate or fully observable impact.

Early studies (Perron, 1989; Zivot and Andrews, 2002; Lee and Strazicich, 2003) addressed this issue by incorporating dummy variables to represent structural breaks. However, this approach can introduce an excessive number of nuisance parameters, limiting its practical usefulness. This limitation has motivated the development of

alternative unit root and stationarity tests. Becker *et al.* (2006), for example, proposed tests that model structural breaks of unknown form as smooth transitions using Fourier transforms. Building on earlier work by Gallant (1981), they showed that Fourier approximations can effectively capture the behavior of unknown functions, even if the function is not periodic. The Fourier-based approach only requires specifying the appropriate frequency in the estimation process, thus reducing the number of parameters that must be estimated. As a result, these tests demonstrate good size and power properties, regardless of the timing or shape of the break, and outperform dummy-based methods. In line with this framework, recent contributions have extended the original approach by Becker *et al.* (2006). Notably, Enders and Lee (2012) proposed a testing framework that incorporates the Fourier transform while avoiding the need to pre-specify the timing, number, or form of the breaks.

Omay (2015) advanced this line of research by combining the methodologies of Becker *et al.* (2006) and Enders and Lee (2012), introducing the use of fractional frequencies to enhance model fit. More recently, Cai and Omay (2022) proposed a Double Fourier frequency test capable of capturing asymmetrically located structural break, as in the case of the nominal crude oil price or relative commodity prices (see Cai and Omay 2022 for further details).

In this paper we move from Cai and Omay's (2022) test, a Dickey-Fuller type test for which the authors derived the asymptotic distribution (tabulated for some specific sample sizes). To the best of our knowledge, no attempt has been made to propose a bootstrap version of the Double Fourier Dickey-Fuller test and, considering the efficacy of bootstrap methods, in this work we intend to address this issue.

Bootstrap methods (Efron, 1979) are a computer intensive approach, based on resampling, to statistical inference issues without any statistical assumption on the underlying data generating process. The bootstrap is often adopted because it has much better performance than the conventional approaches (first order asymptotics) and it provides empirical and efficient inference for complicated problems. However, bootstrap methods cannot be equally applicable to all random processes.

In general, for data that are not independent identically distributed (iid), modifications of the original bootstrap set-up have been put forward in order to be able to resample without ignoring the dependence structure. Traditional bootstrap methods for time series can be categorized into parametric, semiparametric and non parametric approaches. Parametric methods resample residuals from a correctly specified model with parameters estimated from the observed data (Andrews *et al.*, 2006). These methods assume that residuals are independent and identically distributed. Semi and non parametric methods, such as the Sieve Bootstrap (Buhlmann, 1997) and the Block Bootstrap (Kunsch, 1989), resample approximately

independent quantities, like residuals or blocks of data. While these methods are effective for short-memory series, they struggle with unit root processes, where the strong persistence of dependence violates the independence assumption. To address this, alternative strategies, such as pre-filtering the data (Poskitt *et al.*, 2015) or resampling in the frequency domain (Franke and Hardle, 1992), have been developed.

In this paper we propose a Sieve Bootstrap Double Frequency Dickey Fuller (SB-DFDF) test for unit root, by combining the use of the Sieve Bootstrap with the Double Frequency Dickey Fuller test in case the time series might be affected by potential unknown structural breaks, asymmetrically located. In the second section, we will present the Double Frequency Dickey Fuller test. In the third section, we present our algorithm for the Sieve Bootstrap Double Frequency Dickey Fuller test. In the fourth section, we will present our Monte Carlo experiment and some conclusions.

2. Double Frequency Dickey Fuller Test

The modification of the Dickey-Fuller test (Dickey and Fuller, 1979, 1981) to account for a deterministic function d_t moves from the following AR(1) process with a deterministic trend

$$y_t = d_t + \rho y_{t-1} + \varepsilon_t \quad t = 1, \dots, T \quad (1)$$

where the stationary term ε_t has variance σ^2 , d_t is a deterministic function. If d_t is known, model (1) can be directly estimated and, in turn, the unit root hypothesis $H_0: \rho = 1$ can be tested. When d_t is unknown testing for unit root is problematic given the risk of misspecification of d_t . The idea underlying the Fourier expansion-based Dickey-Fuller test is that it is often possible to approximate d_t using the Fourier expansions, as in Enders and Lee (2012):

$$d_t = \alpha_0 + \sum_{k=1}^n \alpha_k \left(\frac{2\pi kt}{T} \right) + \sum_{k=1}^n \beta_k \left(\frac{2\pi kt}{T} \right) \quad n \leq T/2 \quad (2)$$

where n represents the number of cumulative frequencies included in the approximations and k represents a particular frequency. It is interesting to observe that in the absence of a nonlinear trend, all values $\alpha_k = \beta_k = 0$, so that the usual Dickey-Fuller specification appears. Usually the number of frequencies n should be kept small to avoid overfitting; in particular, in the original idea of Enders and Lee (2012), the Fourier approximation is adopted for a single frequency ($n=1$) as follows

$$d_t = \sum_{i=0}^1 c_i t^i + \alpha \sin\left(\frac{2\pi kt}{T}\right) + \beta \cos\left(\frac{2\pi kt}{T}\right) \quad (3)$$

that includes, via the first term in the sum where $i = 0, 1$, both the intercept and the trend plus intercept versions and it also approximates, via the sinusoidal waves the smooth breaks. In expression (3), k is the frequency to be determined over a pre-given interval. However, as pointed by Omay (2015) the breaks caused by sudden geo political events and financial crisis are stochastically distributed and asymmetrically located. Following this logic, Cai and Omay (2022) relax the assumption that the frequency is identical and propose a more general set up where:

$$d_t^{Dfr} = \sum_{i=0}^1 c_i t^i + \alpha \sin\left(\frac{2\pi k_s t}{T}\right) + \beta \cos\left(\frac{2\pi k_c t}{T}\right) \quad (4)$$

and within the framework of a Dickey-Fuller unit root test, the model with optimal frequencies k_s and k_c is:

$$y_t = \sum_{i=0}^1 c_i t^i + \alpha \sin\left(\frac{2\pi k_s t}{T}\right) + \beta \cos\left(\frac{2\pi k_c t}{T}\right) + \rho y_{t-1} + \varepsilon_t, \quad (5)$$

and the Double Frequency Dickey Fuller (DFDF) test statistic for $H_0: \rho = 1$ is:

$$\tau^{Dfr} = \frac{T(\hat{\rho}-1)}{\sqrt{T^2 \delta_{\hat{\rho}}^2}} \quad (6)$$

where $\hat{\rho}$ and $\delta_{\hat{\rho}}^2$ are OLS estimators of ρ and standard errors. The asymptotic distribution of the test statistic τ^{Dfr} only depends on the frequencies k_s and k_c and the critical values are tabulated (Cai and Omay, 2022, table 1).

If a nonlinear trend is not actually present in the data, a standard unit root test, such as Dickey-Fuller (DF) or Augmented Dickey Fuller (ADF, Said and Dickey, 1984) is more powerful and there is no need of Fourier terms. So, before adopting the DFDF test with a predetermined frequency pair (k_s, k_c) , it recommended to test H_0 : *linearity* versus H_1 : *non linearity* via an adjusted F test:

$$F^{Dfr}(k_s, k_c) = \frac{\frac{SSR_0 - SSR_1(k_s, k_c)}{2}}{\frac{SSR_1(k_s, k_c)}{T-q}} \quad (7)$$

SSR_0 and $SSR_1(k_s, k_c)$ represent sum of squared residuals without and with Fourier components, q is the number of regressors. If H_0 is rejected, a functional form with Fourier components is suggested.

Selecting the double frequency is done with a grid search to find the optimal pair (k_s^*, k_c^*) , through the minimization of the SSR. This leads to the modified F test:

$$F^{Dfr}(k_s^*, k_c^*) = \max_{(k_s, k_c)} F^{Dfr}(k_s, k_c)$$

where $(k_s^*, k_c^*) = \operatorname{argmax} F^{Dfr}(k_s, k_c)$. Minimizing SSR is equivalent to maximizing the F^{Dfr} test statistic under the condition of maximum frequency k_{max} and a searching precision of Δk (critical values tabulated).

3. Sieve Bootstrap Double Frequency test for Unit Root

Instead of resorting on tabulated critical values as in the original version of the test by Cai and Omay (2022), here we propose to derive the empirical distribution of the statistics via Sieve Bootstrap. The Sieve Bootstrap (Buhlmann, 1997) approximates a time series with an autoregressive process of increasing order p , from which residuals are resampled. This method is semi-parametric, relying on a flexible model approximation rather than a fully specified data generating process (DGP).

Originally designed for short-memory processes, its applicability has been extended to fractionally integrated and non-invertible processes by Poskitt (2008). Moreover, when strong long-range dependence dominates the data, such as unit root, even advanced resampling techniques may fail to capture the underlying distributional properties. Therefore, Poskitt *et al.* (2015) proposed Pre-Filtered Sieve Bootstrap whose algorithm first takes the first difference of the time series and then applies the Sieve Bootstrap to the filtered (short-memory) series. The final bootstrap sample is obtained by inverting the first difference transformation.

Considering that here, we work within the unit root set-up, our bootstrap version of the DFDF test would be effectively a Prefiltered-Sieve Bootstrap Double Frequency Dickey Fuller test and below it is presented the overall algorithm.

Step	Action	Formula/Description
Start	Initialize	Given a time series y_t , $t = 1, \dots, T$ and a statistic S .
1	Achieve Stationarity	Take the first difference: $x_t = \Delta y_t$
2	Model & Get Residuals	Model x_t , with $AR(p)$ (p chosen with AIC) and get the residuals ε_t
3	Resample Residuals	Resample the residuals ε_t , with replacement to obtain the bootstrap residuals ε_t^*
4	Generate Bootstrap Series (Stationary)	Obtain the bootstrap time series x_t^* using the estimated $AR(p)$ coefficients (α_i) and the resampled residuals: $x_t^* = \alpha_0 + \alpha_1 x_{t-1}^* + \dots + \alpha_p x_{t-p}^*$
5	Reconstruct Bootstrap Series (Original Scale)	Reconstruct the final bootstrap sample y_t^* by "undifferencing" x_t^* : $y_t^* = \Delta^{-1} x_t^*$
6	Compute Statistic	Compute the desired statistic S on the bootstrap sample: $S_b^* = S(y_t^*)$.
Loop	Repeat (B Times)	Repeat Steps 1-6 B times to generate B bootstrap samples y_t^* and calculate B values of the statistic S_b^*
7	Estimate Distribution	Approximate the distribution of the statistic S using the empirical bootstrap distribution FS^* : $FS^* = \frac{1}{B} \sum^B I(S_b^* \leq s) \quad (8)$
End	Result	Bootstrap Distribution of Statistic S

4. Monte Carlo experiment

In this section we present our Monte Carlo experiment to ascertain the finite sample properties of the Sieve Bootstrap Double Frequency Dickey Fuller test (SB-DFDF), in comparison with DFDF test by Cai and Omay (2022). The test is applied using the optimal k_s^*, k_c^* , according to the grid search procedure presented in the second section and no preliminary F test is carried out, meaning that both tests' performance is evaluated assuming that the presence of breaks in the DGP is known. The sample size is $T=50, 150, 300$, the number of simulations is 2000. For the implementation of the SB-DFDF test, the number of bootstrap replications is 500 and the nominal size is 0.05. Simulations have been done with R (Team, 2013).

We consider the following data generating processes (DGPs), following Enders and Lee (2012), where for each of them $\rho = 1, 09, 08, 07$ (the values of the other characterizing parameters are displayed in the result tables).

- AR(1) with smooth shifts with constant level (DGP 1a)

$$y_t = \alpha_0 + \sum_{k=1}^n \alpha_k \left(\frac{2\pi k_s t}{T} \right) + \sum_{k=1}^n \beta_k \left(\frac{2\pi k_c t}{T} \right) + \rho y_{t-1} + \varepsilon_t \quad t = 1, \dots, T$$

- AR(1) with smooth shifts with linear trend (DGP 1b)

$$y_t = \alpha_0 + c_1 t + \sum_{k=1}^n \alpha_k \left(\frac{2\pi k_s t}{T} \right) + \sum_{k=1}^n \beta_k \left(\frac{2\pi k_c t}{T} \right) + \rho y_{t-1} + \varepsilon_t \quad t = 1, \dots, T$$

- Sharp shifts (DGP 2)

$$y_t = T_t + e_t \quad t = 1, \dots, T$$

where $e_t = \rho e_{t-1} + \varepsilon_t$ and $T_t = \begin{cases} b & \text{if } t \leq aT \\ 0 & \text{otherwise} \end{cases}$

- LStar smooth shifts (DGP 3a)

$$y_t = \frac{1}{1 + e^{-\varphi(t-\theta T)}} + e_t \quad t = 1, \dots, T$$

where $e_t = \rho e_{t-1} + \varepsilon_t$

- Estar smooth shifts (DGP 3b)

$$y_t = d \left(1 - e^{-\varphi(t-\theta T)^2} \right) + e_t \quad t = 1, \dots, T$$

where $e_t = \rho e_{t-1} + \varepsilon_t$

The performance of the tests is expressed in terms of percentages of rejections. This percentage represents the empirical size under H_0 , that is when in the DPGs $\rho = 1$, and it represents empirical power under H_1 , that is for the other values of ρ . The results are presented in the set of tables below (tables 1-6).

As can be seen from the tables, the SB-DFDF test shows good performance in terms of empirical size (always around 0.05), being very similar to the DFDF test in this respect. Regarding empirical power, there are some differences between the two tests, indicating a systematically better performance of the SB-DFDF test compared to the DFDF test.

Analyzing the individual DGPs, we can observe that in the cases of DGP1a and DGP1b (Tables 1 and 2), the DGPs that are most similar to the logic of the DF set-up, both tests show very good power, which, as expected, only decreases when the autoregressive parameter ρ approaches 1.

Moving towards the DGPs that are more distant in logic from DF set-up, and starting from DGP2, we can appreciate a drop in the power of both tests in the presence of sharp shifts, which does not seem to be affected by the magnitude of the break or its position in the beginning or end of the series. It should be noted, however, that at sample size 300, the power already reaches excellent levels. Again, proximity of the autoregressive parameter to 1 reduces power.

As for DGP3a and DGP3b, Tables 5-6 show the performance in case of L-star smooth breaks, DGP3a (due to space constraints, the E-star results are not shown, but they are very similar to those of the L-star and available upon request from the authors). As in the previous case, the power performance is somewhat lower compared to the DGP1 cases, but still better than in the DGP2 case. Again, we observe the usual reduction in power as the autoregressive parameter increases from 0.7 to 0.9.

We also note, particularly for DGP2, DGP3a (and DGP3b), that the performance of the test demonstrates robustness regardless of whether the test is implemented with or without a linear trend in the specification.

Table 1 –DGP 1a: $AR(1)$ with constant level, percentage of rejection of null hypothesis (nominal size=5%, critical values for DFDF from Cai and Omay (2022) tables).

ρ	k_s^*, k_c^*	T=50		T=150		T=300	
		DFDF	SB DFDF	DFDF	SB DFDF	DFDF	SB DFDF
0.7	1,1	0.494	0.526	0.994	0.888	1	1
	1,2	0.434	0.514	0.844	0.898	1	1
	2,1	0.406	0.586	0.852	0.876	1	1
	2,2	0.416	0.534	0.904	0.874	1	1
0.8	1,1	0.328	0.444	0.800	0.888	1	1
	1,2	0.356	0.480	0.732	0.856	1	1
	2,1	0.322	0.522	0.878	0.896	1	1
	2,2	0.308	0.518	0.788	0.799	1	1
1	1,1	0.051	0.052	0.048	0.050	0.047	0.049
	1,2	0.052	0.052	0.052	0.051	0.049	0.050
	2,1	0.052	0.052	0.051	0.052	0.050	0.049
	2,2	0.052	0.053	0.054	0.049	0.049	0.050

Overall, we can conclude that, given our empirical results, it seems that the SB-DFDF test manages to improve the performance of the original DFDF, thus leading to powerful tool that is able to handle potentially asymmetrically located structural breaks when testing for nonstationarity, avoiding the use of nonstandard asymptotic

distributions. Moreover, the test SB-DFDF test has reasonable power properties also in the presence of breaks that are not necessarily generated from the trigonometric components in the DGP.

We believe these results are interestingly promising and future research lines include the use of alternative bootstrap methods that can be even more suitable for the peculiarity of the test and data, for example frequency based bootstrap methods.

Table 2 – DGP 1b: AR(1) with linear trend, percentage of rejection of null hypothesis (nominal size=5% critical values for DFDF from Cai and Omay (2022) tables).

ρ	k_s^*, k_c^*	T=50		T=150		T=300	
		DFDF	SB DFDF	DFDF	SB DFDF	DFDF	SB DFDF
0.7	1,1	0.448	0.758	0.894	0.888	0.980	0.999
	1,2	0.416	0.449	0.840	0.898	1	1
	2,1	0.456	0.448	0.798	0.876	0.999	0.998
	2,2	0.434	0.505	0.794	0.874	1	0.999
0.8	1,1	0.274	0.335	0.744	0.888	0.999	0.999
	1,2	0.252	0.323	0.750	0.856	0.970	0.999
	2,1	0.265	0.369	0.714	0.896	0.999	0.999
	2,2	0.255	0.354	0.746	0.799	1	1
1	1,1	0.051	0.052	0.045	0.050	0.045	0.045
	1,2	0.053	0.052	0.051	0.052	0.049	0.049
	2,1	0.050	0.050	0.051	0.053	0.054	0.049
	2,2	0.052	0.051	0.052	0.050	0.049	0.048

Table 3 –DGP 2: Sharp shifts percentage of rejection of null hypothesis, test implemented without linear trend, nominal size=5%, critical values for DFDF from Cai and Omay (2022) tables.

ρ	b	a	T=50		T=150		T=300	
			DFDF	SB DFDF	DFDF	SB DFDF	DFDF	SB DFDF
0.7	1	0.2	0.258	0.342	0.737	0.675	0.985	0.989
		0.8	0.301	0.374	0.662	0.726	0.995	0.985
	5	0.2	0.205	0.180	0.384	0.473	0.821	0.866
		0.8	0.189	0.177	0.422	0.361	0.690	0.650
0.9	1	0.2	0.157	0.154	0.223	0.258	0.225	0.327
		0.8	0.149	0.136	0.189	0.210	0.299	0.296
	5	0.2	0.156	0.154	0.223	0.268	0.215	0.337
		0.8	0.119	0.125	0.170	0.210	0.209	0.204
1	1	0.2	0.053	0.054	0.052	0.050	0.049	0.050
		0.8	0.052	0.052	0.051	0.051	0.050	0.050
	5	0.2	0.052	0.052	0.052	0.052	0.051	0.051
		0.8	0.052	0.051	0.051	0.049	0.047	0.050

Table 4 –DGP 2: Sharp shifts percentage of rejection of null hypothesis, test implemented with linear trend, nominal size=5%, critical values for DFDF from Cai and Omay (2022) tables.

ρ	b	a	T=50		T=150		T=300	
			DFDF	SB DFDF	DFDF	SB DFDF	DFDF	SB DFDF
0.7	1	0.2	0.247	0.347	0.604	0.702	0.927	0.931
		0.8	0.298	0.334	0.625	0.684	0.804	0.804
	5	0.2	0.184	0.180	0.363	0.421	0.661	0.662
		0.8	0.188	0.185	0.335	0.345	0.625	0.631
0.9	1	0.2	0.157	0.160	0.210	0.221	0.333	0.384
		0.8	0.156	0.159	0.198	0.220	0.325	0.365
	5	0.2	0.155	0.159	0.190	0.224	0.302	0.378
		0.8	0.156	0.159	0.188	0.220	0.300	0.375
1	1	0.2	0.050	0.051	0.052	0.052	0.049	0.045
		0.8	0.051	0.050	0.049	0.049	0.050	0.048
	5	0.2	0.050	0.052	0.048	0.048	0.051	0.047
		0.8	0.052	0.051	0.052	0.052	0.047	0.045

Table 5 –DGP 3a: L-star smooth shifts percentage of rejection of null hypothesis, test implemented without linear trend, nominal size=5%, critical values for DFDF from Cai and Omay (2022) tables.

ρ	a	T=50		T=150		T=300	
		DFDF	SB DFDF	DFDF	SB DFDF	DFDF	SB DFDF
0.7	0.25	0.556	0.668	0.745	0.801	0.944	0.984
	0.5	0.498	0.601	0.628	0.703	0.976	0.996
	0.75	0.506	0.628	0.706	0.805	0.928	0.998
0.9	0.25	0.122	0.121	0.140	0.152	0.203	0.190
	0.5	0.122	0.119	0.153	0.144	0.260	0.240
	0.75	0.136	0.124	0.150	0.176	0.214	0.235
1	0.25	0.051	0.050	0.049	0.052	0.048	0.048
	0.5	0.052	0.053	0.054	0.052	0.051	0.045
	0.75	0.052	0.052	0.052	0.052	0.050	0.051

Table 6 –DGP 3a: L-star smooth shifts percentage of rejection of null hypothesis, test implemented with linear trend, nominal size=5%, critical values for DFDF from Cai and Omay (2022) tables.

ρ	a	T=50		T=150		T=300	
		DFDF	SB DFDF	DFDF	SB DFDF	DFDF	SB DFDF
0.7	0.25	0.504	0.618	0.725	0.799	0.924	0.982
	0.5	0.490	0.579	0.632	0.713	0.976	0.996
	0.75	0.516	0.638	0.721	0.845	0.938	0.990
0.9	0.25	0.131	0.121	0.140	0.152	0.203	0.190
	0.5	0.122	0.119	0.153	0.149	0.259	0.238
	0.75	0.139	0.124	0.150	0.176	0.214	0.235
1	0.25	0.052	0.051	0.050	0.052	0.051	0.051
	0.5	0.052	0.053	0.051	0.052	0.049	0.051
	0.75	0.052	0.051	0.052	0.052	0.050	0.049

References

- ANDREWS D., LIEBERMAN O., MARMER V. 2006. Higher-order improvements of the parametric bootstrap for long-memory gaussian processes. *Journal of Econometrics*, Vol. 133, pp. 673–702.
- BECKER R., ENDERS W., LEE J. 2006. A stationarity test in the presence of an unknown number of smooth breaks. *Journal of Time Series Analysis*, Vol. 27, pp. 381–409.
- BUHLMANN P. 1997. Sieve bootstrap for time series. *Bernoulli*, Vol. 3, pp. 123–148.
- CAI Y., OMAI T. 2022. Using double frequency in Fourier Dickey–Fuller unit root test. *Computational Economics*, Vol. 59, pp. 445–470.
- DICKEY D., FULLER W. 1979. Distribution of the estimators for the autoregressive time series with a unit root. *Journal of the American Statistical Association*, Vol. 74, pp. 427–431.
- DICKEY D., FULLER W. 1981. Likelihood ratio statistics for autoregressive Distribution of the estimators for the autoregressive time series with a unit root. *Journal of the American Statistical Association*, Vol. 74, pp. 427–431.
- ENDERS W., LEE J. 2012. A unit root test using a Fourier series to approximate smooth breaks. *Oxford bulletin of Economics and Statistics*, Vol. 74, pp. 574–599.
- EFRON B. 1979. Bootstrap methods: Another look at the jackknife. *The Annals of Statistics*, Vol. 7, pp. 1–26.
- FRANKE J., HARDLE W. 1992. On bootstrapping kernel spectral estimates. *The Annals of Statistics*, Vol. 20, pp. 121–145.

- GALLANT A.R. 1981. On the bias in flexible functional forms and an essentially unbiased form: the Fourier flexible form. *Journal of Econometrics*, Vol.15, pp. 211-245.
- KUNSCH H. 1989. The jackknife and the bootstrap for general stationary observations. *The Annals of Statistics*, Vol. 17, pp. 1217–1241.
- LEE J., STRAZICICH M.C. 2003. Minimum Lagrange multiplier unit root test with two structural breaks. *Review of economics and statistics*, Vol. 85, pp. 1082-1089.
- OMAY T. 2015. Fractional frequency flexible Fourier form to approximate smooth breaks in unit root testing. *Economics letters*, Vol. 134, pp. 123-126
- PERRON P. 1989. The Great Crash, the oil price shock and the unit root hypothesis. *Econometrica*, Vol. 57, pp.1361–401.
- PHILLIPS P., PERRON P. 1988. Testing for a unit root in time series regression. *Biometrika*, Vol. 75, pp. 335–346.
- POSKITT D. 2008. Properties of the sieve bootstrap for fractionally integrated and non-invertible processes. *Journal of Time Series Analysis*, Vol. 29, pp. 224–250.
- POSKITT D., GROSE S., MARTIN G. 2015. Higher-order improvements of the sieve bootstrap for fractionally integrated processes. *Journal of Econometrics*, Vol. 188, pp. 94–110.
- SAID S.E., DICKEY D.A. 1984. Testing for unit roots in autoregressive moving average models with unknown order. *Biometrika*, Vol. 71, pp. 599-607
- TEAM R.C. 2013. R: A language and environment for statistical computing. *R Foundation for Statistical Computing*.
- ZIVOT E., ANDREWS D. 1992. Further evidence on the Great Crash, the oil price shock and the unit root hypothesis. *Journal of Business and Economic Statistics*, Vol. 10, pp. 251–270.

Margherita GEROLIMETTO, Università Ca' Foscari Venezia, Dipartimento di Economia, margherita.gerolimetto@unive.it

Stefano MAGRINI, Università Ca' Foscari Venezia, Dipartimento di Economia., stefano.magrini@unive.it

STATISTICS AND MASS MEDIA: "WRITING WITH NUMBERS"¹

Antonella Bianchino, Valeriana Leporanico, Angela Rosa, Giuseppe Stassi

Abstract. Istat carries out intense media activity using various channels. The project «Writing with numbers: research, processing and presentation of data» was born from the desire to offer journalists useful training to adequately carry out the delicate role of intermediaries in the dissemination of data. The aim of the project is to help media professionals navigate the "deluge of data" and transform it into clear and accessible news for the public. To ensure a targeted contribution to the needs of the profession, in collaboration with *forMedia*® - Institute for Training in Journalism and Multimedia Communication - a survey of statistical training needs was conducted, which was the basis for the design of the courses delivered, to date 16, with the involvement of more than 450 journalists. In this paper, after describing the objectives and goals of the project, the feedback provided by the participants at the end of the course will be presented. Thanks to the coding of open-ended responses through a text pre-processing and text-mining techniques, it was possible to conduct a thorough statistical analysis of the responses. This will allow to carry out operations of evolutionary maintenance of the functional contents to increase the already good results achieved and to promote the traditional dialogue between Istat and the world of the information, to ensure the dissemination of more and more complete and accurate statistical information.

1. Introduction

The project "*Writing with Numbers: Research, Processing, and Presentation of Data*" was created from the awareness that journalists and the media play a key role in how statistical information reaches the public. This made it clear that dedicated training and support are needed to help these professionals better understand and communicate statistics.

¹ This article is the result of the joint contribution of all and, therefore, the individual contribution is considered equal and equivalent to that of the other co-authors.

The authors' points of view expressed in the article do not necessarily reflect the official opinions of the Italian National Institute of Statistics.

The idea behind the project had been developing over time, with the goal of helping improve how data and statistics are shared with the public in an accurate and understandable way.

What makes this project unique is its approach: instead of waiting for journalists to come to them, the Institute went out to meet them directly in their local areas. These sessions helped explain how official statistics are produced and what they really mean. The main goal of the project is to give journalists the tools they need to make sense of today's flood of data, and to turn complex numbers into clear, trustworthy news for their readers.

A key part of the method was to hold in-person sessions across the country or our Regions, especially targeting local newsrooms, where resources for data training may be limited. By connecting directly with journalists on the ground, the Institute was able to make statistical knowledge more practical and relevant to their daily work. Through this project, the Institute also fulfilled one of its main missions: making the results of statistical research accessible and easy to understand for everyone, citizens, businesses, and public institutions. This helps ensure that official statistics don't just stay in reports but become useful tools for society.

2. Context Analysis: The Role of Official Statistics

The role of Istat and official statistics is defined in part by Legislative Decree No. 322/1989, later amended by Presidential Decree No. 166/2010, which assigns Istat the responsibility for guiding, coordinating, providing technical assistance, and training the entities that make up the National Statistical System (Sistan). In carrying out its functions, Istat follows what can be described as the process of generating official statistical information, which consists of three main stages or step:

- a) understanding the questions being asked and translating them into statistical information needs;
- b) producing the information;
- c) disseminating the information.

The first and third stages or step, identifying information needs and effectively disseminating information—are based on relationships with users, whether they are public decision-makers, key research partners, or entities responsible for sharing the information produced. The second stage, the actual production of official statistical information—is primarily guided by considerations related to the quality of the production process (Trivellato, 2022). In line with this mission, Istat has promoted numerous initiatives aimed at spreading statistical literacy, supporting public decision-makers in understanding statistical data, and providing training for users with varying levels of expertise.

In 2022, in response to the growing demand for territorial data and the increasing importance of the media as intermediaries in the dissemination of data, Istat recognized the need to systematically and continuously organize appropriate training initiatives for journalists.

The aim was to offer them a comprehensive overview of the Institute's activities and provide the tools needed for informed and accurate use of statistical data.

3. Analysis of training needs

To ensure a contribution according to needs of the journalistic profession, in agreement with *forMedia*® – Institute for Journalism and Multimedia Communication Training, a survey and analysis of training needs was carried out between September and October 2022. This was done through the administration of a Google Forms questionnaire (implemented on the *forMedia*® platform), which involved, voluntarily and anonymously, nearly 100 journalists from Campania and Basilicata (see Appendix). The Training Needs Survey Questionnaire consists of four sections:

1. Information about the affiliated (or collaborating) news outlet.
2. Knowledge of Istat/Sistan.
3. Training in the field of statistics.
4. Information needs: *In your professional activity, have you used, or do you need to use statistical data? If so, in which area?*

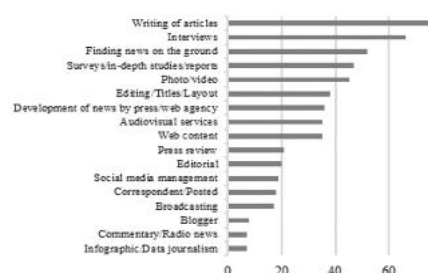
Analysis of the results showed that half of the participants in the survey are involved in collaborations with print, online, or television news organizations (Figure 1) and the main activity is in writing articles and conducting interviews (Figure 2).

Figure 1 - Participants by affiliation category. Percentage values.



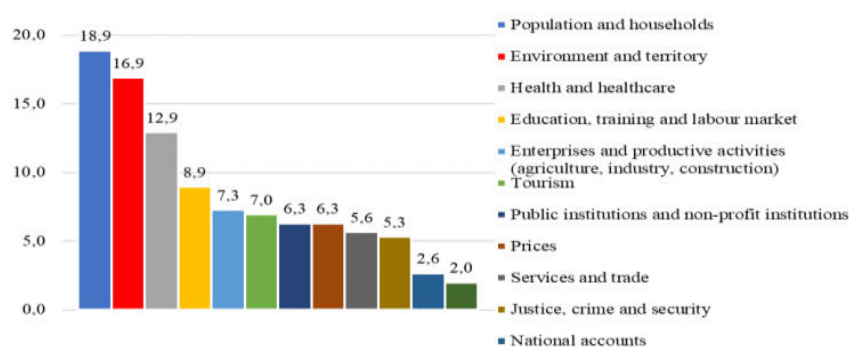
Source: Our data processing from Istat.

Figure 2 - Main activity performed. Percentage values.



For more efficient and effective training, respondents were also asked whether they had previously used statistical data in their professional practice and, if so, in which field. 71% of users reported that they knew and used statistical data, and more precisely, almost 19% of respondents said that they had used demographic data, 17% environmental and territory data and 13% health data (Figure 3).

Figure 3– *Field of use of statistical data. Percentage values.*



Source: Our data processing from Istat.

Having identified the activities carried out by journalists and the areas of data analysis, they were asked about the main difficulties encountered in using statistical data and which topics they would like to explore further. Difficulties in finding data, lack of timeliness, and unavailability of data represent the top three challenges reported by respondents. The sample indicated that it would be very useful to become familiar with the main surveys and to gain knowledge of descriptive statistics, in addition to exploring the tools made available by Istat for data consultation, such as the website, data warehouse, databases, etc. (Table 1).

Table 1 – *Difficulties encountered by respondents in Data Analysis and topics considered useful for their professional activity. Percentage Values.*

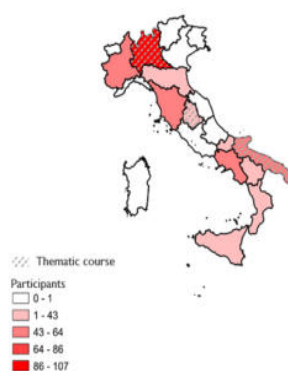
Difficulties encountered by respondents in Data Analysis	%	Topics considered useful for their professional activity	%
Difficulties in Accessing and Using Databases	35.0	Main Istat surveys (censuses, household surveys)	88.2
Outdated data	30.0	Data processing and analysis	88.2
Data not available	27.5	Website of ISTAT/Journalists' Desk	87.1
No ability to synthesise and process independently	2.5	Personal data protection regulations GDPR	78.5
Unclear data to interpret	2.5	Other ISTAT databases	74.2
Lack of availability of data with finer spatial detail	2.5	Eurostat databases	74.2
		Data Warehouse I.Stat (General database of Istat)	73.1
		Publications Istat and Sistan	68.1
		Reference legislation for official statistics	64.5
		Mission and organization of Istat and Sistan	61.3

Source: Our data processing from Istat.

4. The design and delivery phase of the training course

The results of the training needs assessment confirmed the importance of designing a training course specifically for journalists, also helping to shape the selection of proposed topics. On March 9 and 10, 2023, the first training course was held at the *Sala Cirillo* of the Metropolitan City of Naples. The event was organized in collaboration with the Order of Journalists of Campania and provided the mandatory professional development credits required for regulated professions (Article 3, paragraph 5, letter b of Decree-Law No. 138 of August 13, 2011, converted with amendments by Law No. 148/2011). All editions of the course (15 in total at the time of drafting this report) involved colleagues from Istat as well as numerous representatives from local authorities, institutions, and organizations. Depending on the location, the training was delivered either as a full-day session or in two half-day sessions. The program covered the main tools for understanding, accessing, and researching data, key statistical sources, and various thematic insights. The objective of the training course—specifically designed for information and communication professionals—was to provide useful methods and tools to navigate the “data deluge,” a hallmark of today’s “infodemic,” and to support the transformation of data into clear and accessible news. The successful experience in Campania, both in terms of participation and positive feedback (with an average satisfaction rating of 8.4), encouraged the working group responsible for designing and delivering the courses to replicate the format in 14 additional locations. More than 450 journalists were involved, with thematic content adapted each time to the needs of the specific area. In the cities of Milan, Bari, and Perugia, in addition to the basic course, three advanced thematic modules were held, two of *Data Visualization* and a *Focus on the regional economy* (Figure 4).

Figure 4— *Distribution of courses on the territory.*



Source: Our data processing from Istat.

5. Presentation of evaluation results

At the end of each edition, participants were asked to complete a satisfaction/evaluation questionnaire regarding the activity provided, both in terms of the content and the organizational support. The questionnaire, completed on a voluntary and anonymous basis, is adapted from Istat's internal training process (DCRU/CRS), useful, also in this case, to assess the performance, know the topics of greatest interest, test the duration of activities, organizational aspects, the balance between theory and practice, and receiving input and proposals for future developments. The questionnaire proposed for the first nine editions in paper form (Figure 5), with subsequent imputation of the answers by the organizers, has undergone a technical revision in subsequent editions, while maintaining the same substance. Since the Bologna edition (May 6–7, 2024) it has been proposed in digital form, through the distribution of a QR code generated on Forms by Office365, which, framed also by a smartphone, allows to record the answers, by making them confluent in real time into a data base (Excel). This procedure has allowed for timely and accurate collection, analysis and processing.

Figure 5 – *Satisfaction survey.*

The figure displays two versions of a satisfaction survey form. The left version is a paper form titled "QUESTIONARIO DI SODDISFAZIONE" and "RICERCA, ELABORAZIONE E PRESENTAZIONE DEI DATI". It includes sections for "CONTENUTO", "METODI", "ASPETTI ORGANIZZATIVI", and "DURATA". The right version is a digital form titled "QUESTIONARIO DI SODDISFAZIONE" and "RICERCA, ELABORAZIONE E PRESENTAZIONE DEI DATI". It includes sections for "APPLICABILITÀ", "CONTENUTO", "ASPETTI ORGANIZZATIVI", and "DURATA".

Source: Istat.

5.1. Evaluation results of the first training course

Before evaluating overall satisfaction with the training courses, it was deemed appropriate to focus on the results from the questionnaires of the first course held in Naples, considering it a benchmark both in terms of the topics covered and organizational aspects.

The evaluation of the course in Naples was very high: the pupils gave an overall rating of 8.4 (Table 2). On the one hand, such a high opinion has immediately pushed the Institute to continue with this experience in the area, on the other hand, efforts were made to understand the course's strengths and weaknesses. The course was found to be very consistent with the stated training objectives (8.5) and highly appreciated for the information support received (8.5). The most well-received topics were the more practical ones, such as *Transforming Data into Journalistic Information* (8.1) and *Sources of Official Statistics: Databases and Information Systems for Territorial Analysis* (8.0). Conversely, the topic with the lowest rating likely considered more challenging by participants due to the technical skills required—was *Data Visualization* (7.7). Based on the evaluations of the course design and organizational aspects, slightly lower scores were recorded for the teaching tools (slides, documents, links, videos, classroom, etc.) (7.8) and the balance between theory and practice (7.6) (Table 2). These aspects were also mentioned in the observations, suggestions, and final comments provided by the participants.

Table 2 – Average score by topic and by organizational macro-areas – First course in Naples. Average values.

Topics	Mean	Macro-areas	Mean
Turning data into journalistic information	8.1	Information and support received	8.5
Sources of official statistics: databases and information systems for spatial analysis	8.0	Consistency of the course with the stated training objective	8.5
The sources of official statistics: the main Istat surveys	7.8	Overall opinion	8.4
The institutional site of Istat: a compass navigating to the information	7.8	Applicability to the work context	7.8
The basic statistical tools: from raw data to the product "that makes news"	7.8	Teaching materials (slides, documents, links, videos, etc.)	7.8
Data visualization: tools and techniques for data representation and communication	7.7	Course balance with stated training objective	7.6

Source: Our data processing from Istat.

Therefore, after a thorough analysis of the course satisfaction questionnaires, efforts were made to improve the course organization, aiming to foster greater interaction between instructors and participants by reshaping the course structure to resemble more of a collaborative workshop rather than a seminar-style event.

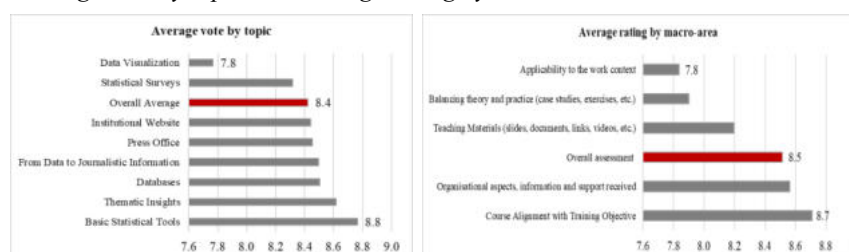
5.2. Results of the overall evaluation

In this paragraph, the main results arising from the analysis of the 200 completed questionnaires will be presented. At the end of the 15 courses, the results of the satisfaction questionnaires were harmonized in order to eliminate differences between the different structures of the questions, open responses were coded, and the information was organized into a single dataset suitable for analysis.

In general, regarding the first section of the questionnaire—which asks for an evaluation of the individual topics covered—respondents expressed a very high level of appreciation for the subjects addressed (overall average score of 8.4) (Figure 6).

The module that received the highest level of appreciation was the “methodological” one, related to the use of basic statistical tools (8.8). Special interest was also shown in the *specific studies* (projects designed to meet local needs) (8.6). Although the vote was largely positive, it is the Data Visualization course that has obtained the lowest score (7.8), but this is most likely due to the structure of the same, it would have required tools and computer skills to be fully exploited. To this is added a not insignificant aspect: for more than 80% of the cases the teaching was held at a distance and not in presence, therefore, despite the recognized competence and communicative effectiveness of the teacher (as reported in the final comments), the course would require the availability (in addition to basic knowledge) of support tools (PC, software), increased interaction and longer time frames, to ensure a balance between theory and practice.

Figure 6— Average vote by topic and average rating by macro-area.

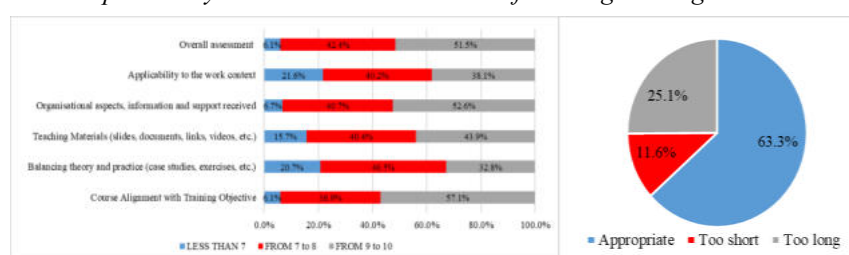


Source: Our data processing from Istat.

The success of the course is undoubtedly due to the high competence of the lecturers and the interest in the proposed topics (training design) but a decisive role is played by the organizational aspects, with the involvement from the beginning of the Human Resources Training area of the Institute. Overall, the course was considered highly consistent with its training objectives (8.7), and both the information provided, and the support received during its implementation were positively evaluated (8.6 and 8.2, respectively). A slightly lower score, and undoubtedly an aspect to work on, is the balance between theoretical and practical moments (7.9) that directly affects the real applicability of the received notions to one's own working context (7.8) (Figure 6). Analyzing the distribution of the highest and lowest scores by organizational macro area (where 1 = completely unsatisfactory and 10 = completely satisfactory), it emerged that over 50% of respondents rated both the course's consistency with the stated training objective (57.1%) and its organizational aspects (52.6%) with a 9 or 10.

One in three respondents considered the course to be perfectly balanced between theory and practice (32.8%). Conversely, one in five respondents gave a score below 7 regarding the applicability of the content to their work context and the balance between theory and practice (21.6% and 20.7%, respectively). In terms of duration, 63% of respondents thought the course was adequate, 25% too long and 12% too short (Figure 7).

Figure 7– *Votes expressed by macro-area and duration of training. Average values.*



Source: Our data processing from Istat.

5.3. Textual analysis of the responses

The final part of the satisfaction questionnaire was designed to give participants the opportunity to share their observations, asking which topics they would like to explore further, reduce, or suggest.

The textual analysis, carried out through word clouds of the responses, led to the identification of the most frequently recurring keywords. The first word cloud visually represents the main themes emerging from the open responses collected, highlighting the interests and priorities perceived by the participants. The larger words, such as data visualization and case studies, indicate a strong demand for concrete, application and related content to the representation of data and statistical deepening through the proposal of case studies (Figure 8).

We also note the importance given to tools such as databases, statistical analysis techniques and spatial analysis, indicating a widespread need to make statistical information more accessible and understandable. In line with the required insights are also the topics proposed: case studies, how to build journalistic information (competence that integrates journalistic professionalism with statistical knowledge), interpret the data and visualize it (Figure 9). The last word cloud represents the topics that participants consider should be reduced within the training path; concepts such as basic statistical tools, Istat history, census, and theory emerge more clearly.

Some comments refer to the length of the introductions or the perceived difficulty of some theoretical parts, suggesting the need for a slimmer, concrete and practice-oriented approach (Figure 10).

This feedback indicates a clear preference for more application-oriented, interactive, and up-to-date learning in line with interest in the use of data in journalism and communication.

Figure 8 – Topics to be explored further.



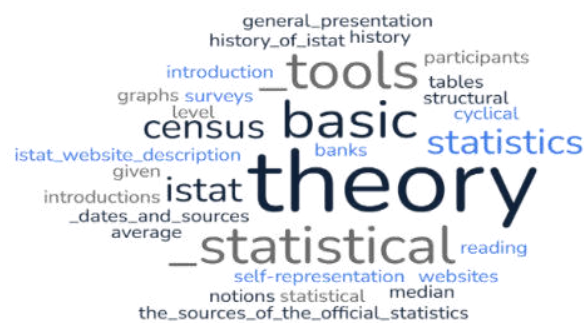
Source: Our data processing from Istat.

Figure 9 – The proposed topics.



Source: Our data processing from Istat.

Figure 10 – Topics to be reduced.



Source: Our data processing from Istat.

From the textual analysis (TAEHO, 2024) of the comments, instead, the request for thematic and methodological insights prevails.

The remaining comments were divided into positive and negative. 56% of the observations are pure appreciations for the course (positive and very positive sentiment), 44% instead highlights suggestions and criticalities mainly related to the widespread demand for breaks during the training day.

6. Prospects and future developments

Field experience and a thorough analysis of the questionnaires have led to envisioning several future developments:

- *Top priority is to ensure coverage of all Italian regions*, bringing the course to areas where it has not yet been offered, in order to provide all journalists with the same training opportunity.
- *An agreement is being considered with the National Council of the Order of Journalists (Cnog)*, aimed at better aligning the supply and demand of statistical training, with increasingly targeted initiatives that meet the real needs of the journalistic profession.
- *Implementation of a training needs questionnaire via LimeSurvey* (in partnership with Cnog) is under evaluation, to allow continuous monitoring of statistical training demand.
- *Enriching the evaluation questionnaire* by including additional information about the respondent, such as gender, age group, educational background, and professional status.
- *Increasing opportunities for meetings and dialogue at the local level*, with the goal of creating a sort of permanent territorial laboratory.
- *Promoting shorter, thematic, hands-on training sessions*, which are self-contained and use open-source software tools for real-time exercises with participants.
- *Encouraging ongoing dialogue with the information and media sector*.
- *Supporting the creation of accurate mailing lists*, inviting journalists to subscribe to Istat's distribution lists voluntarily and explicitly in order to receive updates and institutional information, including at the local level.

Appendix

Tools & Links

- 1) Survey of training needs
- 2) Program

Acknowledgements

A special thanks for our colleague, Agata Maria Madia Carucci, from the Territorial office for Southern regions of Istat, for her scientific contribution.

References

- FRANCESCHETTI M. 2024. *I fabbisogni formativi negli Enti pubblici di ricerca: sperimentazione di un modello di rilevazione, evidenze qualitative e indicazioni per la formazione*. Roma: Inapp.
- Regolamento per la formazione professionale continua degli iscritti dell'Ordine dei giornalisti ex art. 7 del d.P.R. 7 agosto 2012, n. 137. Nuovo Regolamento in sostituzione di quello vigente pubblicato sul B.U. del Ministero della Giustizia n. 10 del 31 maggio 2016. Bollettino Ufficiale del Ministero della Giustizia n. 21 del 15 novembre 2020.*
- TAEHO JO. 2024. *Text Mining. Concepts, Implementation, and Big Data Challenge*. Switzerland: Springer.
- TRIVELLATO U. 2022. Qualità dell'informazione statistica ufficiale e esigenze informative di regioni e città. In *Atti della Sesta Conferenza Nazionale di Statistica*, Roma, pp.39-52.

Antonella BIANCHINO, Istat, bianchin@istat.it
Valeriana LEPORANICO, Istat, valeriana.leporanico@istat.it
Angela ROSA, Istat, angela.rosa@istat.it
Giuseppe STASSI, Istat, stassi@istat.it

YOUTH NIGHTLIFE IN ROME'S VIII MUNICIPALITY: RESULTS FROM SURVEY

Emma Bellotti, Filippo Di Carlo, Cecilia Reynaud

Abstract. In urban settings characterised by demographic ageing and shrinking youth populations, urban space is increasingly shaped by intergenerational asymmetries in visibility, needs, and political attention. However, the implications of these processes for younger cohorts remain underexplored. This study explores how young people engage with evening and night-time life in Rome's VIII sub-municipal subdivision - a territorially heterogeneous area characterised by both advanced population ageing and a strong youth presence linked to universities and cultural infrastructures. An online survey was administered to residents and regular users of the area, stratified by age groups (15-34, 34+), to analyse spatial practices, patterns of nightlife participation, and intergenerational perceptions. Results show that young people are highly present in the area's nightlife and tend to report more negative perceptions of safety and noise, while older respondents express more caution and concern. Although generational differences emerge in rhythms, behaviours, and expectations, the findings also highlight areas of coexistence and shared urban experience. The study offers preliminary insights into how age-based dynamics shape access to and perceptions of urban space during the evening hours.

1. Introduction

Demographic aging and the spatial reconfiguration of territories represent two of the most complex and strategically relevant challenges facing contemporary urban realities, both in Italy and in the European context (Paroli *et al.*, 2020). The process of population aging is reflected in both absolute and relative increase in the elderly population, especially in relation to the overall demographic structure and the shrinking of younger cohorts (Golini, 1999). At the same time, a progressive contraction of the population in younger age groups is occurring, both in absolute numbers and in relative terms (Golini & Rosina, 2011). In Italy, this trend has intensified over the past few decades due to persistently low fertility and the numerical reduction of female cohorts in childbearing age: a phenomenon already evident in earlier demographic cycles. The interaction of these factors has led to a structural decline in reproductive potential, resulting in a continued and steady drop in the annual number of births (Cifoni, Pirone, 2022).

As younger cohorts shrink and older age groups gain demographic and institutional weight, population ageing raises the risk of an imbalance in the distribution of public resources and attention across generations (Golini, Lo Prete, 2019). This becomes particularly visible in urban settings, where different age groups often have competing needs and priorities. Cities are increasingly characterised by intergenerational competition for resources, space, and political recognition (Rosina, 2022). In this context, urban policies often prioritise the needs of the majority age groups, which can lead to a relative under-consideration of younger populations in planning decisions, investments, and service design. One of the most visible consequences of this imbalance concerns the way urban space is used and regulated in the evening and night-time hours (Giordano, Gwiazdzinski, 2018), when young people tend to express their social needs through forms of aggregation that are often marginal in policy agendas (Bonanomi, Rosina, 2022). Evening and night-time hours represent a crucial sphere of youth sociality, autonomy, and spatial appropriation; these dimensions are central to understanding how younger generations relate to the city and construct their everyday lives.

As of January 1st, 2019, the resident population of Rome peaked at 2,820,219; by January 1st, 2024, it had declined to 2,751,747, corresponding to an average annual growth rate of -4.9 per thousand. On that date, the city's population ageing was reflected in a 65+ population share of 23.7% (compared to 24.3% at the national level) and an ageing index - defined as the ratio between the population aged 65 and over and that aged 0-14 - of 195.5, slightly below the national level of 199.8. These data position Rome as a demographically aged city, where population dynamics overlap with the difficulties of sustaining social and spatial balance across an extensive metropolitan area (Caretta, Villante, 2006).

Starting from this demographic and policy background, this study aims to investigate whether, in a city like Rome, these conditions give rise to a situation of intergenerational competition in the use and perception of urban space. The analysis focuses in particular on evening and night-time hours, when differences in generational behaviours, needs, and expectations tend to become more visible, and potential tensions more pronounced. This study explores how these dynamics are reflected in young people's experiences, particularly in terms of access to public space, perceptions of safety, and patterns of social interaction, while also considering how these differ from adults and older residents. Investigating nightlife is not simply about mapping recreational habits, but about capturing broader processes of inclusion, visibility, and urban belonging.

In particular, this study focuses on Rome's VIII sub-municipal subdivision, which is one of the city's fifteen administrative districts and represents an emblematic case. Among the least populated (47.15 km²), it is also one of the oldest in terms of age structure. At the same time, it hosts Roma Tre University and several

cultural institutions, resulting in a spatial and demographic duality that brings intergenerational interaction - and potential tension - into sharp focus.

The study seeks to answer the following questions: Where do young people go in the evening and at night? What factors influence their behaviours and feelings of safety? What barriers - material or symbolic - shape their participation in urban life? And how do other age groups perceive their presence and practices?

2. Data and methods

The first step of the analysis aims to assess the demographic composition of the VIII Municipality, with particular focus on the relative size of the youth population. Drawing on municipal population registers, we analyse key indicators such as the age distribution, the share of residents aged 15–34, and the ageing index. These figures provide a necessary reference for understanding the numerical balance between generations and potential inequalities in access to and use of urban space.

To investigate the intersection of youth behaviours, spatial dynamics, and intergenerational relations, we designed an anonymous survey disseminated both online and in person. It was structured into two main versions: one targeting individuals aged 15–34 and one for respondents over 34. The survey explored six key thematic areas selected in line with the study's objectives: participation in nightlife, alcohol consumption and self-awareness (for the 15–34 group only), mobility and transportation choices, perceptions of safety, exposure to night-time noise, and personal spending. These dimensions allowed for the reconstruction of both the practices of urban nightlife and the potential barriers - material, normative, or perceived- that limit access to evening and night-time spaces. The survey was developed using the LimeSurvey platform and implemented with conditional branching logic to dynamically adapt the questionnaire based on previous responses, including gender-sensitive language. The survey relied on a non-probability sampling approach. Respondents were contacted through multiple channels, including social media dissemination, and in-person recruitment in university classrooms and selected secondary schools within the VIII subdivision. Data collection took place over a period between March and June 2024.

The analysis of the survey responses aimed to identify differences and similarities across age groups in terms of evening and night-time behaviours, perceptions, and use of space. The focus was primarily on the 15–34 age group, while responses from adults and older residents were used for comparison, in order to highlight potential generational asymmetries. A descriptive and exploratory approach was adopted to identify behavioural patterns and perceptions within the studied context.

3. Descriptive results

The VIII sub-municipal subdivision – hereafter, the VIII subdivision – is one of the smallest in Rome in both territorial and demographic terms. As of January 1st, 2024, it had 128,048 residents, accounting for 4.2% of the city's total population. It is one of the sub-municipal subdivisions with the highest levels of population ageing, with the share of residents aged 65 and over reaching 26.5% as of January 1st, 2024. By contrast, the youth population (aged 0–14) is relatively small, accounting for only 11.5% of the total. The target population of this study, those aged 15–34, numbered 23,594 as of January 1st, 2024, accounting for 18.4% of the total. The remaining adult population, aged over 34, amounted to 90,066 individuals, representing 70.3% of the total. Since the University of Roma Tre is located within the VIII subdivision and its students live in or regularly use the area, the survey was extended to include non-resident individuals, although no official reference population is available for this group.

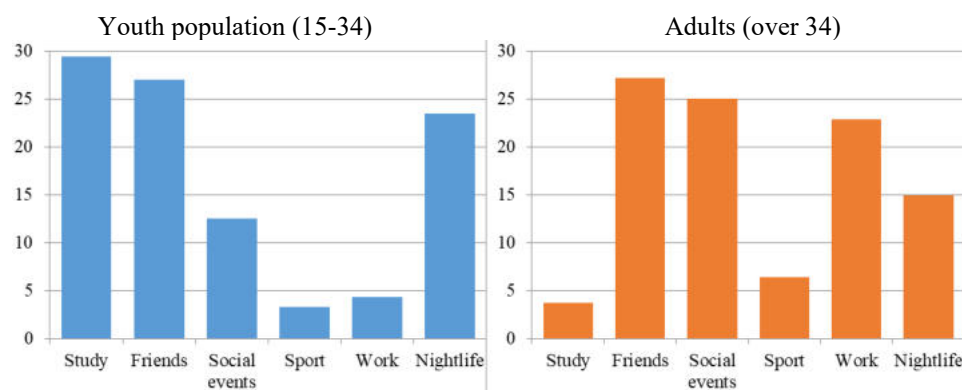
Results are based on 680 responses from individuals aged 15–34 and 331 responses from those aged 35 and above. In both age groups, women are overrepresented compared to men, with a stronger imbalance among older respondents: 54.2% of individuals aged 15–34 and 67.6% of those over 34 identify as women. This gender asymmetry stands in partial contrast to demographic data for the same age groups in the general population, where young men slightly outnumber women. The imbalance observed in the sample likely reflects a greater willingness among women to participate in social research. The results presented in this paper are to be considered preliminary, as the data collection process is still ongoing. The analyses provide an initial interpretation of the main trends emerging from the survey.

Among respondents aged 15–34, 42.5% are not residents of the VIII subdivision, compared to just 18.4% among those aged 35 and over. This marked generational difference highlights how the area attracts a considerable number of young people who actively use its spaces and services. The presence of Roma Tre University, cultural venues, nightlife activities, and accessible public spaces contributes to making the VIII subdivision a multifunctional urban hub for youth from across the city.

The reasons for spending time in the VIII subdivision differ substantially across generations. Among young respondents (15–34), not resident in the VIII subdivision, who are students in 58% of cases, the main motivations are study (29.4%) and nightlife (23.4%), followed by meeting friends (27.0%), reflecting the area's strong role as a social and educational hub. In contrast, adults aged 35 and over report significantly higher shares for work (22.9%) and attending social events (25.0%), while study and nightlife are marginal (3.7% and 14.9%, respectively) (Figure 1).

These patterns reinforce the idea that the subdivision plays a multifunctional role, but one that is experienced very differently depending on age.

Figure 1 – For what reasons do you spend time in the VIII subdivision?.



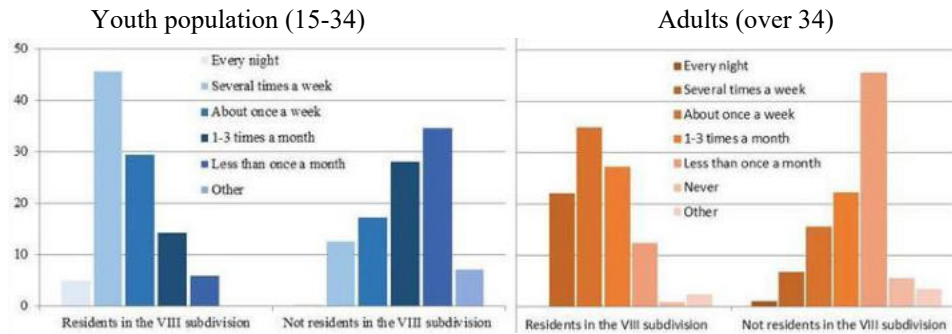
Source: our elaboration on surveys data.

When asked how often they go out in the evening within the VIII subdivision, clear differences emerge not only across generations but also between residents and non-residents (Figure 2). Among young respondents (15–34), those residing in the area show markedly higher levels of participation: nearly half (45.6%) report going out several times a week and 4.9% every night, compared to only 12.5% and 0.3%, respectively, among non-residents. Conversely, non-resident youth are concentrated in the lowest-frequency categories, with over 60% going out less than once a week. A similar pattern appears among adults. Residents go out more regularly than non-residents: about one in five (22.0%) go out several times a week and over one-third (34.9%) about once a week, while among non-residents the shares drop to 6.7% and 15.6%, respectively. Occasional outings (“less than once a month”) are much more common among non-resident adults (45.6%) than among residents (12.4%). Overall the residents—both young and adult— seem to be more deeply involved in the subdivision’s evening life, while non-residents tend to participate more sporadically. These results indicate that the area’s nightlife is not solely youth-driven and that adults also maintain a consistent presence in evening activities.

To investigate perceptions of noise disturbance, respondents were asked to evaluate how much certain sources of night-time noise - such as restaurants, bars, outdoor events, nightclubs, and people in the streets - had disturbed them at home during the past year. Night-time venues contribute to entertainment but also to the urban night-time economy; at the same time, they are among the main generators of

noise and urban disturbance (Crivello, 2019). The analysis aggregates responses across different noise sources to provide a general measure of disturbance.

Figure 2 – *How often do you go out in the evening in the VIII subdivision.*



Source: our elaboration on surveys data.

The results show a high level of tolerance in both age groups, though with a clear generational difference. Among young respondents (15–34), 74.3% reported being “not at all disturbed,” compared to 66.4% of adults aged 35 and over. While the share of those reporting “slightly disturbing” is almost identical (14.0% vs. 14.7%), the gap widens steadily at higher levels of disturbance: 5.8% of young people report being “moderately disturbed,” compared to 9.8% of adults; the shares increase to 3.7% vs. 4.1% for “very disturbing” and 2.3% vs. 5.0% for “extremely disturbing” (Table 1). When distinguishing between residents and non-residents, the same patterns remain: young people show generally high levels of tolerance, with only modest differences between residents and non-residents, while adults—especially residents—are more likely to report stronger disturbance. Among young respondents, residents appear even less disturbed than non-residents, with slightly higher shares reporting no disturbance at all, suggesting a stronger familiarity or habituation to the area’s evening soundscape.

These findings suggest that adults tend to be more sensitive to night-time urban activity, possibly reflecting different routines, expectations, or relationships with the neighbourhood. At the same time, the distributions indicate that negative perceptions are a minority in both groups, tempering common assumptions about widespread intergenerational conflict over noise.

The different ways in which young people and adults experience the VIII subdivision - through different rhythms, motivations, and spatial practices -highlight the presence of generational asymmetries that may influence perceptions, expectations, and forms of coexistence in the area.

Any study on evening and night-time urban life must necessarily engage with the issue of safety, not only as an objective condition but also as a matter of perception. Individuals' sense of personal security plays a crucial role in shaping their decisions about whether, how, and where to move through the city after dark.

Table 1 – *In the past year, after 8:00 p.m., how much have the following sources of noise bothered you while you were at home?*

Level of disturbance	Youth population (15-34)			Adults (over 34)		
	Residents	Not residents	Total	Residents	Not residents	Total
Extremely disturbing	1.6	2.8	2.3	6.8	0.6	5.0
Very disturbing	3.4	3.8	3.7	4.1	3.8	4.1
Moderately disturbing	5.1	6.1	5.8	9.1	12.4	9.8
Slightly disturbing	13.4	14.2	14.0	16.0	11.1	14.7
Not at all disturbing	76.4	73.1	74.3	64.0	72.1	66.4

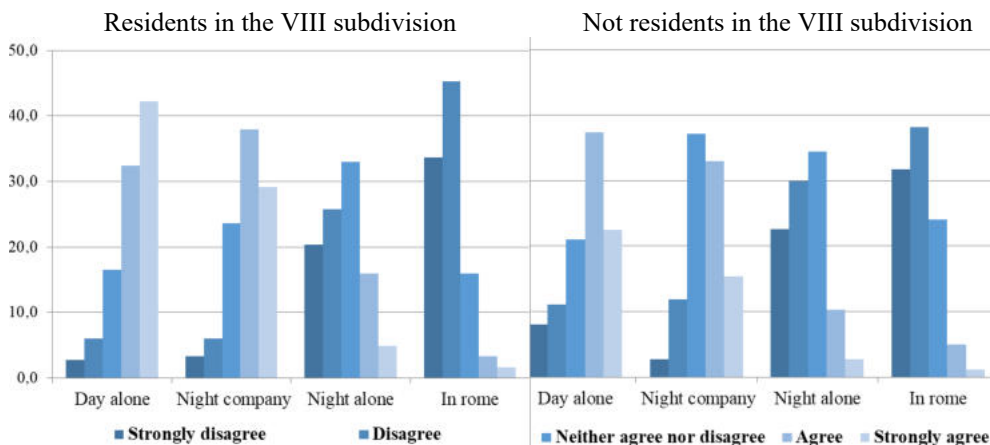
Source: our elaboration on surveys data.

Perceived safety can enable or constrain access to spaces, influence the frequency and nature of social participation, and condition the ways people - particularly young people - experience the urban environment. Safety is a central dimension in the governance of urban nightlife, often shaping both public discourse and local policy interventions. In many European cities, evening and night-time activities are frequently approached through a focus on regulation, surveillance, and the prevention of disorder. This perspective, while partially justified by concerns about public order, risks overshadowing the social, cultural, and relational value that nighttime spaces hold - especially for younger populations (Bichi, Pasqualini, 2018). The VIII subdivision stands out as a context where the presence of young people is particularly strong, and where local politics has shown a willingness - at least in principle - to prioritize youth-oriented initiatives and events, especially in the summer. Among young respondents, perceptions of safety vary significantly depending on time of day, company, and location. During the day, perceptions of safety are generally positive among young respondents, but with notable differences between residents and non-residents: 74.7% of young residents agree or strongly agree that the VIII subdivision is safe to move around alone, compared to 59.9% among non-residents. At night, however, feelings of safety become more fragile and strongly influenced by context. When accompanied, 67.0% of young residents report feeling safe in the VIII subdivision, while the share drops to 48.3% among non-residents. If moving around alone, the perception shifts dramatically for both groups, with only 20.8% of residents and 13.0% of non-residents agreeing that the area is safe, and disagreement becoming the majority position. Neutral responses increase

sharply, indicating hesitation or conditional confidence. Perceptions are even more negative when referring to other parts of Rome: 79.0% of young residents and 69.9% of non-residents disagree that it is safe to move alone at night elsewhere in the city (Figure 4).

These findings point to a clear contrast between day and night and between the VIII subdivision and the wider urban environment, but also underscore how being alone is the most decisive factor in shaping young people's sense of vulnerability after dark. Differences between residents and non-residents remain small when moving alone at night but residents show slightly lower disagreement levels, suggesting a marginally higher familiarity with the area.

Figure 4 – *To what extent do you agree or disagree with each of the following statements? During the day, the VIII subdivision is a safe area to move around alone; At night, the VIII subdivision is a safe area to move around when accompanied; At night, the VIII subdivision is a safe area to move around alone; At night, it is safe to move around alone in other parts of Rome. Youth population 15-34.*

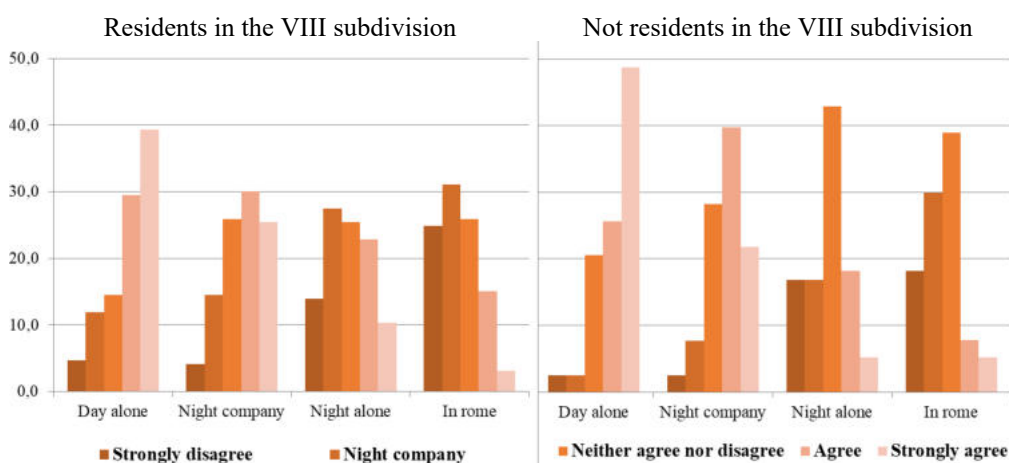


Source: our elaboration on surveys data.

Among adult respondents (35+), perceptions of safety show a similar structure to those of younger individuals, though with a more cautious tone overall. During the day, feelings of safety remain high for both residents and non-residents: 68.9% of adult residents and 74.3% of non-residents agree or strongly agree that the VIII subdivision is safe to move around alone. At night, however, perceptions become more fragile, with higher uncertainty among non-residents and greater polarization among residents. When accompanied, 55.5% of residents and 61.5% of non-residents report feeling safe, and neutrality becomes relatively common in both groups. The perception becomes significantly more critical when moving alone at

night: only 33.2% of adult residents and 23.4% of non-residents feel safe, and disagreement becomes widespread across both groups. These findings confirm the protective role of companionship in shaping safety perceptions: a recurring pattern across age groups that underscores the social dimension of spatial security. The most negative perceptions emerge when referring to moving alone at night in other parts of Rome, where 56.0% of adult residents and 48.1% of non-residents disagree that such movements are safe (Figure 5). Overall, adult non-residents tend to express slightly higher perceived safety than residents—except when moving alone at night within the VIII subdivision, where both groups display similarly low confidence.

Figure 5 – *To what extent do you agree or disagree with each of the following statements? During the day, the VIII subdivision is a safe area to move around alone; At night, the VIII subdivision is a safe area to move around when accompanied; At night, the VIII subdivision is a safe area to move around alone; At night, it is safe to move around alone in other parts of Rome. Adults (over 34).*



Source: our elaboration on surveys data.

The comparison between age groups shows no uniform pattern: while adults tend to report higher perceived safety when alone—especially at night—young respondents express more confidence in some daytime and accompanied situations.. While both groups show a clear drop in perceived safety at night - especially when alone - youth report lower levels of agreement with positive safety statements and upper levels of uncertainty. These differences persist when distinguishing between residents and non-residents, with young residents generally reporting higher perceived safety than their adult counterparts, whereas non-residents in both age groups tend to express greater uncertainty. For example, when moving alone at night in the VIII subdivision, 20.8% of young residents and 13.0% of young non-residents

feel safe, compared to 33.2% of adult residents and 23.4% of adult non-residents. During the day, young respondents also show slightly higher levels of confidence.

Adults, by contrast, are more likely to respond neutrally, especially in contexts outside the subdivision. These patterns suggest that, although safety concerns are present across generations, adult people tend to engage with the urban space in a more cautious manner, although patterns vary by residential status., possibly because they are less conditioned by negative personal experiences or long-standing perceptions of urban insecurity.

4. Discussion and conclusion

In the face of growing population ageing and shrinking youth cohorts, many European cities face growing challenges in balancing the spatial and social needs of different generations. Rome is no exception. With a population of over 2.7 million residents and a steadily increasing ageing index, the city exemplifies the challenges of managing age-related imbalances across a large and socially heterogeneous urban territory. These dynamics raise important questions about the visibility, role, and integration of young people in the life of the city - particularly in relation to their presence in public spaces and their participation in urban rhythms that often diverge from those of older age groups.

This paper has addressed these questions by focusing on a particularly emblematic setting: the VIII sub-municipal subdivision of Rome. This area combines some of the highest levels of population ageing in the city with a strong presence of young people, due largely to the location of Roma Tre University and other cultural and recreational venues. It thus represents a meaningful case for examining how age-based asymmetries play out in the urban experience, especially during the evening and night-time hours, when differences in lifestyles, mobility, and spatial access tend to become more pronounced.

The findings of the survey, of which only a subset of the results have been presented here, underscore the importance of adopting a multidimensional perspective in the study of youth engagement with the urban night.

Patterns of use, perceptions, and behaviours are shaped by a complex interplay of age, residence, motivations, and social context. In Rome's VIII subdivision the analysis reveals a number of both contrasts and commonalities. Younger respondents appear to use the area primarily for study, socialising, and nightlife, confirming its role as a destination rather than a place of residence for many. They have a generally high tolerance for noise, combined with differentiated perceptions of safety depending on time, context, and whether they are alone or accompanied. Adults, on

the other hand, tend to engage with the area once a week and they are more likely to report higher sensitivity to noise..

Despite these differences, the analysis also reveals areas of convergence. In particular, the presence of others - friends, partners, or fellow residents - emerges as a shared factor that increases perceived safety at night across all age groups. This highlights the role of social ties in shaping the urban night as a lived and negotiated space. The coexistence of generational groups with different rhythms, expectations, and needs does not necessarily translate into open conflict, but may generate forms of tension or discomfort that remain unexpressed and should be acknowledged by urban policies.

The coexistence of different age groups in the same urban spaces - particularly in the evening and night-time - requires public policies that go beyond binary logics of regulation versus tolerance. Too often, institutional responses to nightlife are framed in terms of control, with safety and noise as dominant concerns. While these issues are not unfounded, focusing on containment risks overlooking the relational and experiential value of the night for young people. This study invite a shift in perspective: rather than viewing youth presence as a problem to be managed, urban policies should recognise it as a social resource to be supported. This includes investing in accessible spaces for safe and inclusive aggregation, ensuring night-time mobility. At the same time, policies must take into account the needs of older residents, preserving liveability, and quality of life. Balancing these needs requires an approach based on coexistence and mutual recognition rather than generational prioritisation. It also calls for the involvement of young people in shaping the city's night-time agenda—not only as users but as legitimate stakeholders in the urban environment.

This study represents an initial step in a broader research agenda aimed at understanding how young people experience urban space during the evening and night-time hours. The findings discussed here are based on a preliminary set of survey responses, and further data collection is ongoing. As such, the results should be interpreted as exploratory, offering a first set of insights into the spatial and perceptual dynamics that shape youth nightlife in Rome's VIII subdivision.

Future developments of the study will include spatial analyses of aggregation areas, cross-referencing self-reported destinations with territorial characteristics such as accessibility, residential density, and service availability to better understand the motivations and barriers experienced by youth in the urban nightscape. In addition, the analysis will be disaggregated by gender and age groups in order to capture internal diversity within the youth population and identify possible asymmetries in access, perceptions, and expectations. Particular attention will be paid to distinguishing between adults and older residents, in order to assess whether

the presence and practices of young people at night are perceived differently across generations—especially with regard to the tolerance of nightlife.

These further steps aim to refine our understanding of intergenerational relations in the night-time city and to support more inclusive urban policies.

References

- BICHI R., PASQUALINI C. 2018. *La condizione dei millennials in Italia: Rapporto Giovani*. Milano: FrancoAngeli.
- BONANOMI A., ROSINA A. 2022. Employment status and well-being: A longitudinal study on young Italian people. *Social Indicators Research*, Vol. 161, No. 3, pp. 581–598.
- CARETTA A., VILLANTE C. 2006. Il peso dell'invecchiamento della popolazione nel Comune di Roma, *Economia & Lavoro*, Vol. 40, No. 3, pp. 191–205.
- CIFONI L., PIRONE D., 2022. *La trappola delle culle*. Soveria Mannelli: Rubettino Editore
- CRIVELLO S. 2019. I locali notturni tra consumo post-moderno ed economia della notte. In Bonazzi G., Chicchi F., Mormino A. (a cura di), *Enciclopedia sociologica dei luoghi*, Milano, Ledizioni, pp. 161–175.
- GIORDANO E., GWIAZDZINSKI L. 2018. La notte urbana, una nuova frontiera per la ricerca geografica in Italia. *Rivista Geografica Italiana*, Vol. 125, No. 3, pp. 421–436.
- GOLINI A. 1999. *La popolazione del pianeta*. Bologna: Il Mulino.
- GOLINI A., LO PRETE M. V. L. 2019. *Italiani poca gente. Il Paese ai tempi del malessere demografico*. Roma: Luiss University Press.
- GOLINI A., ROSINA A. 2011. *Il secolo degli anziani. Come cambierà l'Italia*. Bologna: Il Mulino.
- PAROLI R., CONSONNI G., ROSINA A. 2020. The measure of population aging in different welfare regimes: A Bayesian dynamic modeling approach, *European Journal of Population*, Vol. 36, No. 2, pp. 363–385.

Emma BELLOTTI, Roma Tre University, emm.bellotti@stud.uniroma3.it

Filippo DI CARLO, Roma Tre University, fil.dicarlo1@stud.uniroma3.it

Cecilia REYNAUD, Roma Tre University, cecilia.reynaud@uniroma3.it

SENTENCED WITHOUT EVIDENCE? AN HONEST DIFF-IN-DIFF EVALUATION OF ITALY'S ANTI-DEPOPULATION NATIONAL STRATEGY FOR INNER AREAS

Gabriele Dore

Abstract. This study investigates the medium-term impact of the National Strategy for Inner Areas (SNAI) on internal emigration dynamics, aiming to assess the policy effectiveness in retaining residents in targeted inner areas. Leveraging Italian Census data (2012-2023 period) and OpenCoesione's 2025 release of SNAI's geocoded project records, a Doubly Robust Difference-in-Differences design, complemented with partial identification, was used to provide robust causal estimates under incremental violations of the identifying assumption. Results suggest that the policy did not produce significant effects on municipalities treated between 2017 and 2019. However, even under modest violations of the parallel trend assumption, causal estimates become fragile and inconclusive. This fragility persists even after accounting for the confounding effect of the COVID-19 pandemic, signalling a structural difficulty in achieving identification via Difference-in-Differences with available data. This calls for caution in attributing conclusive demographic effects to the policy in both the short and medium term.

1. Introduction

In July 2025, the Italian Government formally acknowledged that a significant proportion of Italian inner areas is in a condition of irreversible demographic decline (PSNAI, 2025), foreseeing for these territories institutional support on a “*socially dignified pathway of chronic shrinkage and ageing*” as a Cohesion Policy objective (PSNAI, p. 45). Such acknowledgement reflects the inherent difficulty of reversing decline once it becomes entrenched (Copus *et al.*, 2021). In fact, the phenomenon can not be understood solely as a contraction of the resident population, but rather as a self-perpetuating syndrome of decline where negative natural and migration balance intersects with processes of economic restructuring, geographic disadvantages, and austerity-driven disinvestments (Elshof *et al.*, 2014; Copus *et al.*, 2021; Newsham and Rowe, 2025). This syndrome erodes local tax bases, weakens essential public services, and undermines economic vitality, hampering territories' endogenous capacity to react (Copus *et al.*, 2021).

The unprecedented recalibration of Italy's policy effort to counter depopulation follows nearly a decade of targeted action addressing territorial disparities. Through the National Strategy for Inner Areas (SNAI), Italy established a place-based policy

to reverse negative demographic trends by improving service provision (education, healthcare, transport) and promoting local development (Barca *et al.*, 2014; Lucatelli *et al.*, 2022). Because migration is the most responsive component of population change in the short term (Newsham and Rowe, 2025), SNAI's effects are expected to emerge first through adjustments in internal mobility. Evidence shows that out-migration reacts strongly to both service availability and local economic opportunities: improved service access reduces pressures to leave, while enhanced employment prospects strengthen retention and attraction and can support fertility (Elshof *et al.*, 2014; Sonzogno *et al.*, 2022; Benassi *et al.*, 2023). By acting simultaneously on these determinants of mobility, SNAI potentially creates a coherent pathway through which interventions can curb out-migration and increase the attractiveness of inner areas, laying the groundwork for longer-term demographic stabilisation.

Nevertheless, it remains a matter of debate whether the SNAI is producing the desired demographic outcomes. Empirical evidence on its impact on population dynamics is scarce. The only contribution in this respect is by Monturano *et al.* (2025), who found no evidence of an effect on net migration rates, but positive impacts on new business creation in the short term through a Difference-in-Difference (DiD) design. However, their analysis is based on a short-term evaluation and a sample of treated municipalities as of 2020, which limits the possibility of providing the evidence needed to inform potential policy reforms.

To contribute to the ongoing debate, this study investigates the medium-term effects of the SNAI on internal emigration from Italy's inner areas. The empirical strategy combines the doubly robust properties of Callaway and Sant'Anna (2021)'s estimator with Rambachan and Roth (2023)'s partial identification approach, allowing for causal inference under incrementally relaxed identifying conditions. Compared to the existing literature, this study leverages newly available SNAI-related intervention data extending to 2025, allowing for a larger treated sample and a longer observation window; it adopts an empirical approach suited for medium-term evaluation that accounts for confounding factors such as the COVID-19 pandemic; and it moves beyond aggregated migration indicators by focusing on demographically granular internal emigration flows. By isolating out-migration, this study avoids conflating retention and attraction effects, which may follow different dynamics and temporal patterns after policy interventions. This focus also allows us to provide precise evidence on the capacity of the strategy to retain the resident population.

2. Policy Background and Treatment Assignment Mechanism

The SNAI is a place-based policy launched in 2012 under the EU Cohesion Policy 2014–2020. It is implemented through integrated area-based projects financed by

national resources and EU structural funds (ERDF, ESF, EAFRD) for a total of €1.15 billion (Barca *et al.*, 2014). By the end of the 2014–2020 programming period, 72 project areas had been selected, comprising approximately 1,060 municipalities and around 2 million residents. As of April 2025, only 20% of projects have been completed, and 54% are still ongoing, with a monitored public cost of €538 million, indicating that implementation remains at an early stage operationally.

Delving into the treatment assignment mechanism, unlike traditional open-call procedures, SNAI adopted a multi-level selection and concentration approach. The national territory was first classified by accessibility to essential services: municipalities with upper secondary schools, a DEA Level 1 hospital, and a certified railway station were designated as “centres,” while all others were grouped into belts (up to 20 min), intermediate (20–40 min), peripheral (40–75 min), and ultra-peripheral areas (over 75 min), with the latter three defining inner areas (Lucatelli *et al.*, 2022). Regional governments then proposed aggregates of IA municipalities as candidate project areas. These proposals were assessed by the national *Technical Committee for Inner Areas* using a standardised indicator grid covering demographic, socio-economic, and infrastructural conditions, followed by fieldwork and consultations with local stakeholders. This phase allowed adjustments reflecting territorial cohesion, shared development visions, and local leadership (Lucatelli *et al.*, 2022). Although the process followed a coordinated national framework, the available documentation provides limited detail on how quantitative indicators were used. Similarly, the interplay between quantitative criteria and qualitative judgment introduced discretionary elements. For example, some municipalities in critical demographic conditions were initially excluded from the project areas but later included upon their explicit request; others were selected due to their importance in ensuring the development of the entire project area. These features suggest caution in assuming quasi-randomness or strong comparability between treated and untreated areas.

Importantly, the specificities of selection mechanisms may have direct implications for the plausibility of the parallel trends assumption (PTA) (see Ghanem *et al.*, 2022). In the case of SNAI, these implications are multifold. Initial classifications based on largely stable territorial features could support similar pre-treatment trajectories across units. However, discretionary adjustments may introduce time-varying and unobserved factors, breaking parallel trends. Combined with the intrinsic heterogeneity of Italy's inner areas, this suggests that assuming unconditional parallel trends a priori is unwarranted. While conditioning on key pre-treatment covariates reduces observable differences between treated and eligible units and thereby makes parallel trends more plausible, unobserved or dynamic factors may still generate deviations, so conditional parallel trends may not be guaranteed. This motivates the use of covariate-adjusted, doubly robust estimation

and complementary sensitivity analyses to enhance comparability and assess the robustness of the estimated effects to violations of the identifying assumption.

3. Data and Empirical Strategy

3.1. Data and Sample Construction

This empirical study draws on a balanced panel dataset of Italian municipalities observed annually from 2012 to 2023. The units of analysis are municipalities defined according to 2020 ISTAT administrative boundaries and SNAI 2014-2020's territorial map (2020 last update), ensuring territorial and temporal coherence among data sources.

The outcome variable is the *annual internal emigration rate*, defined as the ratio between the number of individuals relocating from one municipality to another within Italy and the average resident population during the same period, expressed per 1,000 inhabitants. This metric is derived from ISTAT's permanent and reconstructed intercensal population census for the 2012-2023 period.

The treatment variable identifies whether an eligible municipality was exposed to SNAI's intervention during the 2014–2020 programming period. A municipality is considered treated starting from the year in which the first SNAI project officially began its implementation, based on the “*Actual Start Date of Implementation*” recorded in OpenCoesione data (as of February 2025). Treatment status is irreversible: once a municipality is treated, it remains in the treated group for the rest of the observation period.

Additional covariates were selected for their relevance in predicting untreated potential outcomes and the probability of treatment. These include: average resident population, percentage of residents aged +75, percentage of foreigners, and average per capita income (sourced from municipal IRPEF data provided by the Ministry of Economy and Finance).

The initial raw sample included 7,904 municipalities. After data cleaning procedures to remove cases affected by boundary changes and inconsistencies in treatment assignment (i.e., municipalities formally included in a SNAI project but non selected in the SNAI framework), the final sample comprises 7,637 municipalities.

3.2. Empirical Strategy

The study's aim is to estimate the medium-term effects of SNAI-related interventions on municipalities treated within the 2014-2020 SNAI Framework. The target parameter is the *Average Treatment Effect on the Treated* (ATT), which measures the difference, on average, between what happened to units that received

the intervention and what would have happened to them if they had not received it. To estimate the ATT, a *Difference-in-Differences* design was employed, given the non-random nature of the treatment. A key complication in this context arises from the staggered design of the policy: SNAI's interventions began in a staggered fashion from 2015 to 2023, with considerable variation in timing and treated cohorts' sample size. In such a context, standard Two-Way Fixed Effects estimators are prone to produce biased estimates due to inappropriate comparisons between earlier- and later-treated units (Callaway and Sant'Anna, 2021).

To address these issues, the study leveraged Callaway and Sant'Anna (2021)'s Doubly-Robust DiD estimator (DR-DiD). DR-DiD computes *group-time average treatment effects* (ATT_{gt}) (Eq. 1), which under no anticipation, common support, and parallel trends, remain consistent as long as either the outcome model or the generalised propensity score model is correctly specified.

$$ATT(g, t) = E[Y_t(g) - Y_t(0) | G = g] \quad (1)$$

In this setting, anticipating behaviours are unlikely due to both the treatment assignment mechanism nature and the lack of information dissemination from central authorities to local beneficiaries (Monturano *et al.*, 2025). On the other hand, violations of the common support and parallel trends assumptions may be plausible. For the former, due to the relatively small sample sizes of 2015 and 2016 treated cohorts (16 and 7 units, respectively), and for the latter, due to both the COVID-19 pandemic shock that impacted treated cohorts in between their pre- and post-treatment periods, as well as a hybrid selection mechanism that may not accommodate the PTA. Thus, units treated in 2015, 2016, and from 2020 to 2023 were excluded from the sample. These exclusions, while necessary to preserve internal validity, limit the generalisability of the findings. The omitted cohorts may differ systematically in their structural characteristics or exposure to external shocks, meaning that estimated effects should be interpreted as reflective of the 2017–2019 treated municipalities rather than the full set of SNAI beneficiaries.

Additionally, the full time series including COVID-19 years was considered to enable a medium-term evaluation of the strategy. Although the presence of an exogenous shock with heterogeneous impact on inner areas and migration dynamics, such as COVID-19, represents a credible threat to the PTA, the study relies on Rambachan and Roth (2023)'s framework to assess the sensitivity of the estimates to increasing deviations from parallel trends. More precisely, the study, rather than assuming a binary judgment on parallel trends (assumption holds vs. fails), shifts the focus towards a continuous assessment of how robust the estimates are to increasingly severe departures from the identifying assumption.

4. Preliminary Analysis and Identification Checks

SNAI operates within a highly heterogeneous territorial context, where inner areas differ markedly in structural, demographic, and economic terms. This heterogeneity is documented in Table 1, which reports summary statistics comparing “not eligible” (i.e., units not selected under SNAI), “eligible” (i.e., units selected but not yet treated until 2023), and treated units.

Table 1 – *Summary Statistics by Treatment Cohort and Eligibility Status (2012-2016).*

Variable	Not Eligible	Eligible	Treated 2017	Treated 2018	Treated 2019
Obs	32,995	2,720	130	240	555
Emigr. Rate	30.31 (14.58)	29.88 (17.22)	26.86 (9.21)	28.40 (11.84)	29.27 (15.11)
Mean Pop.	3,689.28 (6,102.24)	1,674.46 (1,876.24)	2,977.66 (2,770.90)	2,564.33 (3,973.57)	1,609.20 (1,438.34)
Pop +75	12.68 (2.65)	16.54 (5.11)	15.51 (4.57)	15.22 (6.74)	16.35 (4.87)
Pop. Forgn.	5.82 (4.52)	3.99 (3.29)	6.62 (3.25)	5.11 (3.84)	5.88 (3.99)
Mean Income	17,122.75 (3,552.69)	14,929.92 (2,859.58)	17,260.47 (3,020.98)	17,464.26 (3,423.26)	17,604.49 (3,272)

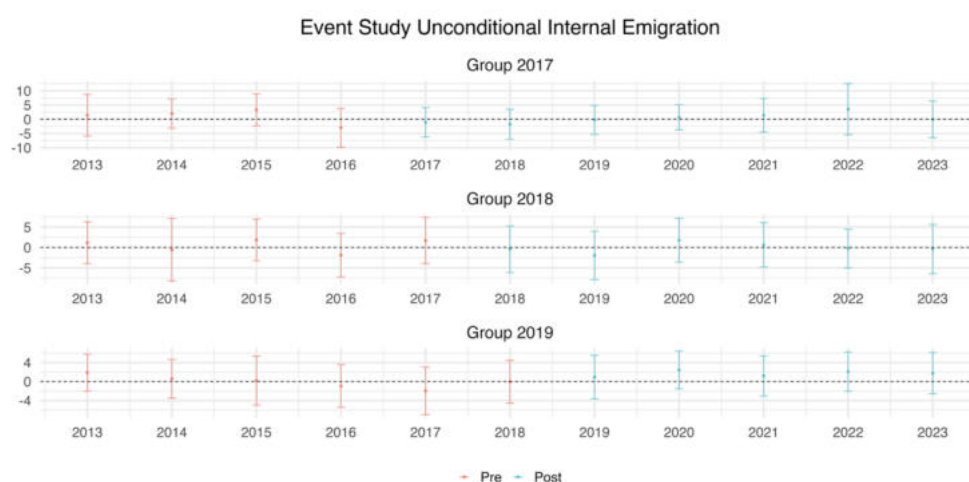
Mean and, in parentheses, Standard Deviations. Own elaboration from the ISTAT population census

Treated units exhibit lower internal emigration rates, less pronounced population ageing, and higher per capita income compared to eligible units. Although eligible units were formally included in the SNAI framework, they appear more structurally vulnerable and underperforming across most indicators than other groups. In contrast, treated municipalities tend to be smaller than non-eligible ones and display more pronounced ageing dynamics, though they report slightly higher income levels and lower emigration rates. Accounting for these differences, the selection of a valid control group was guided by alignment with the strategy’s selection logic. Non-eligible municipalities were excluded, as their characteristics placed them outside the scope of the SNAI. In contrast, eligible units were subject to the same selection mechanism as treated municipalities and were chosen based on their territorial relevance, vulnerability, and internal coherence with the characteristics of their respective pilot areas. Thus, eligible units were considered as an acceptable counterfactual group.

As a second step, the plausibility of parallel trends between treated and eligible units was assessed via an Event-Study plot estimated through the DR-DiD estimator.

Figure 1 presents event-study estimates on the full time series, including the COVID-19 period. Pre-treatment coefficients fluctuate around zero and are not statistically significant, suggesting no evidence of divergence prior to the treatment. However, the Wald test computed on joint pre-treatment coefficients rejects the null hypothesis of equal pre-trends (p-value=0.027).

Figure 1 – Event Study estimates for the Unconditional Parallel Trend Assumption.



ATT(g,t) estimated using Callaway and Sant'Anna (2021)'s Doubly Robust Estimator.

A clear discrepancy emerges between the event-study estimates and the Wald test: single-coefficient pre-treatment estimates are imprecise and therefore have limited power to detect small deviations, whereas the joint Wald test pools information across all pre-treatment periods and is more sensitive to systematic differences. The rejection of the Wald test should be read as circumstantial evidence that unconditional parallel trends are unlikely to hold in this context, plausibly due to residual covariate imbalance between groups. To further explore this, covariate imbalance was assessed by computing *Standardised Mean Differences (SMD)* between each treated cohort and the control group, limiting the sample to the 2012-2016 period and employing in the denominator the treated group's standard deviation. Table 2 reports the computed SMD, highlighting substantial imbalance at the 0.1 threshold level between groups and across all the variables considered. This evidence suggests that systematic differences in observable characteristics may have contributed to the violation of the unconditional PTA and further supports the need to consider covariate-adjusted estimators in the main analysis.

Table 2 – *Standardised Mean Difference Pre-treatment Covariates (2012-2016).*

Variable	Control	Treated 2017	SMD	Treated 2018	SMD	Treated 2019	SMD
Obs	2,720	130		240		555	
Mean	1674.46	2977.66	0.47	2564.32	0.22	1609.20	-0.05
Pop.	(1876.15)	(2770.90)		(3973.57)		(1438.34)	
Pop +75	16.54	15.51	-0.22	15.22	-0.20	16.35	-0.04
	(5.11)	(4.57)		(6.74)		(4.87)	
Pop. Forgn	3.99	6.62	0.81	5.11	0.29	5.88	0.47
	(3.29)	(3.25)		(3.84)		(3.99)	
Mean Income	14929.92	17260.47	0.77	17464.26	0.74	16604.49	0.61
	(2859.58)	(3020.98)		(3423.26)		(2766.12)	

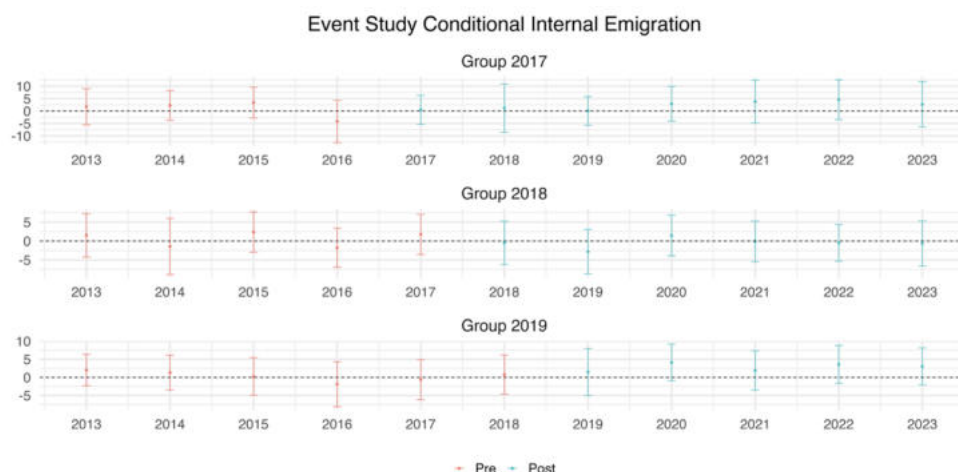
Mean and, in parentheses, Standard Deviations. Own elaboration from ISTAT pop. Census.

5. Results

This section presents the estimated effects of SNAI interventions on internal emigration rates employing the Doubly Robust Difference-in-Differences estimator (Callaway and Sant'Anna, 2021).

Identification checks highlighted the necessity to account for observable differences between treated and control units, as the unconditional PTA is implausible in this context. The estimates, in this respect, are adjusted for imbalanced covariates to re-establish parallelisms, among these: average population, percentage of residents aged +75, percentage of foreign residents, and average per-capita income. Figure 2 displays $ATT(g,t)$ for 2017, 2018, and 2019 treated cohorts. Post-treatment coefficients are not statistically significant across periods and cohorts. However, the direction and magnitude of the estimated effects differ across groups and time horizons.

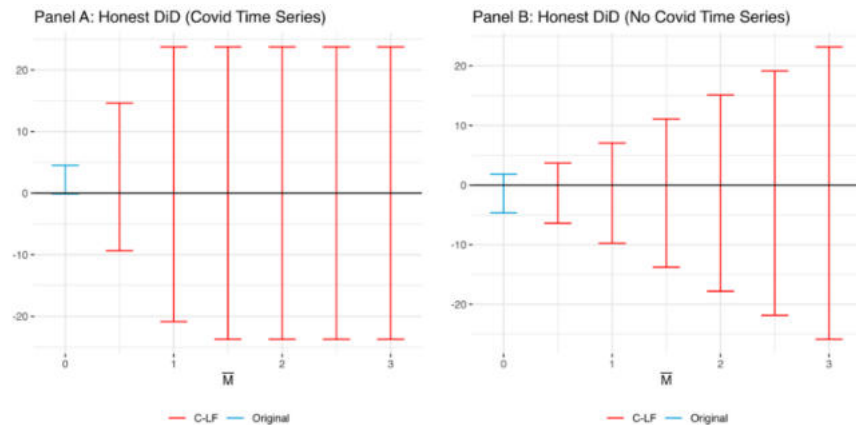
Regarding the conditional PTA, no individual pre-treatment $ATT(g,t)$ is statistically significant, and the Wald test ($p = 0.246$) provides evidence of parallelism in the pre-treatment periods. This reflects improved comparability after controlling for covariates. However, pre-treatment diagnostics alone remain uninformative about the PTA in current periods (Callaway and Sant'Anna, 2021). Thus, while the conditional specification mitigates imbalance-driven discrepancies and provides some evidence of parallelism in the pre-treatment period, it does not eliminate uncertainty about whether the conditional PTA holds.

Figure 2 – Conditional $ATT(g,t)$ Estimates.

Covariates controlled: average population, percentage of residents aged +75, percentage of foreign residents, and average per-capita income.

5.1. Sensitivity Analysis

Given the limited informativeness of the pre-treatment diagnostics, it remains plausible that the conditional PTA may not hold exactly. For this reason, the analysis turns to the partial-identification framework of Rambachan and Roth (2023), which provides a principled way to evaluate how conclusions about the treatment effect change under increasingly conservative departures from the conditional PTA, while accounting for both statistical and identification uncertainty. The sensitivity analysis is performed on both the full time series, including COVID-19 years, and a trimmed time series, restricted to the 2012-2019 period. This allows us to remove a major source of bias and assess whether the evidence obtained in the full time series reflects structural identification issues rather than the confounding effect of COVID-19 alone. In this setting, relative magnitude restrictions are employed. Through the parameter $\bar{M}$, post-treatment deviations from parallel trends are allowed to scale proportionally to the largest violation observed between any two consecutive pre-treatment periods. Specifically, robustness was tested in the fourth year after implementation in the full time series and the first year after treatment in the trimmed series. The fourth period was preferred since all groups were exposed to the strategy for at least 4 years. Figure 3 presents the results obtained using the HonestDiD package separately for the full sample (Panel A) and the restricted sample (Panel B).

Figure 3 – Honest DiD Sensitivity Analysis.

The first coefficient derives from the original ATT computed via dynamic effects and a universal base period.

In Panel A, the baseline $ATT(g,t)$ at event time 4 is 2.20 ($SE=1.21$), with a CI of $[-1.01; 5.41]$. Using the largest pre-treatment deviation (1.55) to calibrate M , the robust CI widens substantially even under mild deviations from parallelism: at $M=1$ (i.e. post-treatment deviations are as large as the deviations observed in the pre-treatment period) it spans $[-20.85; 23.73]$, and at $M=2$ and $M=3$ (i.e. deviations twice as large and three times greater) is $[-23.73; 23.73]$. Importantly, setting the M parameter to 2 or above appears empirically plausible, given that the mean variation in the outcome between 2019 and 2020 was -3.7 per thousand.

Panel B, focusing on short-term effects at event time 1 and excluding pandemic years, produces similarly wide intervals. Starting from an $ATT(g,t)$ of -1.40 ($SE=1.65$) [CI: -5.61; 2.81], and a maximum pre-treatment deviation of -2.13, honest confidence intervals span from $[-9.74; 7.05]$ at $M=1$, to $[-17.81; 15.12]$ at $M=2$.

While these results confirm the non-significance of the treatment effects in both specifications, HonestDiD estimates suggest that even moderate deviations from the conditional PTA are enough to render causal conclusions fragile, highlighting the limited informativeness of the estimates. In this regard, honest intervals include potentially economically significant effects in both directions that can be considered of high relevance for the strategy. Crucially, this fragility is not limited to the specification including COVID-19 years but persists in the trimmed series, where parallelism appeared more plausible. This pattern indicates that the available data do not provide enough information to distinguish between a truly null effect and policy effects that may exist but can not be reliably identified once even modest deviations from conditional PTA are allowed. From a substantive standpoint, the absence of

detectable changes after almost a decade remains consistent with an effect that is either genuinely limited in magnitude or insufficiently identified under the constraints of the available design

6. Conclusions

This study examines the long-term impact of the National Strategy for Inner Areas on internal emigration rates, using a staggered Doubly Robust Difference-in-Differences design combined with a sensitivity analysis grounded in the HonestDiD partial identification framework. Results reveal estimates that are not statistically significant across groups up to four years of exposure to SNAI-related projects. This result is in line with Monturano *et al.* (2025)'s findings on the lack of significant effect of the SNAI on demographic dynamics. However, this null result must be interpreted with caution since the non-significance may not represent conclusive evidence of policy ineffectiveness. Indeed, HonestDiD results suggest that even modest deviations from the conditional PTA generate robust confidence intervals including economically significant effects in both directions. This was expected in light of the COVID-19 confounding effect. However, this fragility persists even when excluding the COVID-19 period. This reinforces the interpretation that issues lie not solely in pandemic-related confounding effects, but in structural limitations of the data and the context under study, which do not provide sufficient information to draw robust causal conclusions under incrementally relaxed identifying conditions.

Taken together, these results suggest that relying solely on visual inspection of pre-treatment coefficients or joint significance tests to assess PTA plausibility may be misleading. In the context of policy evaluation, this poses a tangible risk: it could lead to premature termination or misguided continuation of interventions based on fragile and weakly informative evidence.

Future research on SNAI would benefit from designs that are less vulnerable to violations of parallel trends or that rely on different identifying conditions altogether. Promising avenues include: (i) the use of individual-level microdata, which would allow for capturing behavioural responses obscured in aggregate flows; (ii) leveraging natural experiments; and (iii) adopting alternative methodologies such as Synthetic DiD, panel matching, or augmented synthetic controls to construct more credible counterfactuals based on pre-treatment dynamics. These approaches could substantially improve the ability to capture small but policy-relevant effects in demographically fragile areas.

References

- BARCA F., CASAVOLA P., LUCATELLI S., 2014. Strategia nazionale per le aree interne: definizione, obiettivi, strumenti e governance, *Materiali ULAV*, Vol. 31, No. 10.
- BENASSI F., BUSETTA A., GALLO G., STRANGE M., 2023. Neighbourhood effects and determinants of population changes in Italy: A spatial perspective. *Vienna Yearbook of Population Research*, Vol. 21, pp. 311–338.
- CALLAWAY B., SANT'ANNA P.H.C., 2021. Difference-in-Differences with multiple time periods, *Journal of Econometrics*, Vol. 225, No. 2, pp. 200–230.
- COPUS A., KAHILA P., DAX T., KOVACS K., TAGAI G., WEBER R., GRUNFELDER J., MEREDITH D., ORTEGA-REIG M., PIRAS M., LOFVING L., MOODIE J., FRITSCH M., FERRANDIS A. 2021. European shrinking rural areas: Key messages for a refreshed long-term vision, *TERRA: Revista de Desarrollo Local*, Vol. 8, No. 8.
- ELSHOF H., VAN WISSEN L., MULDER C.H., 2014. The self-reinforcing effects of population decline: An analysis of differences in moving behaviour between rural neighbourhoods with declining and stable populations, *Journal of Rural Studies*, Vol. 36, pp. 285–299.
- GHANEM D., SANT'ANNA P.H., WÜTHRICH K., 2022. Selection and parallel trends. *arXiv preprint arXiv:2203.09001*.
- LUCATELLI S., LUISI D., TANTILLO F., 2022 *L'Italia Lontana. Una politica per le aree interne*. Roma: Donzelli Editore.
- MONTURANO G., RESCE G., VENTURA M., 2025. Short-term Impact of Financial Support to Inner Areas, *Italian Economic Journal*.
- NEWSHAM N., ROWE F. 2025. The Demographic Causes of European Sub-National Population Declines, *European Journal of Population*, Vol. 41, No. 1, pp. 10.
- PCM, March 2025. Piano Strategico Nazionale per le Aree Interne (PSNAI).
- RAMBACHAN A., ROTH J., 2023. A More Credible Approach to Parallel Trends, *Review of Economic Studies*, Vol. 90, No. 5, pp. 2555–2591.
- SONZOGNO G. V., URSO G., FAGGIAN A., 2022. Migration propensity of peripheral youth: insights from Italy. *Regional Studies, Regional Science*, Vol. 9, No. 1, pp. 709–726.

INNOVATIONS IN THE METHODOLOGICAL DESIGN OF THE RECURRING INAPP PLUS SAMPLE SURVEY

Francesca Bergamante, Gianni Corsetti,
Francesca della Ratta-Rinaldi, Andrea Spizzichino

Abstract. The PLUS (Participation, Labor, Unemployment, Survey) is a recurring national sample survey conducted by INAPP on a sample of 45,000 individuals aged 18 to 74 years. This paper aims to analyse the methodological innovations introduced in the 2024 version of the survey (the latest), highlighting the reasons behind these changes, aiming at making the estimates more reliable and addressing the need for transparency and scientific rigor. The innovations concern various aspects of the survey. First of all, the information about the subjective working condition coming from Istat LFS has been considered in order to redefine the key aggregates and the sample strategy. Secondly the final weights calibration has been changed, inserting between the constraints even the occupation (1° digit). Furthermore, has been improved the control and the correction processes for most of the relevant variables.

1. Introduction

This contribution presents the main innovations introduced in the most recent wave of the INAPP-Plus survey, conducted in 2024. These innovations concerned various aspects of the survey design, including both the sampling framework and the weighting procedures, as well as certain processes related to data validation and correction. The overarching objective of these enhancements was to produce more robust and reliable estimates, while improving comparability with LFS data, all the while preserving the core structure of the survey and ensuring the continuity of historical time series.

The paper is structured as follows. The first section provides an overview of the INAPP-Plus survey. The second section presents sampling design characteristics and the improvements inserted in the calibration system. The third section focuses on the improvements implemented in data control and correction procedures. The contribution concludes with final reflections.

2. The recurring INAPP Plus sample survey

PLUS - Participation, Labor, Unemployment, Survey is a biennial recurring national sample survey conducted by INAPP Labour Market Unit¹. The first edition of the survey was conducted in 2005, and since 2006 it has been included in the National Statistical Programme (PSN).

The survey, which is representative of the entire Italian population is conducted on a sample of 45,000 individuals aged 18 to 74 years using the CATI (Computer-Assisted Telephone Interview) technique. The planning of interviews is based on quota sampling, stratified with the definition of partially overlapping study domains. The eleventh edition of the survey was conducted in 2024. The next edition of the survey (the twelfth) is scheduled to be conducted in 2026.

The survey adopts a longitudinal design, employing a non-rotating panel structure consistent with the classical longitudinal framework. This design facilitates dynamic analyses across various individual states—not limited to employment—thus enabling the reconstruction and study of detailed individual labour market trajectories.

The main objective is to analyse specific aspects of the labour market, such as young people's entry into the labour market, the extension in length of employment of the population in older age groups, participation of the female population, and job search patterns. The survey also aims to detect the labour characteristics of employed people and changes in employment status and needs as a result of the health emergency.

The questionnaire is extensive and consists of several modules, some of which are specifically dedicated to different types of employment contracts or different employment status. The questionnaire has a fixed core, but thanks to its flexible design, it is possible to include new questions or modules aimed at investigating novel or emerging aspects deemed important for producing estimates and analyses.

Each wave of the survey produces a dataset along with a methodological note, which supports the use of the dataset and provides insight into the more technical aspects of the survey design. The databases generated through the survey are freely disseminated and are widely used by the research community and academia. Plus data are extensively used within Inapp to produce institutional documents (such as Inapp Policy Briefs²), support parliamentary hearings, contribute to the Inapp annual

¹ <https://www.inapp.gov.it/en/surveys/periodic-surveys/participation-labour-unemployment-survey-plus>

² <https://oa.inapp.gov.it/server/api/core/bitstreams/a5716ef6-5aa6-4fea-ba09-82c04d948175/content>
<https://oa.inapp.gov.it/server/api/core/bitstreams/aa36011a-f9be-4888-a5bf-1de340a3646a/content>
<https://oa.inapp.gov.it/server/api/core/bitstreams/803134bf-5b3a-4690-a38d-d2a6a4e96c3e/content>
<https://oa.inapp.gov.it/server/api/core/bitstreams/0aa54fab-f9f7-4826-a31f-dcbcb85d68f1/content>

Report³, and develop scientific publications as well as presentations for conferences and seminars. Furthermore, in 2022⁴ and 2024⁵, two specific reports were produced, providing estimates and analyses on a wide range of indicators and issues (Inapp, Bergamante, Mandrone 2022; Inapp, Bergamante, Luppi 2024).

3. The INAPP PLUS sample design

The schedule of interviews to be carried out was made on the basis of a stratified quota sampling with definition of partially overlapping domains of study (Corsetti 2002 and 2024). The choice of quota sampling was motivated by the need to greatly reduce the sample size needed to produce statistically significant estimates for small subpopulations of interest (Mandrone 2012). As an alternative we could have chosen to use strategies of classical two-stage sampling (e.g., municipalities and households) but, in addition to requiring fieldwork much more costly, would involve the surrender of a survey of the main features PLUS, one of no proxy respondents.

The sample is divided into ten key target (domain of interest):

1. Young workers, aged between 18 and 29 years;
2. Young students, aged between 18 and 29 years;
3. Young unemployed (student or inactive women), aged between 18 and 29 years;
4. Active women, aged between 18 and 39 years;
5. Inactive women, aged between 18 and 39 years;
6. Active Seniors, aged between 50 and 74 years;
7. Inactive Seniors (retired from work), aged between 50 and 74 years;
8. Unemployed aged between 15 and 74 years;
9. Employed aged between 15 and 74 years;
10. Inactive aged between 15 and 74 years.

In order to provide reliable estimates for the subgroup of these 10 domains (for example, limited to each of the Italian geographical areas) we planned a stratified

<https://oa.inapp.gov.it/server/api/core/bitstreams/4324a2a6-ba16-41d1-9ead-3aa3e582775f/content>

<https://oa.inapp.gov.it/server/api/core/bitstreams/505215c7-aa1d-4fcc-8161-ba3be3b50ea4/content>

³ <https://www.inapp.gov.it/en/publications/inapp-report/published-editions>

⁴ <https://oa.inapp.gov.it/server/api/core/bitstreams/8e277563-6453-4460-a5a3-e1a79b839e43/content>

⁵ <https://inapp.infoteca.it/ricerca/dettaglio/rapporto-plus-osservare-le-traiettorie-del-mercato-del-lavoro/25380#>

sampling, where the layers (sex, age class, employment status, type of municipality, geographical areas) constitute a partition of the sample and (for subsets of layers) of the same domains of study.

The number of interviews to be obtained for each of the layers was determined to provide reliable estimates for the entire reference population and for particular subsets of interest, through the implementation of a procedure for multi-domain allocation, based on resolution a constrained minimization problem. More precisely, a priori minimum variance targets were set for the domains of interest listed above and for their territorial breakdowns by geographical areas and type of municipality (urban, non-metropolitan). The allocation procedure uses LFS estimates as its data source.

The next step, is related to the choice of weighting estimator constrained to be adopted for the calculation of the coefficient to the universe. In particular, it has resorted to the implementation of methods based on the use of the estimator of generalized regression (GREG estimator) (Valliant 2000 e Särndal 2005). It ensures that the estimates of the absolute frequencies of the auxiliary variables used as regressors are coincident with the known observed (LFS 2024) in the total population and imposed as calibration constraints. First, this implies that the demographic composition of the actual population and employment reference is, by construction, reproduced in the analysis.

Furthermore, it allows to correct distortions caused by factors not fully controlled in the design phase of the investigation and related instead to the detection phase, as the self-selection of the sample due to the higher average propensity to answering certain categories of persons.

3.1. Innovation in sample design

Despite the Labour Force Survey (LFS) serving as a fundamental benchmark, the INAPP survey design presents several differences in the definitions used to identify key labour market aggregates—namely, employed, unemployed, and inactive—partly due to the chosen survey technique. While the LFS employs a funnel-based approach, identifying employment status through objective and harmonized criteria (as established at the European level), the PLUS survey, conducted via CATI and based on quota sampling, necessarily begins with a filter question that captures the respondent's self-reported status (subjective definition).

This divergence in definitional criteria was not previously accounted for in the stratification and weighting system, which relied on LFS estimates based on objective definitions of employment and unemployment as calibration constraints. However, since both surveys—albeit through different question sequences—collect

information on both objective and subjective definitions, it is possible to analyse which criterion is more appropriate for determining the calibration constraints to be used in the survey.

In the 2024 revision, a differentiated approach was adopted for employment and unemployment. For employment, the discrepancy between objective and subjective definition is minimal⁶, with a 99.4% concordance in the sample data, closely aligning with the 99.2% reported by LFS for the 2024 average. This high level of agreement supported us to use (as in the past) LFS objective estimate as calibration constraints for employment, also due to the need for additional employment-related information (e.g., working hours, job characteristics, occupation), which would not be available for the small subset of subjectively employed individuals in the LFS.

The situation is different for job seekers, for whom the difference between the two definitions is larger. According to the objective definition, to be considered unemployed, people must have engaged in at least one job-search activity in the four weeks preceding the interview and be available to start work within the following two weeks. The subjective definition, on the other hand, refers to an individual's perception of their own situation. This is not necessarily linked to job-search activities or immediate availability to start work and is often associated with inactivity or discouragement. ISTAT has documented the difference between the objective and subjective conditions of job seekers since 2007 (Istat 2007). Based on these considerations, it was deemed more appropriate to use the subjective response from the LFS questionnaire (QJ01) as the calibration constraints for estimating job seekers. This approach also allows for a more nuanced classification of individuals as employed, unemployed, students, retirees, or other inactive persons.

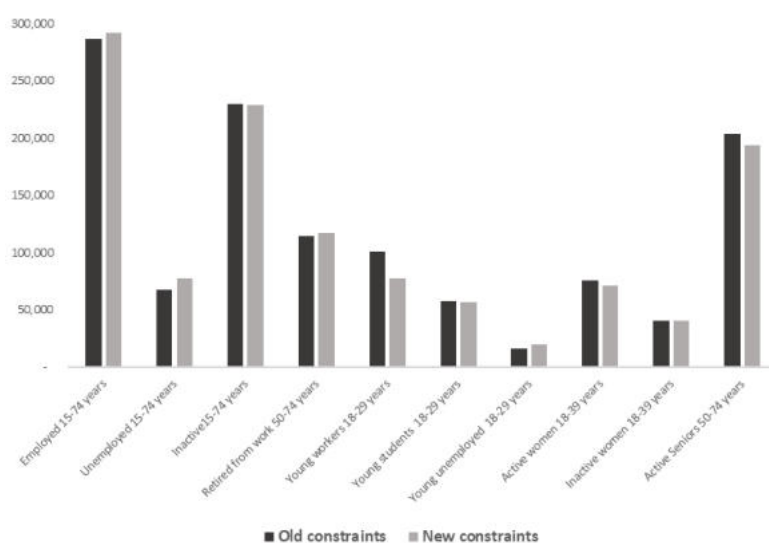
A second innovation in the calibration design concerns the auxiliary variables used for weighting. In addition to working hours and employment, the first-digit occupational classification (the nine major occupational groups) was introduced to enhance consistency between the estimates of the two surveys, particularly for variables closely linked to occupation.

To reach this decision, several tests were conducted using 2022 data, allowing for a comparison between the previous weighting system and various combinations incorporating additional variables selected from those available and highly correlating with key study variables (e.g., occupation, economic activity classification, or a mix of both). The selected solution was the one that minimized overall discrepancies with LFS estimates for certain employment-related variables (not included in the weighting system).

⁶ Since 2022 the PLUS survey has inserted the indicators useful to detect employed also using the objective definition, according to the new definition inserted in 2021 in the European LFS as explained here: <https://www.istat.it/notizia/forze-di-lavoro-2021-come-cambia-la-rilevazione/>.

An analysis of the effects of the new calibration on the reliability of 2022 estimates shows that the systems are closely aligned and that the introduced changes did not increase estimation error—in some cases, they even led to improvements (Figure 1).

Figure 1 - *Estimated value (a.v.) above which 10 percent is exceeded in terms of Coefficient of Variation by domains of interest and type of constraints (Plus 2022).*



Source: INAPP Plus 2022

Further analysis on 2024 data should assess the validity of the choice made, with the aim of further enhancing the comparability and accuracy of labour market indicators derived from the PLUS survey.

4. Innovations in data control and correction

Data control and correction has historically represented a fundamental step in the production process of the survey and has always been characterized by the introduction of innovations that have made it possible to implement and enhance the changes made to the questionnaire.

The innovations introduced allow for a better interpretation of the changes taking place in society and, more specifically, in the labour market. In the latest edition of the survey, specific changes were made to the production process of income variables to account for developments that occurred over the past two years.

The revisions to the procedures for defining income involved several stages of the process. The main changes were related to the treatment of negative income for the self-employed, the adjustment of tax rates used to define gross income for employees, and the use of a variable indicating the number of months worked in 2024 to define a gross income weighted by the actual months of employment.

The control and correction interventions for negative income among the self-employed included the imputation of income for all individuals who declared zero income and reported a loss during the year. The imputation methodology used was the hot deck technique, already applied to other quantitative variables.

Regarding the grossing-up of employee income, it became necessary to apply the new IRPEF income tax rates introduced in 2024 to calculate total annual gross income. Finally, concerning the number of months worked in the last year, this edition of the survey reintroduced the question on the number of months worked in the current job, if it began during the current year. This allowed for the calculation of gross income based only on the months actually worked.

Table 1 presents some results on income, comparing the reported and imputed data from the last two editions of the survey. It can be observed that the mean and median income for the self-employed, employees, and coordinated and continuous collaborators are substantially the same between the observed and imputed data.

Table 1 – Statistical indicators on observed and imputed income (years 2022 and 2024).

CoCoCo					
Year	Imputed	Mean	Median	CV	Kurt
2022	0	1354	1100	59	2
2022	1	1447	1250	69	3
2024	0	1661	1480	52	4
2024	1	1688	1300	58	5
Employees					
Year	Imputed	Mean	Median	CV	Kurt
2022	0	1573	1500	61	236
2022	1	1503	1400	49	155
2024	0	1597	1500	40	499
2024	1	1573	1500	37	170
Self-employed					
Year	Imputed	Mean	Median	CV	Kurt
2022	0	32685	25000	119	50
2022	1	33603	25000	118	47
2024	0	39427	30000	124	67
2024	1	39454	30000	113	55

Source: INAPP Plus2022 e INAPP Plus 2024.

The comparison between the income data for 2022 and 2024, both for the observed and imputed values, shows an increase in the mean income, a decrease in the coefficient of variation (CV), with the exception of self-employed respondents, and an increase in kurtosis. These changes suggest that the income distribution has shifted toward higher values, with less dispersion around the new mean. In other words, incomes have become more concentrated around the central value, but with a higher frequency of extreme values in the tails of the distribution, both at the high end (very high incomes) and at the low end (very low incomes).

The increase in kurtosis indicates that, compared to 2022, there are more outliers in the income data, reflecting a greater occurrence of exceptional economic events (such as extremely high or low incomes). However, the quality of these extreme values is ensured by a rigorous outlier evaluation system that precedes the imputation process. This system ensures that extreme income values are properly handled before being included in the dataset, preventing them from distorting the analysis and preserving the integrity of the data.

5. Conclusions

This paper has illustrated a series of significant innovations introduced into the methodological framework of the 2024 edition of the Inapp-Plus survey as the result of an articulated and rigorous redesign process. However, the analyses of the impacts of the new calibration on the 2024 edition of the survey have not yet been completed, and a definitive assessment will be possible once all tests have been finalized.

Given the longitudinal nature of the survey, a guiding rationale behind these changes was to achieve an appropriate balance between methodological innovation and the preservation of consistency and comparability across historical data series.

The modifications were intended to enhance the internal consistency and overall reliability of the collected data. Subsequent analysis of the final dataset will enable a comprehensive assessment of the impact and implications of these innovations.

In recent years, the increasing difficulties encountered in conducting Computer-Assisted Telephone Interviewing (CATI) surveys—a trend not limited to the Plus survey—have raised critical methodological questions. In particular, the declining response rates and coverage issues (especially for students, employed men in the 30-39 age group and employed women in the 40-49 age group) associated with CATI have prompted reflection on the potential transition to Computer-Assisted Web Interviewing (CAWI) techniques, at least for the selected variables.

At the moment, we correct distortions caused by this factor by implementing a sampling strategy based on the use of the estimator of generalized regression (GREG estimator). It ensures that the estimates of the absolute frequencies of the auxiliary

variables used as regressors are coincident with the known observed in the total population and imposed as calibration constraints.

Looking ahead to future survey cycles, consideration is being given to the use of Municipal Population Registers (Liste Anagrafiche Comunali, LAC) as the primary sampling frame and consequent transition to a probabilistic sample. This shift would offer multiple advantages:

- reduce respondent burden by eliminating the need to collect information already available from administrative sources;
- mitigate the biases introduced by non-random sampling from telephone directories that cause a self-selection of the respondents due to the higher average propensity to answering certain categories of persons.

However, the implementation of this approach would necessitate the adoption of mixed-mode data collection strategies, with implications for both design complexity and data comparability.

Overall, the methodological evolution of the Inapp-Plus survey reflects a broader transformation in the field of social survey research, wherein the integration of administrative data and the adoption of flexible, multimodal strategies are becoming increasingly central to ensuring both efficiency and data quality.

References

- CORSETTI G. 2024. Metodologia dell'Indagine campionaria longitudinale PLUS. In Inapp, Bergamante F., Luppi M. (a cura di). *Rapporto Plus 2023. Osservare le traiettorie del mercato del lavoro*. Roma, Inapp.
- CORSETTI G. 2022. Metodologia dell'Indagine campionaria Inapp-PLUS. In Inapp, Bergamante F., Mandrone E. (a cura di). *Rapporto Plus 2022. Comprendere la complessità del lavoro*. Roma, Inapp.
- DEVILLE J.C., SÄRNDAL C.E. 1992. Calibration Estimators in Survey Sampling, *Journal of the American Statistical Association*, n.87, pp.376-382.
- INAPP, BERGAMANTE F., MANDRONE E. (a cura di). *Rapporto Plus 2022. Comprendere la complessità del lavoro*. Roma, Inapp.
- INAPP, BERGAMANTE F., LUPPI M. (eds). 2024. *Rapporto PLUS 2023. Osservare le traiettorie del mercato del lavoro*. Roma: Inapp.
- ISFOL, MANDRONE E. 2012. Labour Economics: PLUS empirical studies. *Temi&Ricerche*, n.3, Roma, Isfol.
- ISTAT. 2012. Disoccupati, inattivi, sottoccupati. Indicatori complementari al tasso di disoccupazione. *Statistiche report 19 aprile 2012*. (<https://www.istat.it/comunicato-stampa/disoccupati-inattivi-sottoccupati-anno-2011/>)

- SÄRNDAL C.E., LUNDSTRÖM S. 2005. *Estimation in Surveys with Nonresponse*. Chichester (UK), John Wiley & Sons.
- VALLIANT R., DORFMAN A., ROYALL R.M. 2000. *Finite Population Sampling and Inference: A Prediction Approach*. New York, John Wiley.

Francesca BERGAMANTE, Inapp, f.bergamante@inapp.gov.it

Gianni CORSETTI, Istat, giacorsetti@istat.it

Francesca DELLA RATTÀ-RINALDI, Inapp, f.dellaratta@inapp.gov.it

Andrea SPIZZICHINO, Istat, spizzich@istat.it

COGNITIVE DECLINE AMONG OLDER ADULTS IN EUROPE: AN ANALYSIS OF EASYSHARE DATA

Diana Lampertico

Abstract. Today, the progressive aging of the world population represents a crucial issue, with significant consequences implications for public health. Among the most relevant concerns related to third age, cognitive decline and depression have been found to be closely interconnected, both influenced by a wide range of socio-demographic, biological and behavioral factors. Using the easySHARE dataset—a reduced version of the SHARE (Survey of Health, Ageing and Retirement in Europe) study — these phenomena were analyzed by focusing on EU residents aged 64 years and older, as of 2022.

The analyses employed statistical methods, including linear regression models, with the aim of identifying variables strongly associated with cognitive decline. The findings indicate that factors such as educational attainment, self-perceived health, and regular physical activity significantly contribute to reducing cognitive risks. Other factors, such as the cohabitation with a partner or maintaining a healthy diet, also demonstrate protective effects on cognitive well-being.

Notably, depression emerged as a relevant predictor of cognitive decline, highlighting the potential value of psychological support in treating depression as a means to also slow the cognitive decay.

This highlights the urgent need for policies and interventions aimed at promoting active and “successful” aging, ultimately contributing to an improved quality of life for older adults in Europe.

1. Introduction

Aging represents an inevitable stage of life, marked by physiological, cognitive, and social changes. In recent decades, the sharp rise in the elderly population has raised questions about its impact on public health. Projections suggest that by 2050, the global proportion of people over the age of 60 will double, rising from 11% in 2006 to 22% (Galluzzo *et al.*, 2012). This demographic shift is expected to have significant implications across healthcare, economic systems, and society, highlighting the importance of understanding the factors that affect quality of life in later years.

One of the key aspects of healthy aging is the preservation of cognitive abilities. Concepts like successful aging and active aging have gained increasing attention, in recent years (Estebari *et al.*, 2020; Kanungo, 1975). These ideas refer to a condition in which individuals maintain their independence, psychological well-being, and cognitive function, while avoiding or delaying cognitive decline. However, aging is not a uniform process: there are considerable differences between individuals, shaped by genetic, environmental, and lifestyle factors.

Cognitive decline represents one of the major challenges of aging, as cognitive functions—like memory, language, attention, and information processing—are essential for maintaining daily functioning and quality of life. Losing these capacities can lead to debilitating conditions, including dementia, that compromise individual autonomy and increase demands on families and healthcare systems. Identifying both risk and protective factors for cognitive deterioration is therefore critical for the development of effective preventive strategies.

Previous studies, cited below, have highlighted several key variables that significantly influence cognitive function in older adults, underscoring the multifactorial nature of cognitive health:

Educational and social factors: Education plays a crucial role in the development and preservation of cognitive abilities. Evidence indicates that individuals with higher levels of education perform better on cognitive assessments and show a reduced risk of cognitive decline compared to those with lower educational backgrounds (Lövdén *et al.*, 2020; Van Hooren *et al.*, 2007; Yaffe *et al.*, 2009). Engagement in social and volunteer activities also has been associated with a protective effect (Park *et al.*, 2019).

Lifestyle and physical health: Regular physical activity is positively associated with better cognitive performance, while smoking constitutes a notable risk factor for cognitive deterioration (Brewster *et al.*, 2014; Falk *et al.*, 2019). The established link between physical and cognitive health suggests that integrated interventions may promote healthier aging.

Psychological and clinical conditions: Several studies (Champaneria and McArthur, 2022; Schuitevoerder *et al.*, 2013) have identified that disorders such as post-traumatic stress disorder (PTSD) may compromise cognitive function in older adults, increasing susceptibility to memory deficits and decision-making difficulties.

To provide additional support for these findings and to explore how these factors interact in shaping individual cognitive path, the present study draws on data from the 2022 wave of the SHARE dataset (Survey of Health, Ageing and Retirement in Europe). Through the application of regression models, the study identifies the most significant predictors of cognitive decline, with the aim of delineating the characteristics and behaviors associated with successful aging among older adults in the European Union.

This study focuses on the following research questions:

RQ1. What are the main factors that influence cognitive performance in older adults?

RQ2. How do sociodemographic characteristics, lifestyle behaviors, and health conditions impact cognitive functioning in the elderly?

Understanding these mechanisms may contribute to the development of evidence-based public policies and targeted interventions aimed at improving mental health and quality of life in aging populations.

2. Data and Methods

2.1. Data

The present analysis is based on data from the easySHARE dataset, which is a simplified version derived from the SHARE database¹. The sample includes individuals aged over 64 years who participated in wave 9 (year 2022), resulting in a total of 33,436 respondents. The variables included into the regression model cover multiple domains:

- **Demographic factors:** gender, citizenship, and educational attainment.
- **Household composition:** living with a partner in the same household.
- **Social support:** geographic proximity of children and social support.
- **Health status and health-related behaviours:** self-perceived health, the EURO-D depression scale, body mass index, smoking habits, and engagement in vigorous physical activity or sports.
- **Functional limitations:** cognitive performance indicators.

2.2. Methods

Following the selection of the sample, preliminary descriptive analyses were conducted to assess the distribution of the variables of interest within the study population, to explore their characteristics and potential correlations among them.

To evaluate mental health, the 'eurod' variable is employed, an index measuring depressive symptoms based on the questions included in the mental health module (mh002_ to mh017_). This twelve items assessing various symptoms: depressed mood, pessimism, suicidal thoughts, feelings of guilt, hypersomnia, anhedonia,

¹ <https://share-eric.eu/>

irritability, appetite disturbance, fatigue, concentration difficulties, joy, and sadness. The index ranges from 0 (absence of depressive symptoms) to 12 (high levels of depression). This variable was recoded into four categorical levels:

- A (low): scores between 0 and 3
- B (medium-low): scores between 4 and 6
- C (medium-high): scores between 7 and 9
- D (high): scores between 10 and 12

Regarding the cognitive decline, due to the absence of a direct variable in the dataset available, an index was constructed based on four items derived from the module on current cognitive functioning among respondents.

- recall_1: Number of words recalled in the first trial of the word recall task, with scores ranging from 0 to 10.
- recall_2: Number of words recalled in the delayed word recall task. Scores range from 0 to 10.
- orienti: Testing the ability to identify the current year, month, calendar date, and day of the week. Ranges from 0 (poor temporal orientation) to 4.
- numeracy_2: Outcome of a numerical task involving basic subtraction. Score ranges from 0 (low performance) to 5 (high performance).

After rescaling *orienti* and *numeracy_2* to a standardized 0–10 scale, the four variables were aggregated to construct a composite index—referred to as ‘*cognitive*’—which reflects overall cognitive performance in wave 9 (2022), with a total score ranging from 0 to 40.

The statistical approach employed is a linear regression model incorporating categorical independent variables (1). This is an extension of linear regression that allows for the inclusion of qualitative (or categorical) predictors, and in this context, it is utilized to model cognitive decline as a function of several categorical factors:

$$Y = \beta_0 + \beta_1 D_1 + \beta_2 D_2 + \dots + \epsilon, \quad (1)$$

where:

- Y: denotes the *cognitive* index, used as the dependent variable.
- D₁, D₂, ...: represent categorical predictors included as dummy variables: gender, educational level, cohabitation, residential proximity of children, external

assistance, perceived health status, BMI, physical activity, smoking habits, migration background, and level of depressive symptoms.

- β_0 : intercept.
- $\beta_1, \beta_2, \dots$: are the regression coefficients that show the estimated effect of each predictor on the dependent variable.
- ϵ : the residual term capturing unexplained variance

3. Results

3.1. Data Pre-processing

The dataset was checked for missing data, identification of outliers, multicollinearity, and model selection procedures.

Regarding missing data, 1,807 observations were excluded due to the presence of missing values in at least one of the variables included in the model.

To identify influential observations potentially affecting the robustness of the regression estimates, Cook's Distance was employed. Observations flagged as outliers based on this measure were subsequently removed from the analysis.

Multicollinearity was evaluated using Tolerance (TOL) and the Variance Inflation Factor (VIF). A VIF value exceeding 5 indicates problematic multicollinearity, while a low TOL value (approaching 0) similarly suggests high inter-variable correlation.

Finally, to optimize model specification and limit overfitting, a stepwise selection procedure with both forward and backward elimination ("stepwise both") was applied. This approach ensures the retention of statistically relevant predictors only.

Figure 1 – Cook's distance.

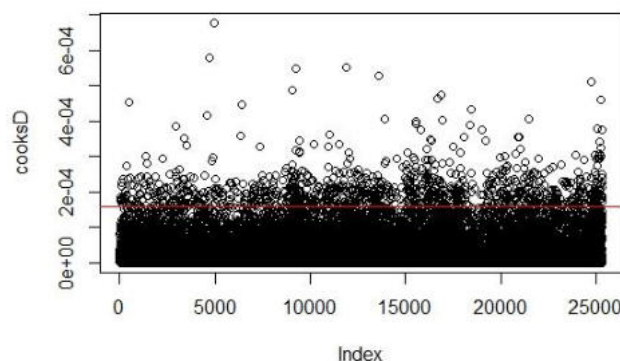


Figure notes: displays Cook's Distance (cookD) plotted against the observation index.

The majority of data points fall just below the threshold line, represented by the red horizontal line, indicating that most observations are not particularly influential on the model estimates. While a few points deviate slightly from the central distribution, the overall spread remains constrained, suggesting a generally stable model fit.

Figure 2 – Q-Q Residuals.

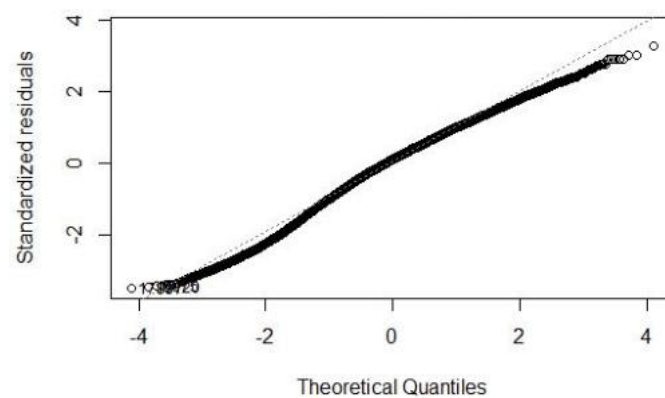


Figure notes: shows the Q-Q plot of the standardized residuals for the regression model.

Most points fall close to the diagonal line, corresponding to the theoretical normal distribution, suggesting that the residuals approximate normality overall. Minor deviations are observed at both tails of the distribution, indicating potential departures from normality at the extremes. However, given the limited extent of these deviations and the substantial sample size, their impact on the validity of model-based inferences is expected to be minimal.

Table 1 – Variance Inflation Factor (VIF) and Tolerance (TOL)

Independent variables	VIF	TOL
Gender	1,144	0,874
Educational Attainment	1,123	0,890
Cohabitation	1,156	0,865
Proximity of children's residence	1,035	0,966
External assistance	1,083	0,923
Self-perceived health	1,338	0,747
Body Mass Index	1,054	0,948
Physical activity	1,142	0,876
Smoking habits	1,016	0,984
Migrant	1,008	0,992
Depression level	1,239	0,807

Table notes: show VIF and TOL values for the set of independent variables

All VIF values are very low (from 1.008 to 1.338), remaining well below the conventional cut-off value of 5, indicating an absence of substantial multicollinearity. Similarly, TOL values are consistently high (between 0.747 and 0.992), above the commonly used threshold of 0.2. These results suggest that each predictor contributes for a meaningful portion of its variance and retains a sufficient degree of independence from the others.

3.2. Linear Regression Model

The regression output reveals that the majority of predictors have statistically significant effects on the dependent variable ($p < 0.001$).

Gender emerges as a significant factor: being female is associated with a 1.0657-point increase in cognitive performance, relative to the male reference category. This suggests a modest but consistent cognitive advantage for women in the sample.

The categorical variable which represent levels of education, demonstrates a clear positive gradient. Relative to individuals with no formal education, those with tertiary education (second cycle) show an increase of 8.0441 units in the cognitive index. These findings underscore the critical role of educational background as a protective factor against age-related cognitive decline.

Table 2 – LINEAR REGRESSION MODEL – Categorical Independent Variables.

Independent variables	Estimate	Std. Error	t-value	Pr(> t)	
Intercept	22,387	0,412	54,283	< 2e-16	***
Gender					
female	1,066	0,059	18,034	< 2e-16	***
Educational Attainment					
primary education	2,193	0,219	10,032	< 2e-16	***
lower secondary education	4,262	0,216	19,695	< 2e-16	***
upper secondary education	5,821	0,212	27,522	< 2e-16	***
post-secondary education	6,545	0,246	26,641	< 2e-16	***
first stage of tertiary education	7,335	0,216	34,015	< 2e-16	***
second stage of tertiary education	8,044	0,376	21,385	< 2e-16	***
still in school	-0,473	2,525	-0,187	< 2e-16	***
other	6,087	0,864	7,048	< 2e-16	***
Cohabitation					
living without a spouse/partner	-0,748	0,062	-12,047	< 2e-16	***
Proximity of children's residence					
no	0,514	0,057	9,054	< 2e-16	***
External assistance					
no	0,127	0,067	1,888	0,05902	.
Self-perceived health					
very good	0,095	0,153	0,616	0,53759	
good	-0,863	0,142	-6,074	1,26e-09	***
fair	-1,890	0,147	-12,893	< 2e-16	***
poor	-3,254	0,172	-18,925	< 2e-16	***
Body Mass Index					
normal	0,861	0,315	2,732	0,00631	**
overweight	1,033	0,315	3,280	0,00104	**
obese	1,356	0,317	4,282	1,86e-05	***
Physical activity					
once a week	-0,251	0,091	-2,748	0,00600	**
one to three times a month	-0,235	0,098	-2,400	0,01641	*
hardly ever, or never	-1,038	0,069	-15,012	< 2e-16	***
Smoking habits					
no	-0,570	0,089	-6,434	1,27e-10	***
Migrant					
yes	0,035	0,215	0,161	0,87189	
Depression level					
medium-low	-0,652	0,071	-9,144	< 2e-16	***
medium-high	-2,341	0,134	-17,497	< 2e-16	***
high	-5,924	0,519	-11,406	< 2e-16	***

Signif. Codes * $p < 0,01$; ** $p < 0,05$; *** $p < 0,001$

Table notes: regression model results

Living alone is associated with a statistically significant decrease of 0.7478 units in the cognitive index, indicating that cohabitation may act as a protective factor for cognitive functioning in older adults.

The Body Mass Index (BMI) has a positive association with cognitive performance, with higher BMI categories linked to higher cognitive scores. These results suggest that lower BMI values— that might indicate undernutrition or frailty in older populations —may be associated with accelerated cognitive decline.

Regarding depression, the negative and significant coefficients confirm its effect on cognitive health. In particular, individuals classified within the highest depression category exhibit a reduction of approximately 6 points in the cognitive index, underscoring the substantial cognitive burden associated with severe depressive symptoms.

Self-perceived health and physical activity levels demonstrate a progressively negative effect, indicating that declines in subjective health status and reductions in physical activity are associated with a deterioration in cognitive performance.

Interestingly, the absence of sons or daughters live within one kilometre of the respondent and the lack of external support from individuals outside the household are associated with improved cognitive outcomes. This may reflect a greater level of autonomy and preserved cognitive functioning among individuals who do not require external assistance.

After the application of stepwise model selection, MIGRANT was the only one excluded, as it did not significantly affect R-squared or adjusted R-squared values.

4. Conclusions

Cognitive decline has effects on the everyday functioning of older adults. However, the severity of cognitive deterioration exhibits considerable variability from person to person and is shaped by a multitude of determinants.

This study contributes to the understanding of this heterogeneity by identifying key determinants associated with slower cognitive deterioration, focusing on sociodemographic characteristics, health status, and behavioral factors.

Educational attainment emerged as a crucial factor in maintaining cognitive functioning. Individuals with higher levels of education consistently achieved superior cognitive scores. This association is likely mediated by better life conditions and enhanced socioeconomic status (Dekhtyar *et al.*, 2015).

This evidence highlights the potential long-term benefits of educational investments during childhood and adolescence, as it could help reduce the personal and social costs of cognitive decline in old age. Furthermore, these findings advocate

for the implementation of public policies that promoting access to education and encouraging lifelong learning, even in adulthood.

Perceived health status also emerged as a key factor of cognitive functioning. A negative perception of one's own health is strongly correlated with cognitive deterioration, underscoring the importance of interventions that enhance subjective well-being. This includes access to comprehensive psychological support services and adequate healthcare infrastructure. Focus on mental health, especially through the prevention and management of depressive disorders, is fundamental, given their robust association with cognitive decline, as supported by previous research (Halfin, 2007; Reynolds *et al.*, 2012). The results also identify social isolation as a major risk factor for cognitive impairment.

Regular physical activity has emerged as a robust predictor of cognitive health. Older individuals who engage in consistent exercise tend to display superior cognitive performance, a finding consistent with the neurobiological literature that highlights the role of physical activity in enhancing neuroplasticity and mitigating the risk of neurodegenerative pathologies.

Overall, this study contributes to the literature by integrating multiple life-course determinants of cognitive aging within the same analytical framework. However, due to the cross-sectional nature of the data, only association can be identified, while causality cannot be determined. Additionally, the self-reported measures may be subject to reporting bias. Future research would benefit from longitudinal approaches to better capture the mechanisms underlying cognitive decline.

In the context of accelerated demographic aging across Europe, the identification of key determinants of mental and cognitive health in late adulthood represents not only a scientific imperative but also a social priority. Promoting the cognitive and emotional well-being of older adults constitutes a strategic investment in the future of society, shifting the narrative of aging from a burden to an opportunity, to recognize the value and potential of an increasingly long-lived population.

References

- BREWSTER P. W., MELROSE R. J., MARQUINE M. J., JOHNSON J. K., NAPOLES A., MACKAY-BRANDT A., FARIAS A., REED S., MUNGAS D. . 2014. Life experience and demographic influences on cognitive function in older adults. *Neuropsychology*, Vol. 28, No. 6, pp. 846-858.
- CHAMPANERIA A., MCARTHUR K. 2022. A Meta-Analysis of Cognitive Functioning in Older Adults with PTSD. In TAMPI, R.R., TAMPI, D.J., YOUNG, J.J., BALASUBRAMANIAM, M., JOSHI, P. (Eds) *Essential Reviews in Geriatric Psychiatry*. Springer, Cham, pp. 87-92.

- ESTEBSARI F., DASTOORPOOR M., KHALIFEHKANDI Z. R., NOURI A., MOSTAFAEI D., HOSSEINI M., ESMAEILI R., AGHABABAEIAN H. 2020. The concept of successful aging: a review article. *Current aging science*, Vol. 13, No. 1, pp. 4-10.
- FALCK R. S., DAVIS J. C., BEST J. R., CROCKETT R. A., LIU-AMBROSE T. 2019. Impact of exercise training on physical and cognitive function among older adults: a systematic review and meta-analysis. *Neurobiology of aging*, Vol. 79, pp. 119-130.
- GALLUZZO L., GANDIN C., GHIRINI S., SCAFATO E. 2012. L'invecchiamento Della Popolazione: Opportunità O Sfida?. Bollettino Epidemiologico Nazionale, No.2, Aprile. <https://www.epicentro.iss.it/ben/2012/aprile/2>
- LÖVDÉN M., FRATIGLIONI L., GLYMOUR M. M., LINDENBERGER U., TUCKER-DROB E. M. 2020. Education and cognitive functioning across the life span. *Psychological science in the public interest*, Vol. 21, No. 1, pp. 6-41.
- KANUNGO, M. S. 1975. A model for ageing. *Journal of Theoretical Biology*, Vol. 53, No. 2, pp. 253-261.
- PARK S., CHOI B., CHOI C., KANG J. M., LEE J. Y. 2019. Relationship between education, leisure activities, and cognitive functions in older adults. *Aging & mental health*, Vol. 23, No. 12, pp. 1651-1660.
- SCHUITEVOERDER S., ROSEN J. W., TWAMLEY E. W., AYERS C. R., SONES H., LOHR J. B., GOETTER M., FONZO A., HOLLOWAY K. J., THORP S. R. 2013. A meta-analysis of cognitive functioning in older adults with PTSD. *Journal of anxiety disorders*, Vol. 27, No. 6, pp. 550-558.
- VAN HOOREN S. A. H., VALENTIJN A. M., BOSMA H., PONDS R. W. H. M., VAN BOXTEL M. P. J., JOLLES J. 2007. Cognitive functioning in healthy older adults aged 64–81: A cohort study into the effects of age, sex, and education. *Aging, Neuropsychology, and Cognition*, Vol. 14, No. 1, pp. 40-54.
- YAFFE K., FIOCCO A. J., LINDQUIST K., VITTINGHOFF E., SIMONSICK E. M., NEWMAN A. B., SATTERFIELD S., ROSANO C., RUBIN S., AYONAYON N., HARRIS T. B. 2009. Predictors of maintaining cognitive function in older adults: the Health ABC study. *Neurology*, Vol. 72, No. 23, pp. 2029-2035.

EXPLORING INEQUALITIES IN CO-AUTHORSHIP NETWORKS AMONG ITALIAN SCHOLARS¹

Gianpaolo Caprino, Viviana Amati

Abstract. Social capital refers to the resources individuals can access through their network of relationships to achieve their goals or navigate challenges. This study examines the structure of collaboration networks in which Italian academics are embedded. Specifically, we analyze inequalities in co-authorship networks among Italian scholars in the fields of Statistics, Management, and General and Applied Sociology. We compiled a list of scholars and their attributes as of 2022 using data from the Ministry of University and Research. By linking each scholar to their Scopus ID, we collected co-authorship data from Scopus publications covering the period from 2012 to 2022. We utilize an egocentric network approach to build personal co-authorship networks. We calculate various structural and compositional indices—such as component ratios, network density, and diversity—to categorize these personal networks and conduct network clustering to identify different network typologies. Our results reveal variations in personal networks across the four disciplines, reflecting the specific academic norms and roles associated with each field.

1. Social capital in Academia

Over the past four decades, the concept of social capital has received significant attention across various disciplines, including economics, sociology, and psychology. A variety of definitions and typologies of social capital have been proposed (see, e.g., Bhandari and Yasunobu, 2009, for a review) since the foundational work of Coleman (1988).

Despite the diversity of definitions, a common theme emerges: social capital is recognized as a resource embedded in the networks and groups to which individuals belong rather than as a personal trait or individual characteristic. Portes (1998, p.6) described social capital as “the ability of actors to secure benefits by virtue of their membership in social networks or other social structures,” emphasizing that while “economic capital is in people’s bank accounts and human capital is inside their heads, social capital resides in the structure of their relationships” (p. 7). Similarly, Lin *et al.* (2001, p. 24) defined social capital as “resources embedded in a network, accessed and

¹Gianpaolo Caprino: research design, analysis, results interpretations, paper writing Viviana Amati: conceptualization, research design, analysis supervision, results interpretations, paper writing, acquiring funding.

used by actors for actions.” The concept highlights social capital's role in maintaining and enhancing social positions through the conversion of resources into other forms of capital, such as economic or cultural capital (Bourdieu, 1986; Coleman, 1988; Durlauf *et al.*, 2005; Veenstra and Abel, 2019). We adopt Lin's definition and regard social capital as the resources and benefits individuals gain from their social networks, which can impact success and perpetuate outcomes.

Understanding social capital is crucial for analyzing how social structures and networks can affect opportunities and inequalities in various contexts, including academic research. In the academic sector, social capital is fostered by collaborative ties between academics and other entities—including fellow scholars, industry, and institutions—and social capital resources can be converted into human capital defined as “the sum of scientific, technical and social knowledge, skills and resources embodied in a particular individual” (Bozeman and Corley, 2004, p. 601).

Numerous studies have explored how social and human capital derived from collaboration between industry and polytechnic universities facilitates the diffusion of innovations and technology transfer, which can enhance academic productivity (Al Tabbaa and Ankrah, 2019; Bikard *et al.*, 2019).

Another area of research has examined how collaboration among scholars influences performance and advancement in academic careers at the individual level. In these studies, collaboration is often measured through co-authorship—the joint publication of scientific manuscripts—which serves as a proxy and indicator of academic collaboration (Abbasi *et al.*, 2011; Abramo *et al.*, 2015; Iglic *et al.*, 2017).

This study aligns with the latter area of research. Based on information collected from the Scopus repository and scholar characteristics provided by the Ministry of University and Research, we construct co-authorship networks of Italian scholars and describe differences in network structures that provide social capital. We focus on four academic fields (Statistics, Management, General Sociology, and Applied Sociology) and compare results both within and between these fields.

The paper is organized as follows: In Section 2, we define ego-networks and review their role in explaining social capital. In Section 3, we introduce the data, and in Section 4, we present the results. We conclude with a discussion of the findings, the limitations of the study, and directions for future research.

2. Social capital and academic networks

The reason why networks are often found interesting is tied to the relevance of networks and their characteristics—such as size and composition—for understanding individual outcomes, including well-being, health, and performance (Vacca, 2020; Amati *et al.*, 2018). Numerous studies have shown that collaboration among scientists influences productivity, evaluation, and research quality.

Research collaboration can take various forms (Katz and Martin, 1997), including informal discussions, student supervision, data sharing, project participation, and co-authorship. Among these, co-authorship is considered the most prominent and easily traceable form of collaboration, thanks to the availability of databases such as Scopus, Web of Science, OpenAlex, and Google Scholar. In collaboration networks, the entities are the authors of scientific manuscripts, and the connections between them are represented by joint publications.

In academic settings, a well-structured network can significantly influence opportunities such as research funding, impactful collaborations, career advancement (Lu *et al.*, 2021; Bellotti *et al.*, 2016), and scientific performance (De Stefano and Zaccarin, 2016). For example, an analysis of Italian physicists over a decade of grant data found that network position strongly predicted funding success (Bellotti, 2012). Notably, what mattered most for a scholar was not merely being highly connected—what Bellotti (2012, p.225) refers to as being a “big fish”—or belonging to a large, prestigious university—a “big pond” (Bellotti, 2012, p.217)—but rather occupying a brokerage position that bridges different research groups. Scholars who acted as connectors between otherwise unlinked teams secured more grant funding, highlighting that diverse and spanning connections provide greater access to resources than sheer network size or institutional prestige.

Additionally, bibliometric studies have linked network structure to research impact. Sparse ego networks—where the scholar serves as a hub between disconnected collaborators—achieved higher citation rates per publication than dense, tightly knit networks (Ortega, 2014). In these networks, the central researcher exercises more control and selectivity in collaborations, leading to greater impact.

Finally, networks can also influence scientific evaluation. A study of career advancements at Italian universities revealed that connections with members of evaluation committees are strong predictors of a candidate’s career success, while nepotism plays only a marginal role (Abramo *et al.*, 2015). In the Spanish academic context, Zinovyeva and Bagues (2015) found similar results. They demonstrated that personal and professional connections—such as PhD advisor-advisee relationships, collegial ties, or co-authorship—between candidates for full professorships and members of promotion committees significantly influenced evaluation outcomes.

All these studies illustrate how the characteristics of collaboration networks in which a scholar is embedded provide social and human capital and determine access to different resources. Based on this, we aim to identify the collaboration behavior of Italian academics and investigate differences across disciplines.

3. Data and methods

3.1. Data Collection and ego-network construction

The dataset includes information on gender, roles, academic sectors, universities, and departments. The population consists of 803 scholars in Statistics, 611 in Management, 571 in general Sociology, and 163 in Applied Sociology. Table 1 presents descriptive statistics regarding the scholars' gender, roles, and disciplinary sectors.

Table 1 - Descriptive statistics of the scholars working in academia as of 2022 by discipline.

Discipline	Statistics	Management	General Sociology	Applied Sociology
N. academics	803	611	571	163
Gender				
Men	53% (424)	51% (312)	51% (293)	55% (89)
Role				
Researchers	27% (217)	28% (169)	30% (172)	31% (50)
Associates	41% (332)	40% (248)	47% (269)	51% (83)
Full	32% (254)	32% (194)	23% (130)	18% (30)
S.S.D.				
	SECS-S/01 (60%)	SECS-P/08 (100%)	SPS/07 (49%),	SPS/09 (67%)
	SECS-S/02 (2%)		SPS/08 (40%),	SPS/10 (33%)
	SECS-S/03 (20%)		SPS/11 (6%)	
	SECS-S/04 (8%)		SPS/12 (5%)	
	SECS-S/05 (10%)			

Each scholar was linked to its Scopus ID, allowing us to retrieve all of its publications indexed in Scopus from 2012 to 2022. We excluded single-authored manuscripts, as they do not provide insights into collaboration, and also excluded publications with more than 20 authors, based on the understanding that meaningful collaboration typically involves a limited number of authors. The dataset includes a total of 28,605 published papers: 11,374 in Statistics, 10,783 in Management, 4,885 in Sociology, and 1,563 in Applied Sociology.

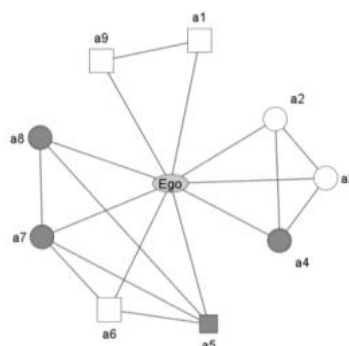
Using this data, we constructed the egocentric network of co-authorship ties for each scholar. An egocentric network is a network seen from the perspective of a focal actor, referred to as “Ego.” It includes Ego and the set of alters to whom it is connected. We distinguish between an egocentric network, which reports only the ties between Ego and the alters, and a personal network, which also incorporates the relationships among the alters (Perry *et al.*, 2018).

Figure 1 illustrates the personal network of an Italian scholar with nine alters. In this representation, Italian academics and their co-authors are represented by nodes, and there is a tie between two nodes if they wrote at least one paper together. Different node shapes and colors indicate the characteristics of the alters.

We analyze the personal networks of Italian academics using compositional and structural indices, as outlined by Perry *et al.* (2018).

Compositional indices describe the characteristics of the alters and the nature of the relationships between Ego (the individual) and its alters. These indices are expressed as percentages and illustrate the distribution of alter attributes in the personal network.

Figure 1 - Example of a personal network. Italian academics and their co-authors are represented by nodes. There is a tie between two nodes if they co-authored at least one paper. Different node shapes and colors indicate the characteristics of the alters.



3.2. Network measures & Clustering

Compositional indices describe the characteristics of the alters and the nature of the relationships between Ego (the individual) and its alters. These indices are expressed as percentages and illustrate the distribution of alter attributes in the personal network.

Structural indices focus on the relationships within the network, examining how the Ego is connected to its alters as well as the connections among the alters themselves. These measures reveal the overall organization of the network, such as how interconnected the alters are, how centralized Ego is within the network, and the degree of fragmentation present.

The *ego network size* refers to the number of co-authors (alters) with whom the ego has collaborated. The *network density*, also known as the availability index, captures the proportion of actual ties among alters compared to all possible connections. This index provides insight into the level of cohesion within each network and is calculated as the ratio of the number of actual ties to the maximum possible ties, incorporating both Ego-alter and alter-alter ties:

$$density = \frac{(N. \text{ actual ties})}{(N. \text{ max of possible ties})} \quad (1)$$

The *Diversity/EI Index* evaluates how likely the ego is to collaborate with similar individuals based on specific attributes. The EI Index focuses solely on Ego-alter ties.

Let E be the number of external ties (connections between Ego and alters with different attribute values) and I the number of internal ties (connections between Ego and alters with the same attribute value).

The EI Index is computed as:

$$EI = \frac{(E - I)}{(E + I)}. \quad (2)$$

It ranges from -1 to 1: a value of 1 indicates perfect heterophily (all external ties), while -1 indicates perfect homophily (all internal ties).

We computed both compositional and structural indices for each personal network and used them as variables to identify personal network typologies among Italian academics. This analysis aims to study inequalities in ties providing social capital resources across different disciplines.

Following Amati *et al.* (2018) and Pelle and Pappadà (2021), we applied hierarchical clustering using Euclidean distance, determined group numbers via dendrogram and silhouette score, and characterized typologies through standardized mean proportions.

4. Results

The following analysis was performed on a subset of Italian scholars. We excluded from the initial population those who have published only solo-papers (Statistics: 3%, 24 individuals; Management: 12%, 81 individuals; General Sociology: 31%, 252 individuals; Applied Sociology: 26%, 59 individuals) and those having all co-authors not affiliated to an Italian university (Statistics: 8%, 68 individuals; Management: 15%, 90 individuals; General Sociology: 47%, 267 individuals; Applied Sociology: 45%, 74 individuals). We made this decision due to the lack of information on the alters. Information on gender, role, and disciplinary sectors are only available for Italian scholars given that the source is MUR.

4.1. Personal network descriptives

Table 2 summarizes the descriptive statistics about the compositional and structural indices for the personal networks of Italian scholars having at least one Italian academic co-author by discipline.

Men dominate in Statistics (55%), Management (55%), and Applied Sociology (57%), while General Sociology is more balanced (51% men). International collaboration is highest in Statistics (71% non-Italian co-authors) and Applied Sociology (62%), followed by Management (57%) and General Sociology (54%).

The analysis of academic roles uncovers two distinct patterns. Statistics and Management scholars collaborate primarily with associate and full professors (~40% each), while Sociologists work mainly with associate professors (~50%), followed by researchers and full professors (~25% each).

Table 2 - Compositional and structural indices of the personal networks of Italian scholars having at least one Italian academic co-author by discipline.

Discipline	Statistics	Management	General Sociology	Applied Sociology
N. Egos	735	521	304	89
Compositional network indices				
Gender				
Men	55% (404)	55% (287)	51% (123)	57% (51)
Affiliation				
Non-Italian scholars	71% (522)	57% (297)	54% (131)	62% (55)
Role				
Researcher	19% (140)	19% (99)	29% (70)	27% (24)
Associates	40% (294)	40% (208)	44% (106)	50% (45)
Full	51% (301)	41% (214)	27% (65)	23% (20)
Academic sector				
	SECS-S/01 (61%)	SECS-P/08 (100%)	SPS/07 (49%)	SPS/09 (67%),
	SECS-S/02 (2%)		SPS/08 (40%)	SPS/10 (33%)
	SECS-S/03 (18%)		SPS/11 (6%)	
	SECS-S/04 (10%)		SPS/12 (5%)	
	SECS-S/05 (9%)			
Structural network indices				
Average network size	10.81	10.1	5.81	2.28
Average density	0.22	0.33	0.31	0.24
Average gender EI	-0.12	-0.09	-0.12	-0.06
Average role EI	0.33	0.31	0.53	0.35
Average S.S.D. EI	-0.45	-	-0.47	-0.72

When examining the composition of academic roles, we find variability across disciplines. Statistics and Management scholars maintain larger networks (~10 co-authors vs. 2-5 for Sociologists), while General Sociology and Management show higher density (0.30 vs. 0.23). EI indices reveal minimal gender homophily (near 0), role heterophily (positive values, highest in General Sociology at 0.53), and strong disciplinary homophily among Applied Sociologists (-0.72).

4.2. Personal network typologies

Clustering results reveal significant disciplinary variation in co-authorship patterns, reflecting differences in academic norms and collaboration (Table 3).

Table 3 - Personal network typologies by discipline.

	Group (count)	Interpretation
Statistics	1 (260)	Outside Italian academia; large network; prevalence of men; role balance; focus on SECS-S/01; S.S.D. homophily
	2 (183)	Outside Italian academia; large network; prevalence of men; role balance; focus on SECS-S/01
	3 (78)	Outside Italian academia; prevalence of women; role balance; focus on SECS-S/04
	4 (62)	Outside Italian academia; prevalence of women; prevalence of associate professors; focus on SECS-S/01
	5 (6)	Outside Italian academia; small network; prevalence of men; prevalence of associate and full professors; focus on SECS-S/02; role heterophily
	6 (99)	Outside Italian academia; large network; prevalence of men; role balance; focus on SECS-S/03; S.S.D. homophily
	7 (23)	Outside Italian academia; prevalence of women; prevalence of associate and full professors; focus on SECS-S/05
	8 (24)	Within Italian academia; dense network; prevalence of women; prevalence of associates and full professors; focus on SECS-S/01; S.S.D. homophily

Statistics (8 clusters) and Management (9 clusters) scholars exhibited larger, more structured networks, while General and Applied Sociology (5 clusters each) displayed smaller, more fragmented networks. Role-based disparities emerged, with role heterophily particularly evident among full professors in certain clusters, suggesting network structure influences career progression and visibility.

Regarding institutional affiliation, Statistics and Sociology showed greater international collaboration, whereas Management and Applied Sociology favored domestic partnerships. Gender dynamics varied considerably: Statistics and Sociology exhibited strong disciplinary closure with women-centered clusters emerging within Italian academia; Management demonstrated lower gender homophily and a pronounced domestic-international divide; Applied Sociology displayed the highest levels of male dominance, disciplinary homophily, and role heterophily.

Table 3 (cont.) - Personal network typologies by discipline.

	Group (count)	Interpretation
Management	1 (104)	Within Italian academia; large network; prevalence of men; prevalence of associates and full professors
	2 (34)	Outside Italian academia; prevalence of women; prevalence of full professors; gender homophily; role heterophily
	3 (61)	Outside Italian academia; prevalence of men; prevalence of full professors; gender homophily
	4 (41)	Within Italian academia; dense network; prevalence of men; prevalence of associate and full professors
	5 (114)	Outside Italian academia; large network; prevalence of women; prevalence of associate; associate and full professors
	6 (87)	Outside Italian academia; prevalence of women; prevalence of researchers
	7 (24)	Outside Italian academia; prevalence of women; prevalence of associate professors; role homophily
	8 (25)	Outside Italian academia; prevalence of men; role balance
	9 (31)	Outside Italian academia; dense network; prevalence of men; prevalence of full professors; gender and role heterophily
General Sociology	1 (10)	Outside Italian academia; gender balance; prevalence of associate and full professors; focus on SPS-12; S.S.D. homophily
	2 (21)	Outside Italian academia; dense network; prevalence of men; prevalence associate professors and researchers; focus on SPS-11; role heterophily
	3 (114)	Outside Italian academia; large network; prevalence of women; prevalence of associate professors and researchers; focus on SPS-07; role heterophily
	4 (64)	Outside Italian academia; prevalence of men; focus on SPS/09; role and S.S.D. heterophily
	5 (95)	Large and dense network; prevalence of women; prevalence of associate professors; focus on SPS-08; role heterophily; S.S.D. homophily
Applied Sociology	1 (18)	Outside Italian academia; prevalence of men; prevalence of full professors; focus on SPS/09; role heterophily
	2 (28)	Large and dense network; prevalence of men; prevalence of associate professors; focus on SPS-09; S.S.D. homophily
	3 (19)	Large and dense network; prevalence of men; prevalence of associate professors; focus on SPS-10; gender and S.S.D. homophily
	4 (13)	Outside Italian academia; prevalence of men; focus on SPS/09; and S.S.D. heterophily
	5 (11)	Outside Italian academia; prevalence of women; prevalence of researchers; focus on SPS-09; role heterophily; S.S.D. homophily

5. Conclusions

This paper investigated personal network structures and composition among scholars in Statistics, Management, General Sociology, and Applied Sociology using hierarchical clustering, with results validated through k-means.

Our findings reveal discipline-specific network structures that influence academic social and human capital. Disparities in social capital—reflected in variations in gender, academic roles, disciplinary sectors, university affiliations, network density, diversity, and size—translate into inequalities in human capital, affecting productivity, research quality, and career advancement of Italian academics. Women's smaller or less international networks may reflect structural barriers and gendered gatekeeping practices in academia (Van den Brink and Benschop, 2012), as informal networks and mentoring opportunities are often less accessible to women, affecting visibility and collaboration opportunities (Bozeman and Gaughan, 2011). Role-based differences, particularly the greater brokerage position of full professors compared to researchers, reflect the hierarchical organization of academic careers in Italy, where seniority strongly influences access to resources and collaborations (Musselin, 2013). Disciplinary variations—larger networks in Statistics compared to more fragmented ones in Sociology—may stem from different "academic tribes and territories" (Becher and Trowler, 2001), as quantitative disciplines privilege multi-authored journal articles, while interpretive fields often value books and small, cohesive collaboration groups (Kyvik, 2003).

This study has important limitations. We used co-authorship as a collaboration proxy, though other cooperation forms exist. Scopus-based data systematically favors bibliometric fields and underrepresents social sciences where monographs and edited volumes are central (Hammarfelt, 2016), making cross-disciplinary comparisons reflect publishing norms alongside collaboration strategies. We constructed networks using binary ties, disregarding collaboration strength indicated by co-authored paper counts. Future work will analyze weighted networks and examine how network typologies impact academic performance.

Acknowledgements

We acknowledge financial support under the National Recovery and Resilience Plan (NRRP), Mission 4, Component 2, Investment 1.1, Call for tender No. 104 published on 2.2.2022 by the Italian Ministry of University and Research (MUR), funded by the European Union – NextGenerationEU– Project Title “Methods for the analysis of scientific collaboration networks”– CUP H53D23005920001- Grant Assignment Decree adopted on by the Italian Ministry of Ministry of University and Research (MUR).

References

- ABBASI A., ALTMANN J., HOSSAIN L. 2011. Identifying the effects of co-authorship networks on the performance of scholars: A correlation and regression analysis of performance measures and social network analysis measures. *Journal of informetrics*, Vol. 5, No. 4, pp. 594-607.
- ABRAMO G., D'ANGELO C. A., ROSATI F. 2015. The determinants of academic career advancement: Evidence from Italy. *Science and Public Policy*, Vol. 42, No. 6, 761-774.
- AL-TABBAA O., ANKTAH S. 2019. Engineered university-industry collaboration: A social capital perspective. *European Management Review*, Vol. 16, No. 3, pp. 543-565.
- AMATI V., MEGGIOLARO S., RIVELLINI G., ZACCARIN S. 2018. Social relations and life satisfaction: the role of friends. *Genus*, Vol. 74, No. 7, pp. 1-18.
- BECHER T., TROWLER P. 2001. *Academic tribes and territories: Intellectual enquiry and the culture of disciplines*. Buckingham: Open University Press/McGraw-Hill.
- BELLOTTI E. 2012. Getting funded. Multi-level network of physicists in Italy. *Social Networks*, Vol. 34, No. 2, pp. 215-229.
- BELLOTTI E., KRONEGGER L., GUADALUPI L. 2016. The evolution of research collaboration within and across disciplines in Italian Academia. *Scientometrics*, Vol. 109, pp. 783-811.
- BHANDARI H., YASUNOBU K. 2009. What is social capital? A comprehensive review of the concept. *Asian Journal of Social Science*, Vol. 37, No. 3, pp. 480-510.
- BIKARD M., MURRAY F., GANS J.S. 2015. Exploring trade-offs in the organization of scientific work: Collaboration and scientific reward. *Management science*, Vol. 61, No. 7, pp. 1473-1495.
- BOURDIEU P. 1986. The forms of capital. In: RICHARDSON J. (Ed.) *Handbook of theory and research for the sociology of education*. New York: Greenwood Press, pp. 241-58.
- BOZEMAN B., CORLEY E. 2004. Scientists' collaboration strategies: implications for scientific and technical human capital. *Research policy*, Vol. 33, No. 4, pp. 599-616.
- BOZEMAN B., GAUGHAN M. 2011. How do men and women differ in research collaborations? *Research Policy*, Vol. 40, No. 10, pp. 1393-1402.
- COLEMAN J. S. 1988. Social capital in the creation of human capital. *American Journal of Sociology*, Vol. 94, pp. 95-120.
- DE STEFANO D., ZACCARIN S. 2016. Co-authorship networks and scientific performance: An empirical analysis using the generalized extreme value distribution. *Journal of Applied Statistics*, Vol. 43, No. 1, pp. 262-279.
- DURLAUF S., FAFCHAMPS M. 2005. Social capital. In AGHION P. and S. DURLAUF S. (Eds.) *Handbook of economic growth*, Amsterdam: Elsevier, pp. 1639-1699.

- HAMMARFELT B. 2016. Beyond coverage: Toward a bibliometrics for the humanities. In OCHSNER M., HUG S. E., DANIEL H. D. (Eds.), *Research Assessment in the Humanities*, Springer, pp. 115-131
- KATZ J.S., MARTIN B.R. 1997. What is research collaboration?. *Research policy*, Vol. 26, No. 1, pp. 1-18.
- KYVIK S. 2003. Changing trends in publishing behaviour among university faculty, 1980–2000. *Scientometrics*, Vol. 58, No. 1, pp. 35-48.
- IGLIČ H., DOREIAN P., KRONEGGER L., FERLIGOJ A. (2017) With whom do researchers collaborate and why?. *Scientometrics*, Vol. 112, pp. 153-174.
- LIN N., FU Y., HSUNG R. 2001. The position generator: a measurement instrument for social capital. In LIN N., COOK K. and BURT R. (Eds.), *Social capital: theory and research*, New York: Aldine de Gruyter, pp. 57–81
- LU W., REN Y., HUANG Y., BU Y., ZHANG Y. 2021. Scientific collaboration and career stages: An ego-centric perspective. *Journal of Informetrics*, Vol. 15, No. 4, 101207.
- MUSSELIN C. 2013. How peer review empowers the academic profession and university managers. *Research Policy*, Vol. 42, No. 5, pp. 1165-1173.
- ORTEGA J.L. 2014. Influence of co-authorship networks in the research impact: Ego network analyses from Microsoft Academic Search. *Journal of Informetrics*, Vol. 8, No. 3, pp. 728-737.
- PELLE E., PAPPADÀ R. 2021. A clustering procedure for mixed-type data to explore ego network typologies: an application to elderly people living alone in Italy. *Statistical Methods & Applications*, Vol. 30, No. 5, pp.1507-1533.
- PERRY B.L., PESCOLIDIO B.A., BORGATTI, S.P. 2018. *Egocentric network analysis: Foundations, methods, and models*. Cambridge university press.
- PORTES A. 1998. Social capital: Its origins and applications in modern sociology. *Annual Review of Sociology*, Vol. 24, pp. 1–24.
- VAN DEN BRINK M., BENSCHOP Y. 2012. Slaying the seven-headed dragon: The quest for gender change in academia. *Gender, Work & Organization*, Vol. 19, No. 1, pp. 71-92.
- VEENSTRA G., ABEL T. 2019. Capital interplays and social inequalities in health. *Scandinavian Journal of Public Health*, Vol. 47, No. 6, pp. 631-634.
- ZINOVYEVAN., BAGUES M. 2015. The role of connections in academic promotions. *American Economic Journal: Applied Economics*, Vol. 7, No.2, pp. 264-292.

Gianpaolo CAPRINO, Department of Statistics and Quantitative Methods,
University of Milano-Bicocca, gianpaolo.caprino@unimib.it
Viviana AMATI, Department of Statistics and Quantitative Methods, University of
Milano-Bicocca, viviana.amati@unimib.it

SOCIO-ECONOMIC IMPLICATIONS OF ENERGY TRANSITION: THE NEW ROLE OF HUMAN CAPITAL

Marina Albanese, Monica Varlese

Abstract. Italy's energy landscape is undergoing a profound transformation, marked by expanding renewable capacity, fluctuating climatic conditions, and evolving market dynamics. In this context, human capital emerges as a critical driver of a just and effective energy transition. This paper investigates how skills, education, and workforce development shape Italy's path toward decarbonization, integrating a systematic review of the literature with empirical evidence on green employment and regional disparities. The analysis highlights that while Italy is advancing in renewable deployment and energy market integration, a persistent gap between labor supply and the skills demanded by emerging green sectors risks constraining progress. Significant territorial imbalances further amplify these challenges, revealing uneven capacities across regions to adapt and benefit from the transition. The findings highlight the need for integrated policies on education, reskilling, and labor inclusion to reinforce human capital and support a fair and sustainable energy transition.

1. Introduction

Recently, Italy's energy landscape exhibited notable shifts that reflect both the ongoing transition toward renewables and the system's responsiveness to varying climatic and market conditions. In March 2025, electricity available for consumption rose from a year earlier, driven mainly by a strong rebound in thermoelectric output and solid gains in solar generation. This expansion was tempered by pronounced declines in hydro and wind power, highlighting the sensitivity of weather-dependent sources to seasonal and climatic variability.

Over the same period, Italy markedly increased its power exports, signalling a stronger role in regional electricity markets and a more efficient use of cross-border interconnections (Terna, 2025). These dynamics underscore the complexity of Italy's energy transition, where increased solar capacity and thermal resilience coexist with fluctuating renewable yields, necessitating integrated strategies for stability and decarbonization. Specifically, current projections underscore the urgency of addressing human capital challenges.

A successful transition to renewable energy is driven not only by technological innovation and policy reforms but also by the critical contribution of workforce development and skill availability in supporting sustainable growth. While technological innovation and financial investment often dominate discussions, the role of human capital—the knowledge, skills, and expertise of the workforce—is increasingly recognized as a decisive factor in the success of this transition. The International Energy Agency (IEA) estimates that achieving net-zero emissions by 2050 will necessitate the creation of 14 million new energy-related jobs by 2030 (International Energy Agency, 2022). This includes positions ranging from highly technical roles, such as renewable energy engineers and grid specialists, to operational roles in project management and maintenance. At the same time, the phasing out of fossil fuels is expected to displace approximately 5 million jobs, resulting in a net gain of 9 million positions globally (Harvey, 2024). These shifts highlight the need for targeted workforce planning and training strategies to balance displacement with opportunities¹. However, there is a growing concern about a significant mismatch between the skills available in the current labor market and those required for the energy transition. For instance, renewable energy sectors like solar power have already encountered difficulties in meeting labor demand² (Di Blanco, 2024). Such shortages risk delaying project timelines and increasing costs, thereby hindering progress toward global energy goals.

Against this backdrop, by integrating a systematic literature review with evidence on Italian green jobs and regional heterogeneity, we investigate the role of human capital in shaping Italy's energy-transition trajectory. Specifically, the paper addresses the following questions: (i) How is the demand for green jobs evolving across different sectors in Italy, and how do skill requirements and shortages influence this process? (ii) How is green employment distributed across Italian regions, and which territories are emerging as leaders or lagging behind in the green transition?

The Italian case is especially relevant given its ambitious climate goals, strong regional disparities, and the increasing role of firms in driving the energy transition.

Moreover, despite the growing body of literature on human capital and the green transition at the international level, there is a notable lack of studies specifically examining the Italian context. This gap limits our understanding of country-specific

¹ Recent macroeconomic modeling suggests that carbon revenues invested in green education significantly enhance long-term green human capital, reinforcing the need for strategic investment in education to support the low-carbon transition in Italy (Albanese, Busato, and Cisco, 2024).

² Reports indicate that while Italy had over 76,000 workers employed in the solar sector in 2023, there remains a significant gap in technical expertise, particularly among installers and technicians. To meet its target of 100,000 solar jobs by 2028, the country must address this skills shortage through targeted training initiatives

challenges and policy needs, particularly in terms of regional labor mismatches and skill development.

The paper is structured as follows: after reviewing the relevant literature on human capital and energy transition, we analyse the evolution of green jobs and regional disparities in Italy labor market tightness for green occupations. Finally, we discuss policy implications for education, training, and workforce planning and propose a framework for enabling a just and inclusive energy transition.

2. Literature review

Human capital plays a central role in improving energy production efficiency and reducing CO₂ emissions, thus serving as a critical enabler of the energy transition. It supports the development and adoption of clean technologies and pollution-free methods, reinforcing its strategic relevance in the shift from non-renewable to renewable energy sources.

A growing body of research investigates the interplay between human capital, technology, globalization, and CO₂ emissions. Kuzmin *et al.* (2023) highlight the contribution of green human capital to energy-technological development³. Ahmed *et al.* (2021), using cointegration analysis for Latin America and the Caribbean, show that human capital and ICT enhance globalization, promote economic growth, and reduce environmental degradation. Similarly, Yao *et al.* (2019) and Sart *et al.* (2024) confirm that human capital is a fundamental driver of sustainable energy transitions, fostering the diffusion of renewables and environmental awareness.

Further empirical evidence supports these findings. Esquivias *et al.* (2022), through panel data from 1990–2019, demonstrate that investment in human capital and renewable technologies improves energy efficiency and reduces CO₂ emissions. Hao *et al.* (2021), focusing on G7 countries, show that education-driven human capital boosts the adoption of eco-friendly technologies and carbon mitigation strategies. Zhang *et al.* (2022), studying OECD countries, find that human capital, technology, and energy pricing policies discourage fossil fuel use and support sustainable energy transitions. Mahmood *et al.* (2019) also include human capital in their analysis of Pakistan, showing that higher education levels promote cleaner production and reduced pollution. On a broader level, Sarkodie *et al.* (2020)

³ In their study, Kuzmin *et al.* (2023) investigate the role of human capital investment in fostering sustainable socio-economic development within the energy sector. Employing a bibliometric methodology, the authors analyze a dataset of 1,933 documents indexed in the Web of Science database from 1991 to 2023. Their findings highlight a growing academic interest in this intersection, emphasizing that investments in human capital are perceived as vital for promoting innovation, accelerating the transition to renewable energy, and achieving long-term sustainability.

conceptualize the link between fossil fuel use, human capital, and climate mitigation in China, noting that renewable energy, income, and education reduce emissions and environmental degradation. Green Human Resource Management (GHRM) further enhances the contribution of human capital to sustainability. Amrutha and Geetha (2020), through a systematic review of 174 studies, demonstrate how GHRM supports environmental goals, corporate social responsibility, and employee well-being in the energy sector. Moreover, human capital influences energy transition not only through labour markets but also through individual consumption behavior. Households' adoption of renewable energy technologies is shaped by education, income, and age, directly impacting what energy is produced and consumed. Vainio *et al.* (2020) emphasize the need to integrate socio-psychological factors into energy transition analyses, while Vesikioja *et al.* (2022) apply a multi-level perspective (MLP) to assess 85 European smart energy systems, underlining the importance of human-centered approaches in digital energy transitions.

3. Data Analysis

This section presents an empirical investigation of the Italian labor market in the context of the green transition. First, we investigate the evolution of green job demand across sectors, examining how skill requirements and shortages shape this transformation. This provides insight into which industries are driving employment growth and how effectively the labour market is adapting to the skills needed for the green transition. Second, we analyse the regional distribution of green employment and labour market tightness, identifying geographic disparities in skill availability. This perspective is crucial for informing region-specific policies that support reskilling, promote equitable access to green jobs, and prevent local gaps in the transition toward a sustainable economy.

3.1. Green skills and green job in Italy

The assessment of green skills in the labour market is limited by the absence of a common definition of green jobs and the lack of detailed data on the environmental content of specific occupations. A key international taxonomy is ONET⁴ (Occupational Information Network) that offers a rare structured list of 204 “green” including “Increased Demand Occupations” (i.e. existing roles with rising demand,

⁴ Developed by the U.S. Department of Labor, it provides one of the most comprehensive resources on occupations and skills, especially for green jobs.

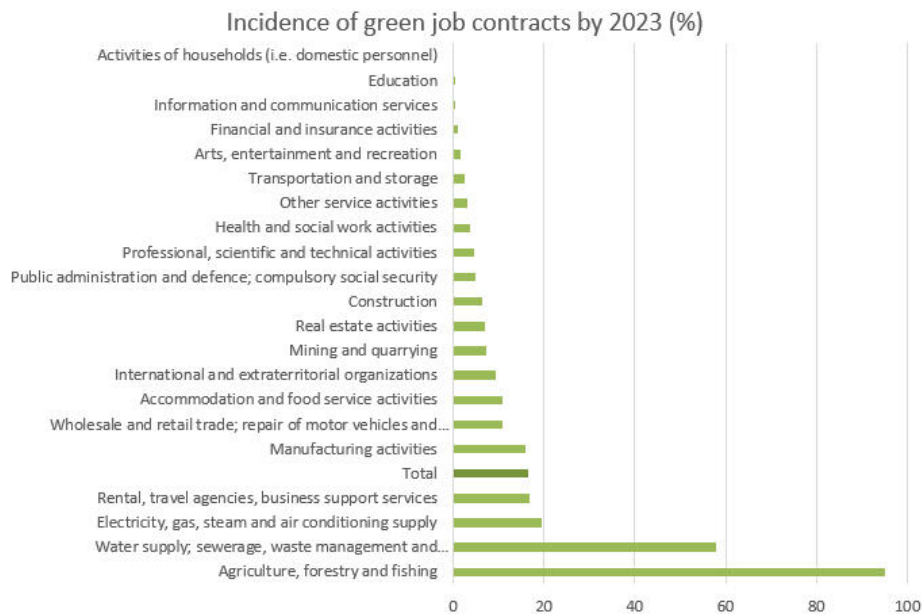
e.g., solar energy technicians), “Enhanced Skills Occupations” (i.e. traditional jobs requiring new environmental skills, e.g., mechanical engineers with green competencies), and “New and Emerging Occupations” (i.e. novel roles created by the green transition, e.g., carbon management specialists) (Sviluppo Lavoro Italia, 2024). In Italy, Unioncamere and Fondazione Symbola have operationalized this framework within the national production system, defining green jobs as work in agriculture, industry, and services that preserves or restores environmental quality and includes activities enhancing efficiency, quality, and eco-innovation (MASE). However, despite these definitional and taxonomic advances, measurement practices too often default to traditional binary classifications that distinguish between “green” and “non green jobs,” which often overlook the hybrid nature of many roles, particularly in sectors like construction and manufacturing (Consoli *et al.*, 2016). To overcome these limitations, recent studies have increasingly adopted a task-based approach, offering a more continuous and nuanced measure of occupational “greenness” (Autor, 2013; Vona *et al.*, 2018). Within this approach, the framework maps emerging green tasks in renewables and energy efficiency (Bradley *et al.*, 2025) and, crucially, detects skill mismatches and training gaps that can inform inclusive labour policies for a just transition (Brunetti *et al.*, 2025).

Overall, in the past decade, the demand for green jobs has followed a complex trajectory, characterized more by the gradual integration of environmental competencies into traditional occupations than by a clear shift toward highly specialized roles. Nevertheless, a persistent skills gap threatens to slow this progress, highlighting the need for targeted reskilling and upskilling. In Italy, data from the Comunicazioni Obbligatorie show no notable rise in demand for high-skilled green professionals: most new contracts are low- or medium-skill, with advanced technical roles concentrated in a few sectors while employment growth largely reflects conventional jobs that are incrementally adding environmental competencies. Specifically, the share of contracts classified as green jobs has fluctuated, moving from 19.7% in 2014 to 16.5% in 2023, with a temporary peak of 22.2% in 2020⁵ (Sviluppo lavoro Italia, 2024). At the same time, green-investing firms are markedly more active in developing their workforce—prioritizing upskilling, reskilling, and targeted training in areas like risk management, transversal, and managerial skills—positioning themselves ahead in sustainable innovation and adaptation (Fondazione Symbola – Unioncamere, 2024).

⁵ The Labour Market Intelligence (LMI) dashboard developed by Sviluppo Lavoro Italia integrates diverse data sources to provide territorial insights on labour demand, skills needs, and the green and digital orientation of over 600 professions. This tool is critical for aligning training systems with emerging labour market dynamics and informing effective policy responses to both ecological and technological transitions (Sviluppo Lavoro Italia, 2024a).

In terms of sectoral distribution, as illustrated in the following figure, green employment is highly concentrated in a few key industries. The agriculture, forestry, and fishing sector shows a particularly high incidence, accounting for 95.1% of contracts—equivalent to 1,357,724 new hires. This is followed by water supply, sewerage, waste management, and remediation activities, which represent 57.8% of green job contracts (30,405 in total), and by the electricity, gas, steam, and air conditioning supply sector, with an incidence of 19.5% (2,089 contracts). Other sectors with a notable presence of green employment include rental, travel agencies, business support services (16.9%, 143,560 contracts) and manufacturing activities (15.9%, 148,198 contracts) (Sviluppo Lavoro Italia, 2024).

Figure 1 – Sectoral distribution of green employment.



Source: Authors' computations from Sviluppo Lavoro Italia (2024), Table 4.3.A.

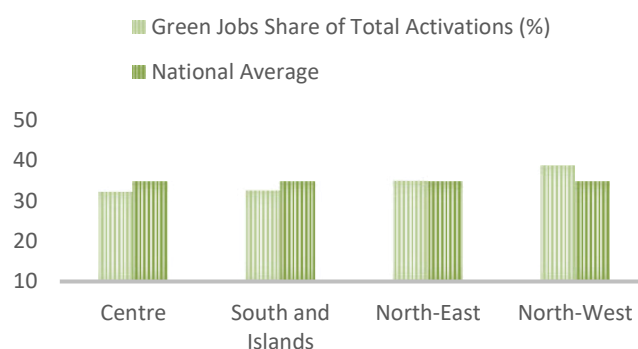
This distribution indicates that the green transition has advanced most rapidly in resource- and energy-intensive industries, and is progressively diffusing into services and manufacturing as firms embed sustainability within core operations. However, the comparatively limited presence of advanced technical and managerial profiles points to a latent skills gap that constrains the transition's transformative potential.

Within this framework, human capital is pivotal. Firms that invest strategically in upskilling and reskilling exhibit greater adaptability and innovative capacity, acting as catalysts that diffuse sustainability practices across value chains. Accordingly, the Fondo Nuove Competenze has emerged as a key instrument in Italy, co-financing firm-level training to support ecological and digital transitions and helping align workforce capabilities with evolving operational needs (Ministero del Lavoro e delle Politiche Sociali, 2024). Overall, the evidence suggests that Italy's green transition will depend more on the quality of workers' skills than on how many green jobs are created.

3.2. Regional disparities

Regional disparities remain a defining feature of Italy's green transition, revealing uneven progress in green job creation, skill availability, and overall labour market dynamics. Evidence from the Green Italy 2024 Report by Fondazione Symbola and Unioncamere confirms that, in 2023, significant territorial imbalances persisted in the distribution of green job activations across the country. The Centre recorded the strongest year-over-year acceleration (+12.6%), suggesting efforts to close the gap with other areas, but it still lagged in absolute levels. The North-West remained the leading area by volume and by the share of green jobs in new contracts (38.7%, above the 34.8% national average), followed by the North-East (34.9%); the South and Islands occupied an intermediate position (32.5%), with the Centre slightly lower (32.2%). Overall, regional differences reduced only marginally, pointing to uneven progress in the diffusion of green employment (Fondazione Symbola–Unioncamere, 2024).

Figure 3 – Green Employment Intensity by Italian Region (% of Total Activations).

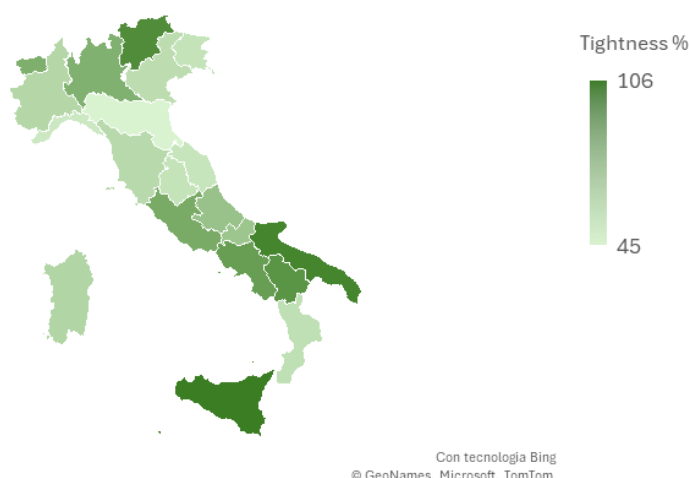


Source: Our own elaboration from Fondazione Symbola – Unioncamere, 2024.

These patterns suggest that Italy's green transition is still regionally unbalanced: gains concentrate where industrial capabilities, innovation assets, and environmental supply chains are already dense, while lagging areas grow slightly faster mainly because the gap is narrowing (i.e. not because their structures are converging). These dynamics point to the need for regionally differentiated strategies that strengthen local innovation ecosystems and workforce capabilities. Without targeted measures to support the Centre and South, the transition may entrench existing territorial disparities and slow the spread of sustainable employment nationwide.

A complementary perspective on territorial imbalances comes from labour-market tightness, which captures the percentage gap between the tightness of green jobs and that of the average job (OECD, 2023)⁶. This indicator highlights that Southern regions post the highest values—Sicily (+106.4%), Apulia (+102.1%), Campania (+89.4%)—signalling acute shortages of green skills; notably, Bolzano and Trento are also above +90%, showing that fast-growing, advanced markets can be equally constrained by skills. By contrast, Emilia-Romagna (+45.3%), Liguria (+50.2%), and Marche (+52.3%) display comparatively lower tightness, consistent with a closer supply–demand alignment (or a slower pace of green-job openings).

Figure 4 – Occupational Tightness in Green Jobs by Italian Region.



Source: Our own elaboration of data from OECD (2023).

⁶ The indicator draws on data from the OECD (2023) report *Job Creation and Local Economic Development 2023: Bridging the Great Green Divide*. It measures, for each regional labour market, the percentage difference between the tightness of green jobs and that of the average job. Labour market tightness is defined as the ratio of vacancies to employment, while green jobs are identified as occupations in which at least 10% of tasks are “green,” following the OECD’s task-based framework.

Overall, the evidence implies that regional disparities reflect not only different employment levels but also heterogeneous matching capacity—hence the need for place-sensitive policies that expand training channels and work-based learning in lagging areas, while scaling advanced, time-to-skill programs in leading regions. Taken together, the evidence from green job creation and labour market tightness highlights that Italy's green transition is advancing at an uneven pace, shaped by both structural and capacity-related differences across regions. Some territories combine strong industrial and innovation assets with growing skill shortages, while others show weaker demand but relatively better alignment between available and required competencies. These dynamics underscore the importance of regionally differentiated strategies that simultaneously strengthen human capital, stimulate green investment, and ensure fair access to quality employment.

4. Conclusions

This paper underscores the pivotal role of human capital in shaping Italy's energy transition, showing that the evolution of green job demand across sectors, together with effective skill development and the reduction of regional disparities, is fundamental to achieving a sustainable and balanced transformation. The analysis provides three main insights. First, the green transition has advanced most rapidly in resource- and energy-intensive industries, gradually extending to services and manufacturing as sustainability becomes embedded in core business operations. Second, a persistent shortage of advanced technical and managerial profiles reveals a structural skills gap that constrains the transformative potential of green growth. Third, significant territorial asymmetries in both job creation and skill matching highlight the need for regionally differentiated strategies to ensure an equitable diffusion of green employment opportunities. To address these challenges, it is essential to adopt a multi-faceted approach to human capital development. First, it would be appropriate to align education systems with emerging industry needs as the transition spreads beyond resource- and energy-intensive sectors. Specifically, it would be useful embed sustainability in formation programs, expand work-integrated learning (apprenticeships, internships) with local firms, and update occupational standards to include green competencies in services and manufacturing. Second, to face the shortage of advanced technical and managerial roles, it appears relevant to implement targeted reskilling/upskilling, namely fast-track programmes and micro-credentials in renewables, grid modernisation, systems integration, and sustainability management, among many others. Third, policymakers might address territorial asymmetries through place-sensitive measures, including developing

regional training hubs tied to local specialisations, harmonising qualifications, and recognising prior learning to ease mobility.

Acknowledgments

This work is supported by the “Network 4 Energy Sustainable Transition - NEST” project (MUR project code PE000021, Concession Decree No. 1561 of 11.10.2022), in the framework of the NextGenerationEu PNRR plan (CUP E63C22002160007).

References

- ALBANESE M., BUSATO F., CISCO G. 2024. Carbon subsidies to greening educational and business activities. *Rivista Italiana di Economia Demografia e Statistica*, Vol. 78, No. 2, pp. 79–90.
- AMRUTHA V. N.; GEETHA S. N. 2020. A systematic review on green human resource management: Implications for social sustainability, *Journal of Cleaner Production*, Vol. 247, 119131.
- AHMED Z.; NATHANIEL S. P.; SHAHBAZ M. 2021. The criticality of information and communication technology and human capital in environmental sustainability: Evidence from Latin American and Caribbean countries, *Journal of Cleaner Production*, Vol. 286, 125529.
- AUTOR D. 2013. The task approach to labor markets: An overview. *Journal of Labor Market Research*, Vol. 46, No. 3, pp. 185–199. <https://doi.org/10.1007/s12651-013-0128-z>
- BRADLEY P.; WHITTARD D.; GREEN E.; BROOKS I.; HANNA R. 2025. Empirical research on green jobs: A review and reflection with practitioners. *Sustainable Futures*, Vol. 9, 100527. <https://doi.org/10.1016/j.sfr.2025.100527>
- CONSOLI D., MARIN G., MARZUCCI A., VONA F. 2016. Do green jobs differ from non-green jobs in terms of skills and human capital? *Research Policy*, 45(5), 1046–1060. <https://doi.org/10.1016/j.respol.2016.01.005>
- DI BLANCO S. 2024, March 19. *Posti di lavoro nel fotovoltaico: Italia quarta in Europa per occupazione.* Rinnovabili.it. <https://www.rinnovabili.it/energia/fotovoltaico/posti-di-lavoro-nel-fotovoltaico-dati-occupazione/>
- ESQUIVIAS M. A., *et al.* 2022. Nexus between technological innovation, renewable energy, and human capital on the environmental sustainability in emerging Asian economies: A panel quantile regression approach, *Energies*, Vol. 15, No. 7, 2451.

- FONDAZIONE SYMBOLA – UNIONCAMERE, 2024. *GreenItaly 2024. Un'economia a misura d'uomo contro le crisi*. Available at <https://www.unioncamere.gov.it/sites/default/files/articoli/2024-10/Greenitaly%202024.pdf>
- HAO L.-N., et al. 2021. *Green growth and low carbon emission in G7 countries: How critical the network of environmental taxes, renewable energy and human capital is?*, *Science of the Total Environment*, Vol. 752, 141853.
- HARVEY T. 2024, July 29. *Bridging the gap, part 1: Not enough renewable energy skills to pay the bills*. Pager Power. <https://www.pagerpower.com/news/bridging-the-gap-part-1-not-enough-renewable-energy-skills-to-pay-the-bills/>
- BRUNETTI I., FRATTINI F. F., KUNTZE M., RICCI A., VONA F. 2025. *Exploring skills in the green transition: New insights from Italian data world* (INAPP Working Paper No. 134). Istituto Nazionale per l'Analisi delle Politiche Pubbliche (INAPP).
- INTERNATIONAL ENERGY AGENCY. 2022. *World energy employment*. <https://www.iea.org/reports/world-energy-employment>
- KUZMIN E., VLASOV M., STRIELKOWSKI W., FAMINSKAYA M., KHARCHENKO K. 2023. *Human capital in the sustainable economic development of the energy sector*. arXiv preprint arXiv:2312.06450. <https://doi.org/10.48550/arXiv.2312.06450>
- MAHMOOD N.; WANG Z.; HASSAN S. T. 2019. *Renewable energy, economic growth, human capital, and CO₂ emission: An empirical analysis*, *Environmental Science and Pollution Research*, Vol. 26, pp. 20619–20630.
- MASE. *Professioni verdi, occupazione giovanile e nuova imprenditorialità: il ruolo della formazione nello sviluppo di competenze innovative a sostegno della green economy e dello sviluppo dei territori*. Available at https://www.mase.gov.it/portale/documents/d/guest/gdl_green_jobs_definitivo-pdf
- MINISTERO DEL LAVORO E DELLE POLITICHE SOCIALI. 2024, May 10. *Le risorse del Fondo Nuove Competenze 3 superano il miliardo*. <https://www.lavoro.gov.it/stampa-e-media/comunicati/pagine/le-risorse-il-fondo-nuove-competenze-3-superano-il-miliardo>
- OECD 2023, *Job Creation and Local Economic Development 2023: Bridging the Great Green Divide*, OECD Publishing. <https://doi.org/10.1787/21db61c1-en>
- SARKODIE S. A., et al. 2020. *Mitigating degradation and emissions in China: The role of environmental sustainability, human capital and renewable energy*, *Science of the Total Environment*, Vol. 719, 137530.
- SART G., ÖZEKICIOĞLU H., DANILINA M., AYTEMİZ L., BAYAR Y. 2024. *The causal nexus among energy dependency, human capital, and renewable*

- energy: An empirical analysis for EU members. *Energies*, Vol. 17, No. 21, 5305. <https://doi.org/10.3390/en17215305>
- SVILUPPO LAVORO ITALIA 2024. *La domanda di lavoro per Bacino di competenza dei Centri per l'Impiego. La vocazione green per l'Italia*. Available at <https://www.sviluppolavoroitalia.it/documents/d/sli/rapporto-sistan-cpi-2024-pdf>
- SVILUPPO LAVORO ITALIA. 2024a. *Il cruscotto di Labour Market Intelligence di Sviluppo Lavoro Italia aggiornato con nuove funzionalità*. <https://www.sviluppolavoro.gov.it/news/il-cruscotto-di-labour-market-intelligence-di-sviluppo-lavoro-italia-aggiornato-con-nuove-funzionalita/>
- TERNA. 2025. *Monthly Report on the Electricity System – March 2025*. Retrieved from <https://www.terna.it/>
- WORLD ECONOMIC FORUM. 2025. *Future of jobs report 2025*. <https://www.weforum.org/reports/the-future-of-jobs-report-2025/>
- VAINIO A., et al. 2020. Citizens' sustainable, future-oriented energy behaviours in energy transition, *Journal of Cleaner Production*, Vol. 245, 118801.
- VESKIOJA K.; SOE R.-M.; KISEL E. 2022. *Implications of digitalization in facilitating socio-technical energy transitions in Europe*, *Energy Research & Social Science*, Vol. 91, 102720.
- VONA F., MARIN G., CONSOLI D., POPP D. 2018. Environmental regulation and green skills: An empirical exploration. *Journal of the Association of Environmental and Resource Economists*, Vol. 5, No. 4, pp. 713–753. <https://doi.org/10.1086/698859>
- YAO Y., IVANOVSKI K., INEKWE J., SMYTH R. 2019. Human capital and energy consumption: Evidence from OECD countries. *Energy Economics*, Vol. 84, 104534. <https://doi.org/10.1016/j.eneco.2019.104534>
- ZHANG Y., et al. 2022. The eco-innovative technologies, human capital, and energy pricing: Evidence of sustainable energy transition in developed economies, *Applied Energy*, Vol. 325, 119729.

A REGIONAL PERSPECTIVE ON ITALIAN LIFE EXPECTANCY DECELERATION

Gianni Carboni

Abstract. Using ISTAT period life tables, we traced annual life expectancy at birth for Italy's macro-areas (NUTS1) and regions (NUTS2) from 1980 to 2019. An unconstrained segmented-regression search identified breakpoints clustered around 2008—the first full year of the nationwide spending freeze and the regional deficit-recovery plans—suggesting a near-simultaneous inflection across the country. Taking 2008 as a policy-salient breakpoint, we then fitted interrupted time-series models to each regional trajectory. Almost all regions showed a statistically significant post-2008 flattening for the pooled sexes, and significance held for both men and women in all but a handful of small, data-sparse territories. Where significant, the estimated slope implies regions lost 0.5–2.0 years of life expectancy progression over the ensuing decade. The slowdown was almost universally sharper for women than for men, with only three regions displaying no gender gap. The striking synchrony of the breakpoint—first across macro-areas, then across regions aligns with an exogenous, nation-wide period shock tied to the 2008 wave of health-care austerity.

1. Introduction

For more than a century, life expectancy¹ in the world's affluent nations has climbed almost without interruption, sustained first by steep declines in infant mortality and infectious disease and later by sustained gains in nutrition, living standards, and chronic-disease prevention and care (Riley, 2001; Cutler *et al.*, 2006). Recently, however, that steady ascent has begun to slow down: across most OECD countries a clear slowdown has been evident since around 2011 (Raleigh, 2019). Outside the extraordinary shock of the COVID-19 pandemic, the modern longevity curve had previously dipped only in the wake of the two World Wars and the 1918 influenza pandemic (Dattani *et al.*, 2023).

Much of the recent work on this slowdown has focused on national aggregates, tracing it to a dwindling pace of progress against cardiovascular disease and several

¹ Throughout the paper, we focus on period life expectancy at birth as a summary measure of mortality conditions. While life expectancy is sometimes loosely referred to as longevity in the broader literature, we use the two terms with care: life expectancy denotes the specific demographic indicator analysed here, whereas longevity is used only in a general descriptive sense.

major cancers (OECD/The King's Fund, 2020; Steel *et al.*, 2025). At the same time, countervailing trends in upstream risks—rising exposure to high body-mass index, sub-optimal diet, physical inactivity and harmful alcohol use—along with a loss of momentum in controlling LDL-cholesterol and systolic blood pressure, have eroded the earlier gains won through falling smoking prevalence (Steel *et al.*, 2025).

A parallel body of research stresses the role of broad social and macro-economic currents: widening socioeconomic mortality gaps, mounting pressures on health systems, and, above all, the fiscal *austerity* that followed the 2008 financial crisis seem to have each been implicated in the recent stagnation of longevity (McCartney *et al.*, 2022).

Italy offers a particularly revealing setting for probing this “austerity hypothesis”. Although service delivery is highly regionalised, the Italian National Health Service is financed largely through a central block grant (de Belvis *et al.*, 2022); after 2008 that grant levelled off in real terms across every region, effectively freezing per-capita health expenditure (Ciocci & Spagnolo, 2020). Crucially, this spending freeze coincided with a steady rise in the share of older residents—an age group that drives much of the demand for medical care—so that the system's resource base remained flat (if not actually declining) while the clinical workload kept expanding (the population aged 65+ grew by about 17 percent between 2007 and 2019).

A further element underscores why 2008 stands out in the Italian health narrative. Starting from 2007, the central government activated a series of “recovery plans” (*piani di rientro*)—deficit-recovery plans that targeted regions whose health accounts had slipped deep into the red. The mechanism was straightforward but stern: regions signing a plan received advance transfers only if they met tight quarterly targets for payroll cuts, bed reductions, hospital mergers and higher co-payments; falling short of those targets triggered automatic claw-backs and even tighter oversight (Aimone Gigio *et al.*, 2018). Because the plans were layered on top of the nationwide spending freeze, they delivered an extra dose of austerity to large portion of the Italian population, including such populous regions as Lazio, Campania and Sicily. Recent evidence confirms that the tightening was not cost-free: regions under a deficit-recovery plans experienced a measurable rise in avoidable mortality relative to those outside the scheme (Arcà *et al.*, 2020). Moreover, health austerity appears to have affected not only absolute mortality levels but also the long-running process of regional convergence. Periods of major cost-containment coincide with stalls in the narrowing of Italian North–South survival gaps, suggesting that fiscally weaker territories bear a disproportionate share of the burden and fall further behind the country's more prosperous regions (Carboni *et al.*, 2024; De Santis *et al.*, forthcoming).

Strikingly, the national mortality slowdown begins in the same period these measures took effect. Using causal approach, Salinari *et al.* (2023) show that Italy

forfeited about 30 percent of its life-expectancy progression starting from 2008—a loss that precedes the modal OECD deceleration by three years.

Taken together, these coincidences strengthen the case for an austerity hypothesis: the concurrence of the 2008 national health-expenditure cap, the simultaneous launch of deficit-recovery plans in several regions, and the first signs of both a country-wide slowdown in life-expectancy gains and a stall in regional convergence all within the same brief interval points to a common cause.

At the national level, several complementary interpretations have been proposed to explain the post-2008 slowdown in life expectancy gains, emphasizing the role of the Great Recession and changes in age- and cause-specific mortality patterns (e.g. Egidi & Demuru, 2018). While these contributions highlight important mechanisms operating at the aggregate level, the present study adopts a different perspective by focusing on the temporal synchronization and territorial pervasiveness of the slowdown, with the aim of assessing whether the observed deceleration reflects a shared period shock rather than heterogeneous regional dynamics.

The aim of this study is therefore straightforward: we look for statistical evidence that the slowdown's geography is consistent with this policy shock. Specifically, we ask whether the deceleration begins at roughly the same time across Italy's territories (signalling synchrony) and whether that timing aligns with the launch of health-care austerity measures (2008). A positive answer to both questions would lend support to the view that fiscal retrenchment set Italy's longevity onto a slower path.

2. Methodological strategy

We analyse annual life expectancy at birth (e_0) for each Italian macro-area (NUTS1) and for all regions (NUTS2), using the official period life tables produced by ISTAT (the Italian Statistical Institute). Italy's formal NUTS1 map consists of five units: North-West, North-East, Centre, South and Islands. In addition to these, we examine every meaningful combination of contiguous units, yielding seven macro-area series in total: North-West, North-East, their aggregate North, the Centre, the official pairing South & Islands, and its two constituents analysed separately (South and Islands). On the contrary, the NUTS2 layer covers 20 territorial units.

The ISTAT's life tables are built directly from the complete register of deaths and mid-year population counts and apply a uniform methodology across territories, ensuring strict comparability in both space and time. Moreover, e_0 gives a single, policy-salient indicator that summarises mortality at all ages while retaining the raw year-to-year variability, an important feature when we search for structural breaks in regional trends.

From these annual life tables, we extract the period 1980–2019, a window long enough to detect structural shifts yet narrow enough to capture the late-2000s slowdown while excluding the disruptive effects of the COVID-19 pandemic that begins in 2020.

Our empirical strategy proceeds in two stages.

The first stage applies segmented regression to each macro-area series, letting the algorithm search freely for structural breakpoints and date them. If the breakpoints that emerge are consistent with the 2008-austerity hypothesis, we treat 2008 as the policy-salient breakpoint for the second stage, fitting an interrupted time-series model to every NUTS2 regional series.

Let's look at these two stages in detail.

2.1. Stage one: Segmented regression

Segmented (or piece-wise) regression extends ordinary least squares by permitting the slope of a time trend to shift at one or more unknown calendar years (breakpoints). Instead of guessing those dates a priori, the algorithm searches iteratively for the hinge points that best partition the series into straight-line segments. In our setting the practical question is: *does a given macro-area display a particular year after which the long-running rise in life expectancy flattens (steepens) in a statistically detectable way?*

The procedure treats each segment as linear, an assumption well suited to life-expectancy trajectories. In high-income countries, in fact, e_0 has advanced with near-constant annual gains for decades, a regularity documented by Riley (2001) for national averages and by Oeppen and Vaupel (2002) for best-practice records, among others. Local linearity therefore provides a reasonable baseline against which to test for structural breaks in the life expectancy series.

For each fixed macro-area we then model the annual life expectancy (Y_t accounts for $e_{0,t}$, with $t = 1980, \dots, 2019$), as

$$Y_t = \beta_0 + \beta_1 t + \beta_2 (t - \tau) I_{\{t > \tau\}} + \varepsilon_t, \quad (1)$$

where $I_{\{t > \tau\}}$ is an indicator function that equals 1 after the breakpoint τ and 0 otherwise; β_0 is the intercept, β_1 is the pre-break slope, β_2 captures the change in slope after τ , and ε_t is an independent error term.

Since life expectancy at birth has marched upward for decades, a negative post-break change in slope ($\beta_2 < 0$) flattens that trajectory: e_0 is still rising, but more

slowly, so improvements decelerate.² In contrast, a $\beta_2 > 0$ steepens the climb, indicating an acceleration in longevity gains.

Breakpoints and coefficients of model (1) are estimated with the iterative procedure proposed by Muggeo (2008)'s *segmented* R package, which also allows the computation of confidence intervals for τ .

Because the 1980–2019 trajectories may harbour more than one structural shift, we follow recent joinpoint applications to life-expectancy data (Minton *et al.*, 2023; Zazueta-Borboa *et al.*, 2024) and let the algorithm search for up to two breakpoints in each e_0 series. In some cases, a single hinge may be enough; when additional breaks emerge, we document them yet focus our interpretation on the most recent one, as that is most germane to the late-2000s slowdown under study.

2.2. Stage two: Basic interrupted time series

If Stage one identifies 2008 as lying within the plausible break window, Stage two tests whether that same year can account for the trend shift in every regional series. Here the question is: *Can a single calendar year (2008, where applicable) account for the trend change in every region (NUTS2) series?* In such case, this would mean that 2008 alters the life-expectancy slope in (almost) every region and then the slowdown must stem from a nation-wide period shock

Concretely, we run the same basic interrupted time-series model for each region, always imposing a single predetermined year as the breakpoint. Formally:

$$Y_t = \beta_0 + \beta_1 t + \beta_2 I_{\{t > \bar{t}\}} + \beta_3 t I_{\{t > \bar{t}\}} + \varepsilon_t. \quad (2)$$

Here β_1 captures the pre-break yearly change in e_0 , β_2 measures any immediate jump (up or down) *exactly* at year $\bar{t}$ and, finally, β_3 quantifies how much the post-break slope differs from the pre-break slope.

The form of model (2) is deliberately more flexible than the segmented-regression model (1). Now we fix a single, ex-ante breakpoint for all regions. Allowing both a level change (β_2) and an independent slope change (β_3) ensures that any departure from the pre- $\bar{t}$ trend can be detected. If the austerity hypothesis holds, then we would have $\bar{t} = 2008$.

At this stage our attention centres on the coefficient β_3 . A statistically significant negative β_3 signals that the post- $\bar{t}$ slope has flattened relative to the pre- $\bar{t}$ trend,

² Note: Theoretically, if the absolute value of β_2 exceeds that of the pre-break slope β_1 , the post-break slope ($\beta_1 + \beta_2$) becomes zero or negative. In that extreme case life expectancy would plateau or even decline, rather than merely rising more slowly. All this also applies in the opposite direction.

indicating a deceleration in life-expectancy gains; a significant positive value would imply the opposite. In this stage, we estimate the models separately for men and women to check whether the break affects both sexes in the same way.

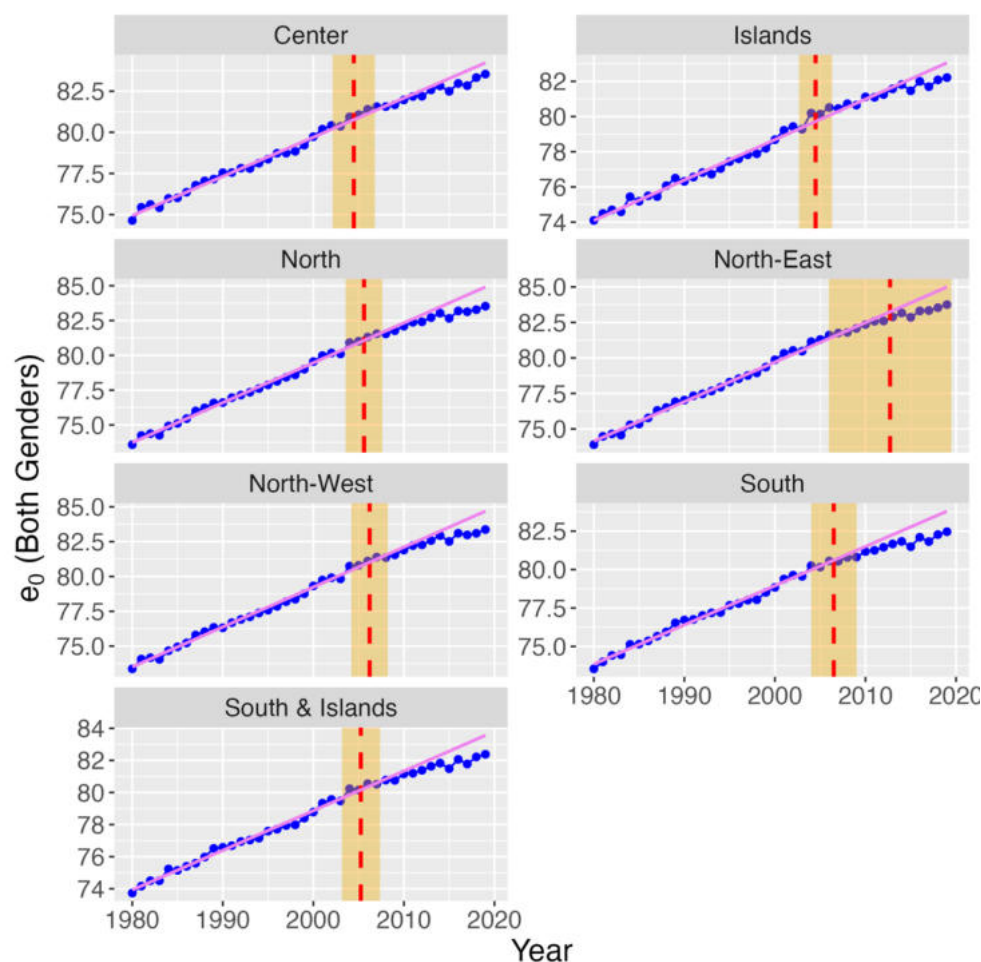
3. Results

Figure 1 charts annual life expectancy at birth (e_0) for the seven macro-areas “combinations”: blue points and lines show the observed series; the red dashed line marks the breakpoint estimated by the segmented-regression model, and the orange ribbon represents its 95% confidence interval. The purple line projects the pre-break slope beyond the breakpoint, illustrating how e_0 would have evolved had the earlier trend continued unchanged.

Several points are immediately apparent. Firstly, the direction of change is identical: in every panel the post-break slope lies below the projected purple line, signalling a deceleration in longevity gains. In other words, the rise in e_0 flattened simultaneously across the whole peninsula. Secondly, the breakpoints confidence bands overlap almost entirely, indicating that the North, Centre, and South & Islands all experienced an inflection in life-expectancy trends at virtually the same historical moment. Lastly, the 95% confidence bands in every macro-area stretch far enough to include 2008. This overlap means that choosing 2008 as the reference point does not contradict any of the segmented-regression results: it falls inside the statistical margin for basically every series. The lone outlier, a slightly later break in the North-East, likely reflects the noisier series of this relatively small macro-area and does not alter the overall pattern. We therefore carry 2008 forward into Stage two as the policy-salient breakpoint, confident that it is both empirically acceptable and substantively meaningful.

The next stage tests whether the 2008-same breakpoint can account for a significant slope change in each of the 20 NUTS2 regions.

Figure 2 shows the p-values for the post-2008 slope-change coefficient (β_3) from our interrupted time-series models (model 2), run separately for each of Italy’s 20 NUTS2 regions and for females, males, and the combined population. Region codes appear on the horizontal axis, and the red dashed line marks the 0.05 significance threshold. We anchor the breakpoint to 2008 to test whether that single policy-inflection date coincides with a statistically detectable change in the life-expectancy trend everywhere in the country and in both sexes.

Figure 1 – (Stage one) Breakpoints in Italian macro-area e_0 trends, Italy 1980 – 2019.

Blue lines show annual e_0 for Italian macro-areas, 1980-2019. The red dashed line marks the breakpoint estimated by segmented regression; the orange rectangle is its 95% confidence interval. The purple line projects the pre-break trend beyond the breakpoint.

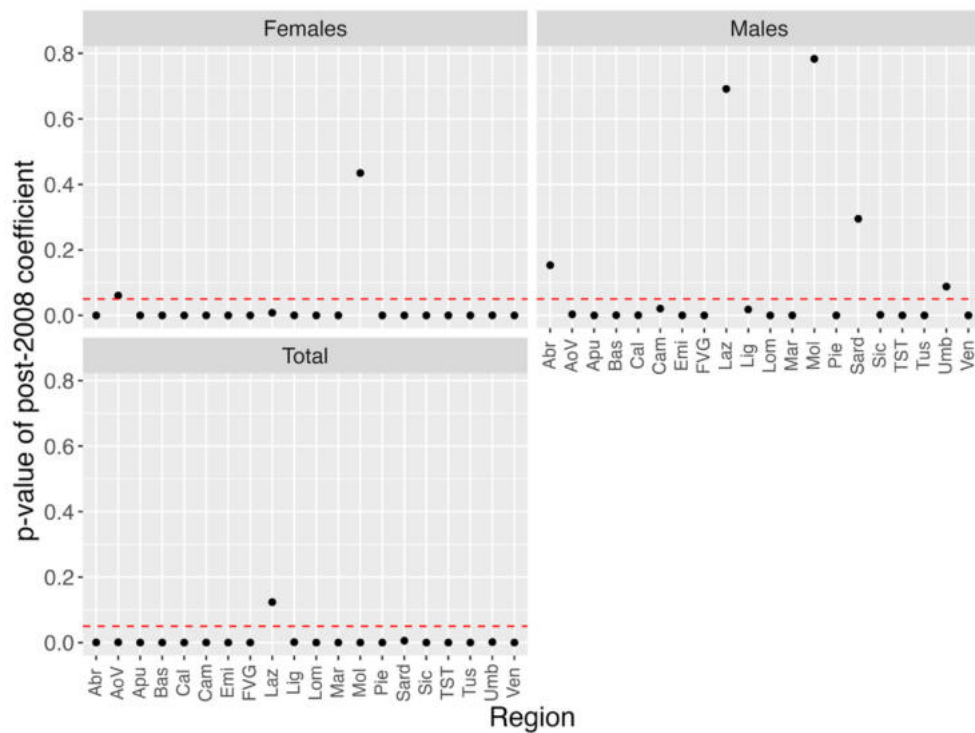
Source: Our elaboration on ISTAT data.

Across the pooled-sex specification (bottom panel) almost nearly the whole country shows the same pattern: every region except Lazio posts a p-value below 0.05, indicating that 2008 coincides with a statistically significant shift in their life-expectancy trajectories. Splitting the analysis by sex refines the picture. In the female series Lazio becomes significant, and only the two least-populated regions (Aosta

Valley and Molise) fail to clear the 0.05 threshold. For males the result is reversed in Lazio (non-significant) and loses significance in four mid-small regions: Abruzzo, Molise, Sardinia, and Umbria. The handful of non-significant cases share two salient features: small population size and, most probably, higher year-to-year volatility. Exploring these local idiosyncrasies lies beyond our scope, yet the broad pattern is clear: with very few exceptions, regions register a synchronous deceleration after 2008. Where significant, the estimated β_3 values are uniformly negative, confirming that the post-2008 trend is flatter than the pre-break trajectory.

Beyond their statistical meaning, the patterns displayed in Figure 2 carry a clear substantive interpretation.

Figure 2 – (Stage two) *p*-values for the post-2008 slope-change coefficient (β_3), by region and sex, Italy 1980–2019.



Each dot reports the *p*-value for the post-2008 slope-change coefficient (β_3) from the basic interrupted time-series model with a common breakpoint fixed at 2008, shown separately by region and sex. The red dashed line indicates the 0.05 significance threshold. Region abbreviations: Piedmont (Pie), Aosta Valley (AoV), Liguria (Lig), Lombardy (Lom); Trentino-South Tyrol (TST), Veneto (Ven), Friuli-Venezia Giulia (FVG), Emilia-Romagna (Emi); Tuscany (Tus), Umbria (Umb), Marche (Mar), Lazio (Laz); Abruzzo (Abr), Molise (Mol), Campania (Cam), Apulia (Apu), Basilicata (Bas), Calabria (Cal); Sicily (Sic) and Sardinia (Sard).

Source: Our elaboration on ISTAT data.

The widespread significance of the post-2008 slope change indicates that the slowdown in life expectancy gains was not confined to specific regions or contexts, but instead emerged as a broadly shared national phenomenon. The fact that this result holds for almost all regions in the pooled-sex analysis, and for the vast majority when sexes are analysed separately, supports the interpretation of a common period shock rather than locally staggered dynamics.

In the pooled-sex series the β_3 coefficients span roughly -0.04 to -0.16 years per calendar year (median ≈ -0.12). That is to say, regions lost between about half a month and two months of annual e_0 improvement; over the decade this cumulates to 0.5–2 years of life expectancy that would have been realised had the earlier trend continued. In other terms, this pattern implies a contemporaneous and country-wide deceleration in mortality improvements, consistent with a nation-wide disruption rather than region-specific or cohort-driven processes.

Furthermore, this deceleration is geographically broad-based. Northern industrial regions such as Veneto (-0.15), Friuli-Venezia Giulia (-0.12) and Emilia-Romagna (-0.12) display magnitudes similar to those in many southern regions—e.g. Basilicata (-0.16) and Calabria (-0.12).

Lazio is the clear outlier: its pooled-sex coefficient (-0.04) is less than half the national median, mirroring the region's borderline significance in the Stage two “p-value test”. Although Lazio faced one of the most stringent and prolonged deficit-recovery regimes (Aimone Gigio *et al.*, 2018), its preservation of essential care standards, the potential buffering effect of high-profile facilities, and its greater fiscal capacity to cover lingering deficits likely cushioned the direct impact on life expectancy, helping to explain its comparatively muted post-2008 slowdown.

Concerning the gender gap of deceleration, in every region but one (Aosta Valley) the female post-2008 coefficient is more negative than the male counterpart, indicating a sharper deceleration in women's life-expectancy gains. Aosta Valley is the sole reversal, showing a steeper male slowdown, a result that likely reflects the volatility of a very small population base. Three northern regions (Friuli-Venezia Giulia, Trentino-South Tyrol and Lombardy) stand out for having virtually no gender gap: here the male and female coefficients are nearly identical, suggesting that whatever forces curbed longevity progress did so with equal intensity in both sexes.

Taken as a whole, the pattern points to a country-wide deceleration that began around 2008, lending strong support to the period-effect interpretation and leaving little room for staggered, cohort-specific dynamics (see conclusion).

4. Conclusion and discussion

This study asked whether the slowdown in Italian life-expectancy gains—widely noted in national analyses—also emerges when the country is viewed through its territorial mosaic.

We combined a segmented-regression scan across macro-areas with a region-by-region interrupted time-series test that fixed the breakpoint at 2008, the first full year of the spending freeze and the deficit-recovery plans. The two stages told a consistent story. Every macro-area exhibited a statistically indistinguishable hinge in the second half of the 2000s, and when 2008 was imposed on all 20 regions almost all registered a significant flattening of the e_0 slope. In short, the deceleration proves stubbornly synchronous—first across macro-areas and then, at finer resolution, across regions.

Such geographic concordance challenges any explanation that relies primarily on cohort dynamics. Each region has its own age structure, migration history and cohort composition, conditions that should yield locally staggered turning points if cohort effects were dominant. Yet the inflection arrives everywhere at practically the same calendar moment. The simpler reading is a period shock, and the timing singles out the 2008 wave of health-care austerity.

Why might mortality react so swiftly to fiscal restraint? Evidence from other high-income settings shows that the lag can be surprisingly short (McCartney *et al.*, 2022). Whether through longer waiting times, delayed adoption of new treatments, or stress on community-care networks, even seemingly modest cuts—or simply the failure to expand budgets in step with demand driven by an ageing population—rarely come without cost. Experience shows they can stall—even reverse—survival gains within just one planning cycle.

A limitation of this study considered on its own is that it relies on period life expectancy at birth as a summary indicator of mortality. As with any aggregate measure, life expectancy cannot capture heterogeneity by age, cause of death or population subgroups, and thus does not directly inform on the distributional mechanisms underlying the observed trends. This choice, however, is deliberate and closely aligned with the paper's objective, which is to identify the timing and geographic synchrony of structural breaks in mortality trajectories across Italian regions. In this respect, period life expectancy provides a stable, policy-relevant and fully comparable indicator over time and space, particularly well suited to detecting broad period shocks.

Importantly, ongoing and related work by the authors explicitly examines age-specific mortality patterns and cohort dynamics, with preliminary evidence suggesting that the post-2008 deceleration is difficult to reconcile with a purely

cohort-based explanation and remains consistent with a dominant period effect linked to health-care austerity (Carboni *et al.*, forthcoming).

Most studies of the post-2008 slowdown have emphasised its cross-national synchrony. We show that the synchrony is resilient when the lens is narrowed to the regional level inside one country. Any convincing account of Europe's longevity slowdown must therefore explain not only why many nations turned at once, but also why, within Italy, northern, central and southern regions did so together.

Acknowledgements

Financial support from the Italian MUR (PRIN 2022 n° 2022CENE9F, "The pre Covid 19 stall in life expectancy in Italy: looking for explanations") is gratefully acknowledged.

References

- AIMONE GIGIO L., ALAMPI D., CAMUSSI S.A., CIACCIO G., GUAITINI P., LOZZI M., ... PAOLICELLI M. 2018. La Sanità in Italia: Il difficile equilibrio tra vincoli di bilancio e qualità dei servizi nelle regioni in piano di rientro, *Bank of Italy Occasional Paper*, No. 427.
- ARCÀ E., PRINCIPE F., VAN DOORSLAER E. 2020. Death by Austerity? The Impact of Cost Containment on Avoidable Mortality in Italy, *Health Economics*, Vol. 29, No. 12, pp. 1500-1516.
- CARBONI G., SALINARI G., DE SANTIS G., BENASSI F. 2024. Mortality Evolution in Italy: The End of Regional Convergence?, *Genus*, Vol. 80, No. 1, p. 28.
- CIOCCI M., SPAGNOLO F. 2020. La spesa in Sanità: i dati CPT per un'analisi in serie storica a livello territoriale, Sistema Conti Pubblici Territoriali
- CUTLER D., DEATON A., LLERAS-MUNEY A. 2006. The Determinants of Mortality, *Journal of Economic Perspectives*, Vol. 20, No. 3, pp. 97-120.
- EGIDI V., DEMURU E. 2018. Impatto delle grandi crisi economiche su salute e mortalità: il caso italiano, La società italiana e le grandi crisi economiche 1929–2016, Istat, *Annali di Statistica*, pp. 57–82.
- McCARTNEY G., McMASTER R., POPHAM F., DUNDAS R., WALSH D. 2022. Is Austerity a Cause of Slower Improvements in Mortality in High-Income Countries? A Panel Analysis, *Social Science & Medicine*, Vol. 313, pp. 115397.
- MINTON J., HIAM L., McKEE M., DORLING D. 2023. Slowing Down or Returning to Normal? Life Expectancy Improvements in Britain Compared to Five

- Large European Countries Before the COVID-19 Pandemic, *British Medical Bulletin*, Vol. 145, No. 1, pp. 6-16.
- MUGGEO V.M. 2008. Segmented: An R Package to Fit Regression Models with Broken-Line Relationships, *R News*, Vol. 8, No. 1, pp. 20-25.
- OECD, THE KING'S FUND. 2020. Is Cardiovascular Disease Slowing Improvements in Life Expectancy? OECD/The King's Fund Workshop Proceedings, OECD Publishing, Paris
- OEPPEN J., VAUPEL J.W. 2002. Broken Limits to Life Expectancy, *Science*, Vol. 296, No. 5570, pp. 1029-1031.
- RALEIGH V.S. 2018. Stalling Life Expectancy in the UK, *BMJ*, Vol. 362, k4050.
- RILEY J.C. 2001. *Rising Life Expectancy: A Global History*, Cambridge University Press, Cambridge.
- SALINARI G., BENASSI F., CARBONI G. 2023. The Effect of the Great Recession on Italian Life Expectancy, *Population Research and Policy Review*, Vol. 42, No. 1, p. 3.
- DATTANI S., RODÉS-GUIRAO L., RITCHIE H., ORTIZ-OSPINA E., ROSER M. 2023. Life Expectancy, *Our World in Data*.
- DE SANTIS G., BENASSI F., CARBONI G., MALTAGLIATI M. Forthcoming. Local Mortality Patterns in Italy at the Beginning of the 21st Century, *Genus* (forthcoming)
- STEEL N., BAUER-STAEB C.M.M., FORD J.A., ABBAFATI C., ABDALLA M.A., ABDELKADER A., ... DEMETRIADES A.K. 2025. Changing Life Expectancy in European Countries 1990–2021: A Subanalysis of Causes and Risk Factors from the Global Burden of Disease Study 2021, *The Lancet Public Health*, Vol. 10, No. 3, pp. e172-e188.
- ZAZUETA-BORBOA J.D., VAN HEMELRIJCK W.M., ZENGARINI N., SIZER A., KUNST A.E., MARTIKAINEN P., JANSSEN F. 2024. Long-Term Trends in Educational Inequalities in Alcohol-Attributable Mortality, and Their Impact on Trends in Educational Inequalities in Life Expectancy, *Frontiers in Public Health*, Vol. 12, Article 1355840.

STRUCTURAL BREAKS IN ITALIAN AGE-SPECIFIC MORTALITY TRENDS: ASSESSING THE COHORT-EFFECT HYPOTHESIS¹

Gianni Carboni, Giambattista Salinari

Abstract. Using Human Mortality Database cohort life-tables for Italy, we reconstructed calendar-year log-mortality rates for five-year age groups between 50–54 and 85–89 from 1980 to 2019. An unconstrained segmented-regression search located one or two structural breaks per series; almost all fell within 2008–2010. Treating 2008 as a common breakpoint, basic interrupted time-series models then estimated separate slopes before and after that year. The post-2008 slope is significantly flatter for essentially every age group, implying that annual improvements in age-specific mortality slowed by roughly 0.6 % to 2.2%. Men experience the sharper early-old-age slowdown, but the effect tapers after their mid-sixties; among women it grows with age and peaks near 80. The near-synchronous timing of the breaks across cohorts, their consistency across sexes, and their alignment with the onset of Italian health-care austerity are difficult to reconcile with a cohort-driven explanation. Instead, they point to a period effect that dampened mortality gains almost overnight.

1. Introduction

Life expectancy in high-income nations has followed an almost uninterrupted upward trajectory for well over a century, driven by remarkable improvements in infant mortality, nutrition, living standards, and the control of infectious diseases, as well as by subsequent improvements in chronic-disease prevention and treatment (Riley, 2001; Cutler *et al.*, 2006).

Yet this secular rise has shown clear signs of deceleration since about 2011 across most OECD members (Raleigh, 2018). This is a major phenomenon since, with the exception of the recent COVID-19 pandemic, this secular rise in life expectancy had previously been temporarily interrupted only during the two World Wars and the 1918 flu pandemic.

Recent literature has focused on the causes of death most connected to this process. Life expectancy decompositions indicate that the slowdown is concentrated in the waning pace of mortality reductions from cardiovascular disease and several

¹ Gianni Carboni: Data curation, Coding, Original draft preparation. Giambattista Salinari: Conceptualization, Methodology, Reviewing and Editing.

common cancers (OECD/The King's Fund, 2020; Steel *et al.* 2025). Parallel trends in upstream risks—most notably the sustained increase in population exposure to high body-mass index, sub-optimal diet, low physical activity and harmful alcohol use—together with the stalling or reversal of progress in lowering elevated LDL-cholesterol and systolic blood pressure, have offset the earlier gains achieved through declining smoking prevalence (Steel *et al.* 2025).

A complementary line of inquiry invokes wider social and macro-economic forces at play. Growing socioeconomic inequalities in mortality, health-system pressures, and the fiscal austerity that followed the 2008 financial crisis have all been linked to stalling longevity, particularly in disadvantaged groups (Karanikolos *et al.*, 2013; Van Gool & Pearson, 2014).

An alternative hypothesis attributes the recent slowdown to cohort effects. Some scholars argue that successive birth cohorts may now be brushing up against an intrinsic ceiling of human longevity (Dong *et al.*, 2016; Olshansky *et al.*, 2024). More recently, Andrade *et al.* (2025) have extended the cohort perspective using a forecasting approach: applying multiple mortality projection methods, they document a marked reduction in the pace of cohort life expectancy improvements, suggesting that the slowdown may not be confined to period indicators alone.

These two latter explanatory avenues are in our opinion potentially at odds: if a cohort mechanism—especially one predicated on an impending biological ceiling to human lifespan—were truly dominant, the onset of deceleration should unfold asynchronously across nations with diverse demographic histories, rather than clustering in the same calendar years as the near-synchronous slowdown we currently observe. The deceleration we are observing in developed countries seems to be marked by a striking temporal synchrony, a feature that aligns more convincingly with a period effect—an exogenous shock acting on all populations simultaneously—than with a cohort-driven explanation.

But there is more. The experience of a handful of Nordic and Benelux countries—Norway foremost—demonstrates that continued life-expectancy gains are possible when cardiovascular and cancer mortality keep improving and risk-factor exposures are effectively contained. These same countries showed remarkable resilience during the 2019-21 COVID-19 shock (Steel *et al.* 2025). If the hypothesis of approaching a ceiling holds true, it remains to be explained why countries such as Norway, Sweden, Iceland, Belgium, and Denmark have not exhibited similar patterns. In other words, such heterogeneity suggests that the post-2011 slowdown is contingent, not inevitable.

Drawing on these considerations, our study seeks to determine whether a detailed, country-level inquiry can resolve, at least locally, the apparent tension between a predominance of cohort effects (whatever they might be) and the near-synchronous onset of the slowdown.

Italy, with its distinctive timing and policy context, provides an instructive test case for adjudicating between these competing explanations.

Italian national time-series, in fact, reveal an earlier inflection, with the slope of life-expectancy improvement flattening around 2008, a full three years before the modal OECD pattern (Salinari *et al.*, 2023; Carboni *et al.* 2024). That timing coincides with a nationwide flattening of public health-care expenditure and the subsequent intensification of austerity through region-specific deficit-recovery plans (*piani di rientro*), a suite of austerity measures that curtailed hospital capacity and, according to causal analyses, precipitated a measurable rise in avoidable mortality (Arcà *et al.*, 2020).

To probe whether cohort forces are truly at play in the Italian case, we therefore asked whether the deceleration emerges at the same historical moment across all age groups. This approach builds on earlier work by Ouellette, Barbieri, and Wilmoth (2014), who showed that major turning points in adult mortality trends across high-income countries can be used to discriminate between cohort-driven and period-driven processes. In their framework, discontinuities that occur at roughly the same calendar time across a wide age range point to contemporaneous, period-based forces, whereas cohort mechanisms imply age-staggered turning points that shift forward in time as cohorts age. The underlying logic in our Italian case is quite similar. If the national slowdown begins in 2008 yet its onset varies markedly by age—appearing earlier for some cohorts and later for others—the pattern would point to age-linked, cohort-specific mechanisms. By contrast, if the break occurs synchronously across the age spectrum, and that synchrony aligns with the rollout of health-care austerity, the evidence would favour a period effect driven by a system-wide shock. In the latter scenario, a common external force—as opposed to the life-course histories of distinct cohorts—must be acting on the entire population, regardless of birth year (and then cohort), to curb further gains in longevity. Our contribution differs in both scope and empirical strategy from that of Andrade *et al.* (2025). Rather than forecasting cohort life expectancy, we focus on observed age-specific mortality trends at older adult ages and examine whether the timing of their deceleration is consistent with staggered cohort dynamics or instead points to a synchronous period shock.

2. Methodological strategy

We use five-year age-group log mortality rates derived from cohort life tables available in the Human Mortality Database (HMD). Cohort tables are preferable here because the underlying single-year death rates ($m_{x,x+4}$) are released without the smoothing that HMD applies to period data, letting us analyse trends free of model-

imposed structure (see HMD Methods Protocol, version 6, for details). After retrieving the cohort rates, we rearrange them into a calendar-year matrix, simply by adding the cohort year to the central age of each class. In doing so, each cell records mortality at age-class $(x, x + 4)$ in year t .

From this matrix we retain the years 1980–2019, a span long enough to detect structural changes yet narrow enough to centre on the late-2000s slowdown while stopping short of the COVID-19 perturbation that begins in 2020.

The analysis is confined to the 50 to 89-year bracket. This range captures the ages most clearly implicated in the international slowdown (those in which cardiovascular disease and cancers dominate the burden of death) and produces cleaner signals by avoiding the volatility that characterises age outside that range.

Equally important, it steers clear of younger ages whose mortality trends in Italy were strongly perturbed by the mid-1980s heroin crisis and the first HIV/AIDS wave, shocks that hit men in their twenties and thirties particularly hard (Conti *et al.*, 1994; Conti *et al.* 1997) and would inject unrelated noise into our estimates. By concentrating on 50+ we therefore focus on the part of the life course where the deceleration appears to be most pronounced while minimising confounding from epidemic phenomena outside our research scope.

The analytical strategy unfolds in two stages.

In the first stage we apply segmented regression to each five-year age-group series, allowing the algorithm to search, without prior constraints, for structural breakpoints and to estimate their timing.

The second stage tackles the same problem from the opposite direction. Guided by the stage-one results, we posit a single breakpoint common to all series. That breakpoint corresponds to the year most often selected in the initial search. In this way, we fit a basic interrupted time-series model to every age group. The model estimates separate linear trends before and after this year. If the slope difference proves statistically significant, the break is deemed to capture a genuine shift in the underlying mortality trajectory.

2.1. Stage one: Segmented regression

Segmented (or piece-wise) regression is a flexible extension of ordinary least-squares regression that allows the slope of a continuous time trend to change at one or more unknown points, termed breakpoints. Rather than pre-specifying the dates at which the relationship might shift, the method iteratively searches for the location(s) that best reconcile the data with two or more linear segments. In practical terms, it asks: *Is there a calendar year after which the rate of mortality improvement slows (or speeds up) in a statistically detectable way?*

To answer that question, segmented regression treats each portion of the series as linear. This assumption fits log-mortality rates time-series well, because, barring major shocks, their evolution tends to follow an almost straight-line trend over time, a regularity first documented by Lee and Carter (1992) and later confirmed for both mid-life and old-age mortality (Kannisto *et al.*, 1994; Wilmoth, 1995; Thatcher *et al.*, 1998).

For each fixed age group we then model the annual log mortality rate Y_t (with $t = 1980, \dots, 2019$) as

$$Y_t = \beta_0 + \beta_1 t + \beta_2 (t - \tau) I_{\{t > \tau\}} + \varepsilon_t, \quad (1)$$

where $I_{\{t > \tau\}}$ is an indicator function that equals 1 after the breakpoint τ and 0 otherwise; β_0 is the intercept, β_1 is the pre-break slope, β_2 captures the change in slope after τ , and ε_t is an independent error term.

Since age-specific mortality rates have been trending downward for decades, a more negative slope ($\beta_2 < 0$) translates into a faster decline in death rates and larger annual gains in life expectancy (good news). Conversely, a positive post-break change in slope ($\beta_2 > 0$) makes the slope less negative: mortality is still falling, but more slowly, so improvements in life expectancy decelerate (bad news). The same interpretation applies whether the series are expressed in levels or in logs; the log transformation merely stabilises variances without altering the direction of change.

Breakpoints and coefficients of model (1) are estimated with the iterative procedure proposed by Muggeo (2008)'s *segmented* R package, which also allows the computation of confidence intervals for τ .

Because the 1980–2019 series could plausibly contain more than one historical shift, we followed the practice adopted in recent segmented/joinpoint-regression studies of life-expectancy trends (Minton *et al.*, 2023; Zazueta-Borboa *et al.*, 2024) and allowed the algorithm to search for no more than two breakpoints in each age-group series. In practice, some age-groups show only one; when a second appears, we report it but centre our discussion on the later break, as doing so aligns the analysis with the contemporaneous nature of the phenomenon we aim to analyse. Our approach differs only in the response variable: whereas those studies analyse life expectancy, we model age-group log-mortality rates, a choice justified by the aforementioned evidence that such rates also evolve approximately linearly over time.

2.2. Stage two: Basic interrupted time series

The second phase asks a simple question: *Can a single calendar year account for the trend change in every age-group series?* If such a common breakpoint exists, the pattern would be hard to square with a cohort explanation (cohorts age at different calendar times) but fully consistent with a population-wide period shock. Stage two fixes the year most frequently identified as breakpoint in Stage one for all series and asks whether the slope before that year differs significantly from the slope after.

Concretely, we run the same basic interrupted time-series model for each five-year age group, always imposing a single predetermined year as the breakpoint. Formally:

$$Y_t = \beta_0 + \beta_1 t + \beta_2 I_{\{t > \bar{t}\}} + \beta_3 t I_{\{t > \bar{t}\}} + \varepsilon_t. \quad (2)$$

Here β_1 captures the pre-break yearly change in log mortality, β_2 measures any shift in the level of the series associated with the post-break period and, finally, β_3 quantifies how much the post-break slope differs from the pre-break slope.

The form of model (2) is deliberately more flexible than the segmented-regression model (1). Now we fix a single, ex-ante breakpoint for all age groups. Allowing both a level shift (β_2) and an independent slope change (β_3) ensures that any departure from the pre- $\bar{t}$ trend can be detected.

At this stage, then, our primary focus is on the coefficient β_3 . A statistically significant positive β_3 confirms that the trend after $\bar{t}$ diverges from that before $\bar{t}$. In this second stage, we also separated the analysis by gender.

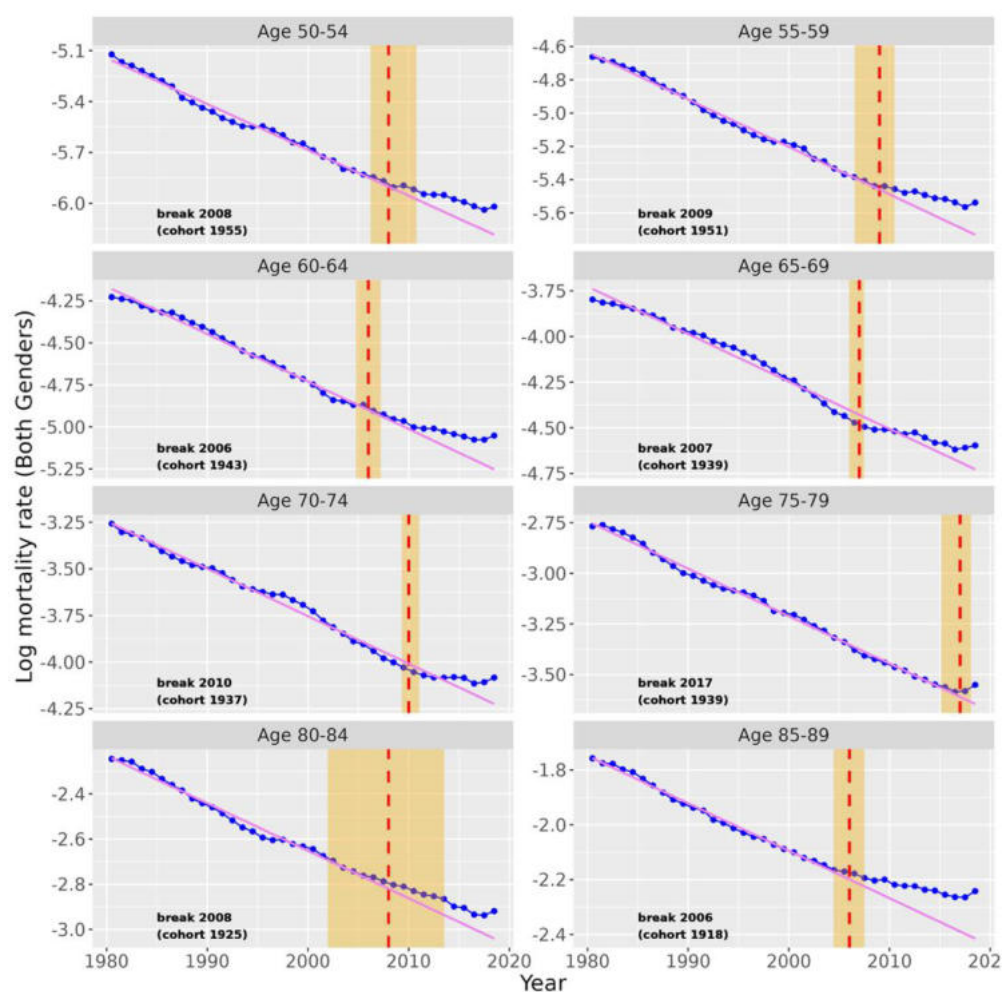
3. Results

Figure 1 plots the calendar-year (period) log-mortality rates for eight age classes (50–54 through 85–89) in the combined male-and-female population. Blue dots and line trace the observed series from 1980 to 2019; the red dashed line marks the breakpoint returned by the segmented-regression model, while the orange band gives its 95 % confidence interval. The purple line extends the pre-break slope forward, illustrating how mortality would have evolved had the earlier trajectory persisted. The caption in each panel records the point estimate of the break year and the birth cohort experiencing it (calculated as break year minus the midpoint age of the class).

Several features stand out. First, despite the independent estimation for each age group, the breakpoints crowd tightly around 2008–2010. Even allowing for the confidence interval, the overlap is substantial, indicating that disparate cohorts

encountered a similar inflection at roughly the same historical moment. Only the 75–79 group deviate slightly, breaking a few years later, yet still falls within a decade-wide window centred on the late-2000s.

Figure 1 – (Stage one) Breakpoints in age-specific log-mortality trends, Italy 1980 – 2019.



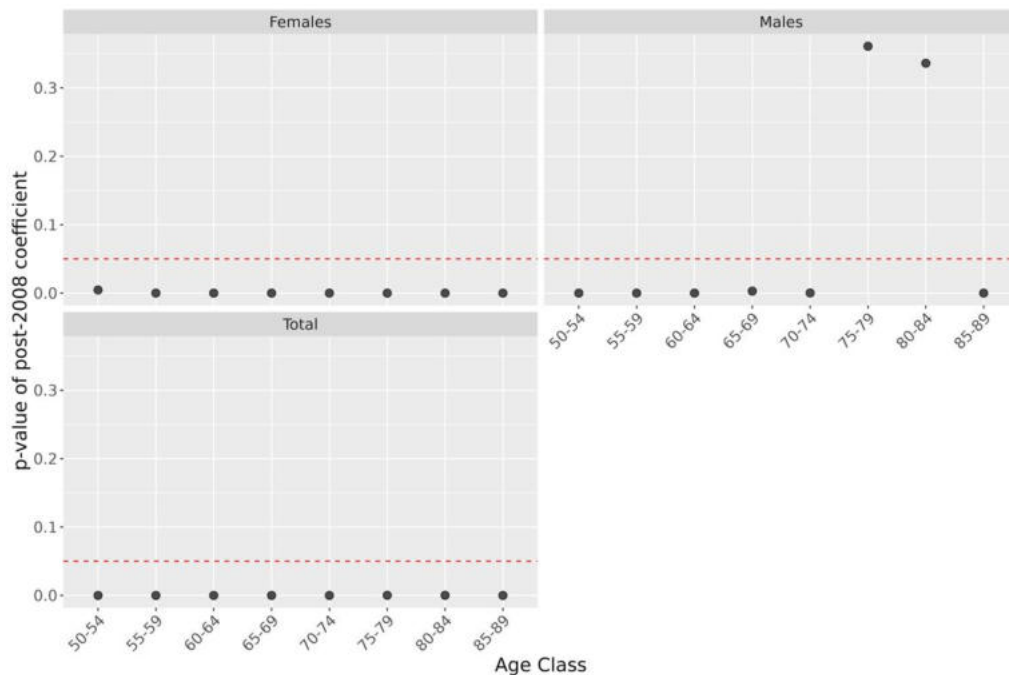
Blue lines show annual log-mortality rates for eight five-year age groups (50–54 to 85–89) in Italy, 1980–2019. The red dashed line marks the breakpoint estimated by segmented regression; the orange rectangle is its 95 % confidence interval. The purple line projects the pre-break trend beyond the breakpoint. Each panel reports the break year and the birth cohort to which it applies.

Source: Our elaboration on Human Mortality Database data.

Second, the direction of change is uniform: in every panel the post-break slope is less steep than the extrapolated purple line, signaling a slowdown in the pace at which mortality was falling. Put differently, improvements in survival diminished simultaneously across virtually the whole adult age spectrum.

Taken together, these patterns suggest a system-wide shock affecting all cohorts simultaneously rather than age-staggered dynamics consistent with a cohort mechanism. The second stage strengthens this evidence by formally testing whether the slope changes highlighted here remain statistically robust in basic interrupted-time-series models.

Figure 2 – (Stage two) *p*-values for the post-2008 slope-change coefficient (β_3), by age class and sex, Italy 1980–2019.



Each dot reports the *p*-value for the post-2008 slope-change coefficient (β_3) from the basic interrupted time-series model with a common breakpoint fixed at 2008, shown separately by five-year age class and sex. The red dashed line indicates the 0.05 significance threshold.

Source: Our elaboration on Human Mortality Database data.

Figure 2 displays the *p*-values for the post-2008 slope-change coefficient (β_3) obtained from the basic interrupted time-series models (model (2) with $\bar{t} = 2008$), plotted by age class and sex. The red dashed line marks the 0.05 threshold. We fix 2008 because it marks the onset of nationwide health-care austerity measures,

allowing us to test whether that single policy-inflection year can account for a shift in mortality trends across all age groups and both sexes.

Across the pooled-sex specification (right-hand panel) the evidence is unequivocal: every age group registers a p-value well below 0.05, confirming that 2008 corresponds to a statistically significant shift in the mortality trend. When the analysis is split by sex, the picture remains essentially unchanged: all female and male age classes return significant results except two cases: males 75-79 and 80-84. Their higher p-values are not straightforward to explain. One possibility is cohort selection: the men aged 75-84 in 2008 were born roughly between 1926 and 1931, placing their young adulthood squarely in the Second World War. Such cohort-specific factors may dampen the detectable change in slope, without altering the overall period-effect pattern. It is important to note that, although Figure 2 visualises only p-values, the underlying β_3 estimates are positive in every case that reaches statistical significance (p-value < 0.05). A positive β_3 means the post-2008 trend is less steeply negative, i.e. the decline in mortality slowed. In terms of size, β_3 estimates cluster between ≈ 0.006 and ≈ 0.022 log-points per year, implying that the annual pace of mortality decline slowed by roughly 0.6% to 2.2%. In early-old ages (50-54 and 55-59) the slowdown is clearly steeper for men than for women. The differential all but vanishes at 60-64, and from 65-69 onward the sign flips: the deceleration becomes progressively larger among women, reaching its widest margin around 80-84. In the final class, 85-89, the gap narrows again—yet the female slowdown still edges out the male one.

Taken together, these results reinforce the picture drawn in Stage one. Setting 2008 as a common breakpoint explains a statistically meaningful change in the slope of log-mortality for virtually the entire adult population, in both sexes. Moreover, all significant β_3 coefficients are positive, indicating that the decline in death rates slowed after 2008, regardless of cohort. A system-wide deceleration in mortality improvements began in 2008, consistent with a period effect rather than staggered, cohort-specific dynamics.

4. Conclusion and discussion

This study set out to weigh two contrasting interpretations of Italy's recent longevity slowdown: the possibility that it reflects a biological ceiling manifesting through cohort ageing versus a population-wide period shock rooted in the post-2008 wave of health-care austerity. To do so we combined an exploratory segmented-regression search for structural breaks with a confirmatory interrupted time-series test that fixed the candidate break year at 2008.

The two empirical stages converged on remarkably similar results. Across every age class from 50–54 to 85–89, the segmented model located an inflection in the late 2000s, with confidence intervals that overlap almost perfectly. When we then imposed 2008 as the breakpoint, the basic interrupted time-series models showed that the post-2008 slope became less steep in virtually every case. The result of this analysis appears clear: different cohorts, in their respective stages of the life course, encountered the same turning point at the same historical phase, and for every subpopulation that turning point signalled a slackening of mortality improvement.

Such synchrony is at odds with a dominant cohort mechanism, which would be expected to play out in a staggered fashion as successive birth cohorts age into later life. It is far more consistent with a period effect—an exogenous force acting simultaneously on the whole population.

The temporal match with Italy's fiscal retrenchment is striking. Public health-care spending stopped climbing in 2008 (Ciocci & Spagnolo, 2020), and the region-specific *piani di rientro* (a targeted boost of health austerity) soon followed, trimming hospital capacity and tightening budgets precisely when our data suggest that mortality gains began to slow (Aimone Gigio *et al.*, 2018).

Comparative work in other high-income countries indicates that mortality can react quickly to fiscal retrenchment (e.g. McCartney *et al.*, 2022), so a short lag in Italy would not be unusual.

Whether the channel is delayed diagnostics, slower diffusion of new therapies, or strain on community care, the key empirical fact remains: improvements slowed almost simultaneously across the whole adult age spectrum.

Any convincing explanation of Italy's post-2008 deceleration must therefore begin by accounting for this temporal synchrony.

Acknowledgements

Financial support from the Italian MUR (PRIN 2022 n° 2022CENE9F, "The pre Covid 19 stall in life expectancy in Italy: looking for explanations") is gratefully acknowledged.

References

- AIMONE GIGIO L., ALAMPI D., CAMUSSI S.A., CIACCIO G., GUAITINI P., LOZZI M., ... PAOLICELLI M. 2018. La Sanità in Italia: Il difficile equilibrio tra vincoli di bilancio e qualità dei servizi nelle regioni in piano di rientro, *Bank of Italy Occasional Paper*, No. 427.

- ANDRADE J., CAMARDA C.G., PIFARRÉ I AROLAS H. 2025. Cohort mortality forecasts indicate signs of deceleration in life expectancy gains, *Proceedings of the National Academy of Sciences*, Vol. 122, No. 35, Article e2519179122.
- ARCÀ E., PRINCIPE F., VAN DOORSLAER E. 2020. Death by Austerity? The Impact of Cost Containment on Avoidable Mortality in Italy, *Health Economics*, Vol. 29, No. 12, pp. 1500-1516.
- CARBONI G., SALINARI G., DE SANTIS G., BENASSI F. 2024. Mortality Evolution in Italy: The End of Regional Convergence?, *Genus*, Vol. 80, No. 1, p. 28.
- CIOCCI M., SPAGNOLO F. 2020. La spesa in Sanità: i dati CPT per un'analisi in serie storica a livello territoriale, Sistema Conti Pubblici Territoriali
- CONTI S., FARCHI G., PRATI S. 1994. AIDS as a Leading Cause of Death among Young Adults in Italy, *European Journal of Epidemiology*, Vol. 10, No. 6, pp. 669-673.
- CONTI S., MASOCCO M., FARCHI G., REZZA G., TOCCACELI V. 1997. Premature Mortality in Italy during the First Decade of the AIDS Epidemic: 1984-1993, *International Journal of Epidemiology*, Vol. 26, No. 4, pp. 873-879.
- CUTLER D., DEATON A., LLERAS-MUNEY A. 2006. The Determinants of Mortality, *Journal of Economic Perspectives*, Vol. 20, No. 3, pp. 97-120.
- DONG X., MILHOLLAND B., VIJG J. 2016. Evidence for a Limit to Human Lifespan, *Nature*, Vol. 538, No. 7624, pp. 257-259.
- KANNISTO V., LAURITSEN J., THATCHER A.R., VAUPEL J.W. 1994. Reductions in Mortality at Advanced Ages: Several Decades of Evidence from 27 Countries, *Population and Development Review*, Vol. 20, No. 4, pp. 793-810.
- KARANIKOLOS M., MLADOVSKY P., CYLUS J., THOMSON S., BASU S., STUCKLER D., McKEE M. 2013. Financial Crisis, Austerity, and Health in Europe, *The Lancet*, Vol. 381, No. 9874, pp. 1323-1331.
- LEE R.D., CARTER L.R. 1992. Modeling and Forecasting U.S. Mortality, *Journal of the American Statistical Association*, Vol. 87, No. 419, pp. 659-671.
- McCARTNEY G., McMASTER R., POPHAM F., DUNDAS R., WALSH D. 2022. Is Austerity a Cause of Slower Improvements in Mortality in High-Income Countries? A Panel Analysis, *Social Science & Medicine*, Vol. 313, Article 115397
- MINTON J., HIAM L., McKEE M., DORLING D. 2023. Slowing Down or Returning to Normal? Life Expectancy Improvements in Britain Compared to Five Large European Countries Before the COVID-19 Pandemic, *British Medical Bulletin*, Vol. 145, No. 1, pp. 6-16.
- MUGGEO V.M. 2008. Segmented: An R Package to Fit Regression Models with Broken-Line Relationships, *R News*, Vol. 8, No. 1, pp. 20-25.

- OECD, THE KING'S FUND. 2020. *Is Cardiovascular Disease Slowing Improvements in Life Expectancy? OECD/The King's Fund Workshop Proceedings*, OECD Publishing, Paris
- OLSHANSKY S.J., WILLCOX B.J., DEMETRIUS L., BELTRÁN-SÁNCHEZ H. 2024. Implausibility of Radical Life Extension in Humans in the Twenty-First Century, *Nature Aging*, Vol. 4, No. 11, pp. 1635-1642.
- OUELLETTE N., BARBIERI M., WILMOTH J.R. 2014. Period-based mortality change: turning points in trends since 1950, *Population and Development Review*, Vol. 40, No. 1, pp. 77-106.
- RALEIGH V.S. 2018. Stalling Life Expectancy in the UK, *BMJ*, Vol. 362, k4050.
- RILEY J.C. 2001. *Rising Life Expectancy: A Global History*, Cambridge University Press, Cambridge.
- SALINARI G., BENASSI F., CARBONI G. 2023. The Effect of the Great Recession on Italian Life Expectancy, *Population Research and Policy Review*, Vol. 42, No. 1, p. 3.
- STEEL N., BAUER-STAEB C.M.M., FORD J.A., ABBAFATI C., ABDALLA M.A., ABDELKADER A., ... DEMETRIADES A.K. 2025. Changing Life Expectancy in European Countries 1990–2021: A Subanalysis of Causes and Risk Factors from the Global Burden of Disease Study 2021, *The Lancet Public Health*, Vol. 10, No. 3, pp. e172-e188.
- THATCHER A.R., KANNISTO V., VAUPEL J.W. 1998. *The Force of Mortality at Ages 80 to 120*, Odense University Press, Odense.
- VAN GOOL K., PEARSON M. 2014. Health, Austerity and Economic Crisis: Assessing the Short-Term Impact in OECD Countries, *OECD Health Working Papers*, No. 76.
- WILMOTH J.R. 1995. Are Mortality Rates Falling at Extremely High Ages? An Investigation Based on a Model Proposed by Coale and Kisker, *Population Studies*, Vol. 49, No. 2, pp. 281-295.
- ZAZUETA-BORBOA J.D., VAN HEMELRIJCK W.M., ZENGARINI N., SIZER A., KUNST A.E., MARTIKAINEN P., JANSSEN F. 2024. Long-Term Trends in Educational Inequalities in Alcohol-Attributable Mortality, and Their Impact on Trends in Educational Inequalities in Life Expectancy, *Frontiers in Public Health*, Vol. 12, Article 1355840.

THE FIRST VICTORY: AN EMPIRICAL SURVIVAL STUDY OF CAREER DYNAMICS IN THE ITALIAN JUDICIARY¹

Maria Filomeno, Irene Rocchetti, Antonello Maruotti

Abstract. This study investigates judicial career mobility in Italy, focusing on the probability of judges attaining managerial or semi-managerial roles. Using a comprehensive dataset of aspirants and winners of competitions for such roles, we combine exploratory and statistical analyses to uncover structural patterns and differences in career progression.

Demographic, professional, and institutional variables were considered, including gender, age, service length, office of origin/destination, office type and size, regional location, and the availability of positions. Additional variables, such as average evaluation time, annual staff numbers, and judicial district data, were further computed to enrich the analysis and create a unique database.

A detailed descriptive analysis reveals that judges tend to apply for roles within their geographic area and in similarly sized offices. Origin-destination matrices further illustrate these mobility preferences.

A key novelty of this work is the application of survival models to estimate the “survival to victory” curve: the probability that a judge has not yet obtained a managerial or semi-managerial role over time. The curve remains flat for the first 20 years—when such roles are legally inaccessible—then declines sharply, reaching a 50% survival rate at 45 years of service.

The analysis has been carried out also by stratifying by gender providing a novel empirical evidence on how gender and seniority interact to shape career trajectories within the Italian judiciary.

1. Introduction

Understanding the career dynamics of judges is essential for evaluating the functioning and effectiveness of judicial institutions. Yet in Italy, as in many other countries, empirical research on the judiciary has been severely constrained by a lack of systematic data. This paper presents the first comprehensive dataset tracking the careers of employed Italian judges, offering a novel and detailed view into judicial mobility, appointment outcomes, and competition for leadership roles across the system.

¹ The views and opinions expressed are those of the authors and do not necessarily reflect the official policy or position of the Italian National Institute of Statistics - Istat.

Constructed from administrative records and competition notices issued by the High Council of the Judiciary (CSM), the dataset covers more than 55,000 applications for managerial and semi-managerial positions between 2007 and 2022. It includes detailed information on applicants' demographics, positions held, assessment outcomes, application histories, and institutional characteristics of the offices involved. This is, to our knowledge, the first empirical database of its kind in the Italian context, and one of the few in Europe offering such depth and breadth on judicial career paths.

The relevance of judicial career analysis has been increasingly acknowledged in the international empirical research (Ploscowe, 1934; Mayoral *et al.*, 2014; Jäckle, 2016; Banasik *et al.*, 2022). Studies have examined the role of political affiliation, gender, and professional background in judicial appointments and promotions (e.g., Schneider, 2005; Garoupa *et al.*, 2012, Aiello *et al.*, 2024, Giancotti *et al.*, 2024), though such investigations are rare, often due to data constraints (Azaria *et al.*, 2025). Some existing work has looked at career incentives and performance evaluation in judicial systems (Antonucci *et al.*, 2014), but few have had access to detailed, individual-level data. In the Italian case, despite the centrality of the CSM in managing judicial careers, research on how judges move through the ranks, what positions they compete for, and who eventually succeeds has remained mostly descriptive or institutional in nature (Rullo, 2022; Aguiar Aguilar *et al.*, 2024). The dataset presented here makes it possible to go further and engage in rigorous statistical and time-dependent analysis of career dynamics.

This paper makes two distinct contributions. First, we provide a detailed description of the dataset, highlighting its structure, coverage, and the types of information it includes. Through a series of exploratory analyses, we illustrate the richness of the data by documenting patterns in applications, success rates, age and gender dynamics, and institutional mobility across geographic and functional dimensions. Second, we demonstrate the analytical potential of the data by applying a survival model to estimate the probability and timing of a judge's first "victory", defined as the first successful appointment to a managerial or semi-managerial role. Using the Kaplan-Meier method, stratified by position type and gender, we model the temporal dimension of competition outcomes, showing how judges "survive" in the system before achieving promotion. This modeling effort is not only methodologically appropriate for censored career data but also serves as a concrete example of how the dataset can inform questions about access, meritocracy, and advancement in the judiciary.

The focus on managerial and semi-managerial functions is particularly relevant in the Italian context, where these roles are filled through competitive procedures overseen by the CSM, and represent key steps in career advancement. The assignment of such functions is based on evaluations of merit and managerial

aptitude, yet how these criteria translate into outcomes over time — and who tends to succeed — has rarely been analyzed through a statistical lens, where the focus is more on the performance of the judges (e.g., Guerra and Tagliapietra, 2017; Nissi *et al.*, 2019; Mazzocchi *et al.*, 2024; Di Vita *et al.*, 2024). Our approach allows time to quantify delays, bottlenecks, and differences in career trajectories within the judiciary.

This study, therefore, on one side offers a descriptive account or a technical modeling exercise; on the other side, it lays the foundation for a new line of empirical research into judicial careers in Italy — one grounded in data, driven by statistical reasoning, and attentive to institutional realities.

The remainder of this paper is structured as follows. Section 2 describes the dataset and its construction. Section 3 presents key results from the exploratory analysis. Section 4 introduces and discusses the survival model and its findings. Section 5 concludes with reflections on the broader implications of this work and potential future research directions.

2. A primer on the Italian judiciary database

2.1 Data source and description

Empirical research on judicial careers in Italy has long been hampered by the absence of structured and accessible data. In this context, the dataset developed and employed in this study represents a significant and original contribution. Constructed through a detailed integration of administrative records published by the CSM, this dataset offers the first longitudinal and individual-level resource enabling systematic analysis of judges' career trajectories, competition outcomes, and professional characteristics over a fifteen-year period (2007–2022).

The core of the dataset consists of 55,591 application records, corresponding to 3,084 public competition notices published for 3,117 managerial and semi-managerial positions across the judiciary (Table 1). These positions include top roles (e.g. president of court, public prosecutor) as well as semi-managerial roles with intermediate responsibility. Each application record links the candidate to a specific competition, capturing both the demographic and professional attributes of the applicant and details about the office and position being competed for.

Crucially, the dataset identifies whether a candidate won the position, enabling an event-history structure suitable for survival and longitudinal analysis. From these records, a panel of 5,078 unique judges was reconstructed, allowing us to track the professional paths, application histories, and appointment outcomes of individual magistrates over time.

In addition to core application data, the dataset includes a rich array of contextual variables: demographics (date of birth, gender, professional function at the time of

application), career assessments (periodic evaluations, up to seven per judge, with timing and outcomes), institutional variables (size and staffing levels of judicial offices, type and location of each published position, and number of available managerial roles by office and year), application dynamics (number of applications per judge, type of positions applied for managerial/semi-managerial, origin and destination offices, and geographical mobility).

Data construction involved extensive cleaning and harmonization. Applications prior to 2007 were excluded due to regulatory changes in that year (Law 111/2007) affecting eligibility criteria. Positions for which no information was available about the appointed judge (e.g. newly created roles) were also filtered out. Approximately 0.5% of records were excluded due to missing or incomplete career information.

Table 1 – Number of published notices from 2007 to 2022 by office type.

Type of office	Managerial	Semi-managerial	Total
Court of Cassation	191		191
General Prosecutor's Office at the Court of Cassation	33		33
National Anti-Mafia Directorate	3	2	5
Superior Court of Public Waters	8		8
Court of Appeal	74	538	612
General power of attorney	76	52	128
Court of first instance	369	962	1.331
Public Prosecutor's Office at the Court	345	229	574
Juvenile Court	61		61
Public Prosecutor's Office for minors	71		71
Surveillance court	70		70
Total	1301	1783	3084

2.2 Exploratory analysis

This dataset enables multiple levels of analysis. For example, origin-destination matrices capture patterns of mobility between different types of judicial offices; age and gender breakdowns help identify differences in career timing; and application volumes shed light on competitiveness across offices and functions. Moreover, the capacity to compute longitudinal variables — such as time in service before first appointment, frequency of applications, and career interruptions — enables statistical modeling of career dynamics previously inaccessible to researchers. Let us get in detail of the potential information to be drawn from the data.

An initial look at the data reveals a substantial variation in competition intensity across judicial offices and position types. On average, each published position attracts 18 applicants, with a median of 13 and an interquartile range between 8 and

22. However, these numbers conceal significant disparities. The Court of Cassation, for instance, sees the highest applicant-per-position ratio, averaging 47 candidates per managerial position. Among prosecutorial offices, small-sized Public Prosecutor's Offices and large metropolitan ones also stand out, averaging 27 and 22 applicants respectively.

When disaggregating by type of position and type of office, we observe that managerial roles consistently attract more applicants. Besides the Supreme Court (Corte di Cassazione) receives an average of 47 candidates per managerial post, the National Anti-Mafia Directorate (DNA) attracts 25 applicants for semi-managerial positions and 11 for managerial ones. Similar intensities are found in the Public Prosecutor's Offices at the Court, where 25 and 20 candidates compete on average for managerial and semi-managerial roles, respectively.

Geographical breakdowns further confirm this pattern. The central regions of Italy are the most competitive: managerial and semi-managerial roles in Public Prosecutor's Offices in central Italy attract 36 and 28 applicants per position, respectively. Similarly, managerial positions in the Courts of Appeal in this region receive around 25 applicants each.

In the 87% of cases, magistrates apply for positions representing a higher function than their current role, while only 13% apply for equivalent roles. This reflects a strong upward mobility motivation within the judiciary.

To better understand patterns of institutional mobility, we analyse origin-destination matrices (OD) that compare an applicant's office of origin with the type of office to which they are applying. The OD matrix (row percentages) shows that 73% of judges working in Courts of first instance apply for managerial or semi-managerial roles within the same type of court, indicating a preference for internal mobility (change of location or function) over cross-institutional change. Similar patterns emerge for prosecutors: 34% of applicants from the Juvenile Prosecutor's Office apply to the Public Prosecutor's Office at the Court, 13% to the General Prosecutor's Office at the Court of Appeal and 29% to the Juvenile Prosecutors office.

Conversely the OD matrix, column percentages, reveals the composition of applicant pools for each office type. For instance, 73% of applicants for positions in the Public Prosecutor's Office at the Court come from the same type of office, with 11% from the General Prosecutor's Office and 7% from the Courts of first instance. For juvenile prosecutorial positions, 31% of candidates come from Public Prosecutor's Offices at the Court, and 21% from juvenile institutions.

A similar origin-destination matrix was constructed for competition winners, showing that 77% of winners from Courts remained in the same type of institution, while 81% of winners from Juvenile Prosecutor's Offices stayed within their

institutional category. These findings suggest limited cross-institutional promotion, pointing to a segmented structure of career mobility.

Between 2007 and 2022, a total of 3,084 competition notices were published: 1,301 for managerial and 1,783 for semi-managerial positions. Notably, this exceeds the currently active positions (490 managerial and 829 semi-managerial), indicating a high turnover in managerial posts. The Courts of first instance and the Public Prosecutor's Offices at the Court are the most frequent publishers of both types of positions. Overall, 55,591 applications were submitted during this period by 5,078 individual judges, implying an average of 11 applications per magistrate. The majority of applications came from judges with ordinary functions (70%), and most of them targeted managerial positions in central Italy (20%) or semi-managerial positions in the south (22%).

Applicant age is another key dimension of career dynamics. The average age at the time of application is approximately 58 years, both for the total applicant pool and for successful candidates. Unsurprisingly, judges applying for semi-managerial roles tend to be younger than those targeting managerial ones, with a gap of around 4–5 years.

Figure 1 shows that for managerial roles, there is no consistent age gap between applicants and winners across years. By contrast, Figure 2 reveals that for semi-managerial roles, winners are consistently older than the average applicant, suggesting that experience may be a more decisive factor for these roles.

Age also varies by gender and function. Women are, on average, younger than men when applying. Judges with out-of-role or ordinary functions tend to be younger than those already holding semi-managerial or managerial roles. Interestingly, this age gradient persists even among winners, reinforcing the idea that career advancement is correlated with seniority and institutional experience.

Mobility patterns also reflect regional preferences. Most judges apply to offices within their own geographical division. For instance, 72% of applicants to central Italian offices originate from the same region, with 18% from the south.

Institutional size is another important factor. Applicants from large or metropolitan offices tend to seek similar-sized institutions, while those from small or medium-small offices often aim to remain within that structure. For example:

- 67% of applicants from large offices apply to large offices.
- 50% of applicants from small offices prefer to remain in small offices, and 21% aim to move to large offices.

This pattern must be interpreted in light of the higher number of positions published in small offices, which structurally shape applicant flows.

Figure 1 – Average age of applicants and winners of managerial positions by year of resolution.

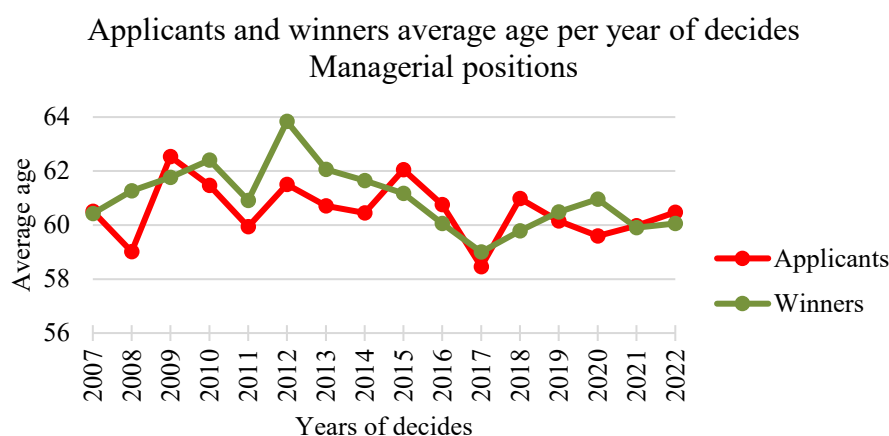
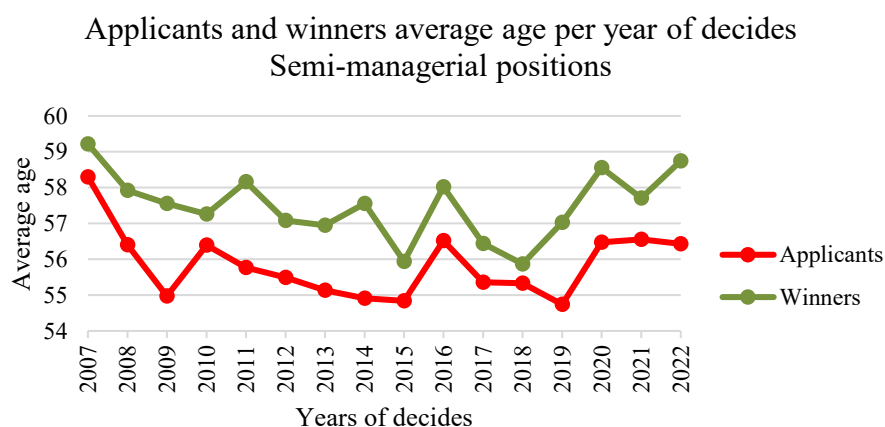


Figure 2 – Average age of applicants and winners of semi-managerial positions by year of resolution.



3. Survival patterns in the race for managerial positions

In order to demonstrate the analytical potential of the newly developed dataset, a survival model was employed to study the timing of judges' first successful applications to managerial or semi-managerial roles. Survival analysis is particularly well-suited to this context, as it allows us to model the "time to event" — in this case, the time between a judge's entry into the judiciary and their first "victory" in a competitive appointment process. The model accounts for right-censored

observations, such as judges who had not yet won a position by the end of the observation period (31/12/2022) or those who reached retirement age before securing an appointment. Judges already holding managerial or semi-managerial positions at the beginning of the period were excluded from the analysis due to left-censoring.

The survival probability at time t is defined as

$$S(\hat{t}) = \prod_{i \leq t} \hat{p}_i = \prod_{i \leq t} (n_i - d_i)/n_i$$

where

- d_i represents the number of individuals experimenting the event at time i , thus the number of judges who won a competition, managerial or semi-managerial, at time i ;
- n_i is the number of judges at risk at time i (not having experimented the event victory before that time);
- $\hat{p}_i$ is the estimated conditional survival probability at time i , in formula $P(T > i | T > i - 1)$ where T is the observed survival time;
- obviously d_i/n_i is the conditional probability that a judge experiments the victory event in the i th interval, given that he did not experiment it in the just precedent interval.

Different survival models have been carried out by stratifying also by type of published positions, corresponding to the higher number of applications made by each aspirant. A Survival analysis stratified by gender has been carried out as well. The log rank test has been used to compare the curves and to test if the eventual difference between them is statistically significant or is due to change. The log rank test is no longer indicated when the survival curves cross each other path.

The survival function was estimated using the Kaplan-Meier method, producing a curve that tracks the probability of not yet having obtained a managerial or semi-managerial position over time. This approach enables a visual and statistical assessment of how long judges remain in the system before achieving their first promotion and how this likelihood varies depending on personal and institutional characteristics.

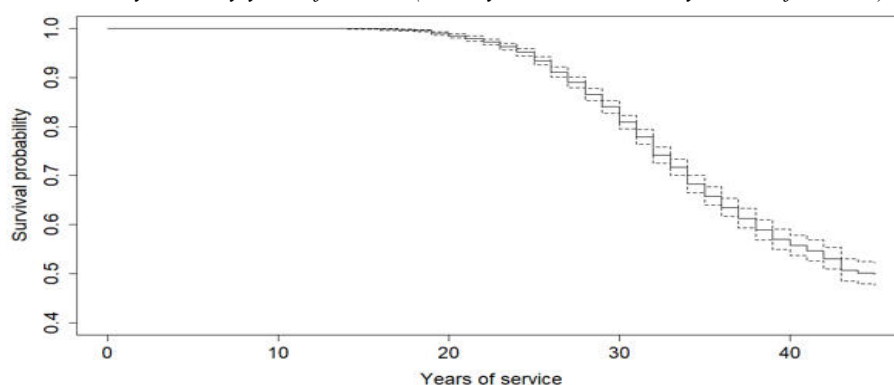
The overall survival curve shows that the probability of obtaining a managerial or semi-managerial role remains close to unity for the first 20 years of service, indicating that such appointments are virtually non-existent during the early stages of a judge's career. Between 20 and 40 years of service, the survival curve declines more steeply, suggesting that this is the critical period in which most judges who will obtain such roles actually do so. By 45 years of service, only about half of the judges in the sample had experienced a "victory," highlighting the relatively selective and competitive nature of the appointment process (see Figure 3).

To explore variation in these trajectories, the analysis stratified judges by the type of position they most frequently applied for — managerial or semi-managerial. The results reveal a clear divergence: judges who predominantly applied for managerial positions tend to experience longer waiting times and lower overall success probabilities compared to those targeting semi-managerial roles. Around the 35th year of service, only 22 percent of managerial-track applicants had won a position, compared to 42 percent of those pursuing semi-managerial roles. At 40 years of service, this gap remains substantial, with 34 percent of managerial applicants and 50 percent of semi-managerial applicants having obtained their desired role. A log-rank test confirms that these differences are statistically significant (see Figure 4).

Gender-based differences in career trajectories were also assessed through a survival analysis stratified by sex. The results show that women, although fewer in number, tend to experience shorter waiting times before achieving their first appointment. By 35 years of service, 41 percent of female applicants had won a managerial or semi-managerial position, compared to just 30 percent of male applicants. This trend persists over time: at 42 years of service, the share of women experiencing a victory reaches 52 percent, while the corresponding figure for men is 44 percent. The observed difference is statistically significant, suggesting gender-based variation in competition outcomes (see Figure 5).

These findings can be partly explained by differences in the type of positions won by male and female judges. Women are more likely to win semi-managerial positions, which tend to have higher success rates and lower barriers to entry. In contrast, men dominate managerial appointments, which are more competitive and often require a longer career trajectory. While these results may reflect broader institutional dynamics and role preferences, they also point to underlying gender-based differences in judicial careers.

Figure 3 – *Distribution of the percentage of aspirants who have not (yet) experienced a victory event by year of service (Victory Survival Curve by Years of Service).*



Note: The three lines represent respectively the survival one and the Confident Intervals related.

Figure 4 – Distribution of the percentage of applicants who have not (yet) experienced a victory event by year of service and by type of position for which they most competed (Victory survival curve by years of service, stratified by type of position aspirants apply most).

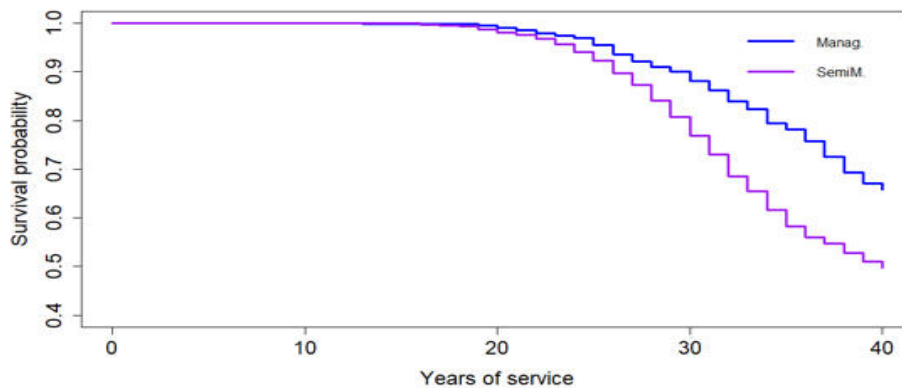
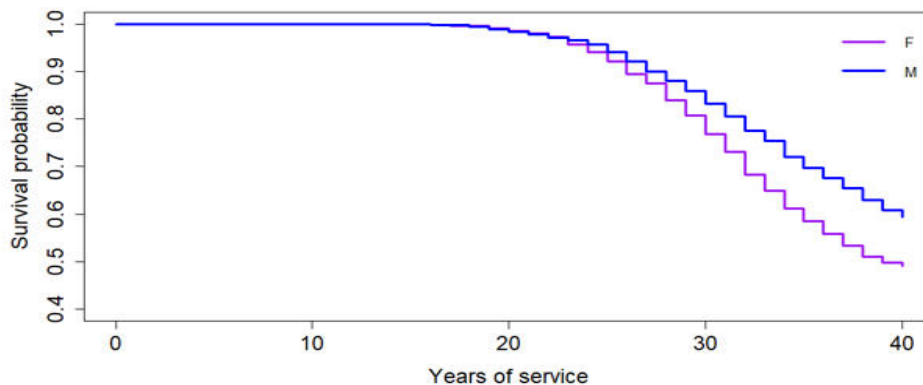


Figure 5 – Distribution of the percentage of applicants who have not (yet) experienced a victory event by year of service and by their gender (Victory survival curve by years of service, stratified by aspirants' gender).



4. Conclusions and future research

Overall, the survival analysis confirms that the path to a first managerial or semi-managerial position in the Italian judiciary is lengthy, highly selective, and shaped by both structural and demographic factors. The results complement the descriptive findings presented earlier and illustrate how the dataset can be leveraged to uncover systematic patterns in judicial career development. Although this first application focuses on the initial “victory,” the longitudinal structure of the data also makes it

possible to study repeated events, conditional probabilities of advancement, and time-dependent covariates — all promising directions for future research.

More broadly, this study underscores the importance of data-driven approaches to understanding judicial careers, particularly in civil law systems. By constructing and analyzing a rich, individual-level dataset that spans more than a decade and includes over 55,000 applications by currently employed judges, this paper provides the first large-scale statistical portrait of career mobility in the Italian judiciary. It demonstrates the value of integrating administrative data with statistical modeling to assess not only how judicial careers unfold, but also where barriers and asymmetries may exist.

References

- AGUIAR AGUILAR AZUL A. 2024. The Internal Dynamics of the Judiciary: Recruitment and Judicial Career. *Legal Culture, Sociopolitical Origins and Professional Careers of Judges in Mexico*. Cham: Springer Nature Switzerland, pp. 89–109.
- AIELLO F., BONANNO G., FOGLIA F. 2024. A meta-regression analysis on judicial efficiency literature: the role of methodological and courts diversity. *Journal of Applied Economics*, Vol. 27, No 1.
- ANTONUCCI L., CROCETTA C., D'OVIDIO F. D. 2014. Evaluation of Italian judicial system. *Procedia Economics and Finance*, Vol. 17, pp. 121–130.
- AZARIA S., ALEXANDER C., BARON O., KRASS, D. 2025. Access to Data for Access to Justice: Unpacking Judicial Congestion Using an Event Log. *Available at SSRN 5254276*.
- BANASIK P., METELSKA-SZANIAWSKA K., GODLEWSKA M., MORAWSKA S. 2022. Determinants of judges' career choices and productivity: a Polish case study. *European Journal of Law and Economics*, Vol. 53, No 1, pp. 81–107.
- DI VITA, G., FERRARA, P.L., PATTI, A. 2024. An empirical study of administrative justice at times of COVID-19 in Italy. *Regional Studies, Regional Science*, Vol. 11, No 1, pp. 558–582.
- GAROUPA N., GILI M., GÓMEZ-POMAR F. 2012. Political influence and career judges: an empirical analysis of administrative review by the Spanish supreme court. *Journal of Empirical Legal Studies*, Vol. 9, No 4, pp. 795–826.
- GIANCOTTI M., ROTUNDO G., MAURO M. 2024. Factors affecting judicial system efficiency: A systematic mapping review with a focus on Italy. *International Journal of Productivity and Performance Management*, Vol. 73, No 9, pp. 2951–2971.

- GUERRA A., TAGLIAPIETRA, C. 2017. Does judge turnover affect judicial performance? Evidence from Italian court records. *Justice System Journal*, Vol. 38, No 1, pp. 52–77.
- JÄCKLE S. 2016. Pathways to Karlsruhe: A sequence analysis of the careers of German Federal Constitutional Court Judges. *German Politics*, Vol. 25, No 1, pp. 25–53.
- MAYORAL J. A., JAREMBA U., NOWAK T. 2014. Creating EU law judges: the role of generational differences, legal education and judicial career paths in national judges' assessment regarding EU law knowledge. *Journal of European Public Policy*, Vol. 21, No 8, pp. 1120–1141.
- MAZZOCCHI P., QUINTANO C., ROCCA A. 2024. Efficiency analysis using SBM and PLS-SEM: insights from the Italian judicial system. *Quality & Quantity*, Vol. 58, No 6, pp. 5621–5654.
- NISSI E., GIACALONE M., CUSATELLI C. 2019. The efficiency of the Italian judicial system: A two stage data envelopment analysis approach. *Social Indicators Research*, Vol. 146, No 1, pp. 395–407.
- PLOSCOWE M. 1934. The Career of Judges and Prosecutors in Continental Countries. *Yale LJ*, Vol. 44, pp. 268–291.
- RULLO L. 2022. The Road to Palazzo della Consulta: Profiles and Careers of Italian Constitutional Judges. *Italian Political Science*, Vol. 17, No 3, pp. 226–245.
- SCHNEIDER M. R. 2005. Judicial career incentives and court performance: an empirical study of the German labour courts of appeal. *European Journal of Law and Economics*, Vol. 20, pp. 127–144.

Maria FILOMENO, Consiglio Superiore della Magistratura, m.filomeno@csm.it
Irene ROCCHETTI, Consiglio Superiore della Magistratura, i.rocchetti@csm.it
Antonello MARUOTTI, Dipartimento di Giurisprudenza, Economia, Politica e
Lingue Moderne, Libera Università Maria Ss. Assunta, a.maruotti@lumsa.it

DECODING ITALY'S COMMERCIAL DESERTIFICATION: CHALLENGES, CAUSES, AND SUSTAINABLE SOLUTIONS¹

Agata Maria Madia Carucci, Annamaria Fiore, Valeria Marzocca,
Roberto Antonello Palumbo

Abstract. Commercial desertification—defined as the progressive decline of retail outlets—has emerged as a critical issue affecting urban and peripheral areas across Italy, with implications for local economies, social cohesion, and territorial equity. Between 2014 and 2022, while the total number of local units nationwide increased by 8.5%, the retail trade sector in non-specialised stores (NACE 47.1) experienced a marked contraction of 12.2%, reaching 18.1% in Southern regions. Paradoxically, employment in the sector rose by 5.6%, suggesting a structural shift in the composition and scale of retail activity.

This study investigates changes in the number of retail units at the municipal level across Italy by comparing percentage variations between 2014 and 2022, using data obtained from the Statistical Register of Local Units (ASIA-UL)² – that annually compiles structural data on business establishments operating in Italy, integrating administrative sources and statistical surveys to describe territorial distribution, economic activity, and local employment – and data from ‘A misura di comune’³ – an output of Istat’s experimental statistics; this system disseminates municipal-level indicators across various thematic areas, drawing upon both official and non-official statistical sources – for the socio-demographic and economic indicators at the municipal level.

The results reveal significant spatial disparities, with smaller and inland municipalities exhibiting greater vulnerability to retail closures. Key predictors include demographic trends, income levels, accessibility, and sectoral performance. The findings underscore the need for place-based, inclusive policies to counteract commercial desertification and support the sustainable revitalisation of local commerce in the context of ongoing socio-economic transitions.

1. Introduction

Over the last years, several socio-economic studies have analysed the transformation of the retail sector, highlighting the processes of commercial desertification (Anquez, 1993) alongside urban gentrification (Hubbard, 2018). Both

¹ This article is the result of joint work by the authors. Section 2 was written by Carucci; Sections 1 and 4 by Fiore; Sections 3.1 and 3.2 by Marzocca; and Sections 3.3 and 3.4 by Palumbo. The views expressed in this paper do not necessarily reflect those of the authors’ affiliated institutions.

² <https://www.istat.it/scheda-qualita/registro-statistico-delle-unita-locali-asia-ul/>

³ <https://www.istat.it/statistica-sperimentale/aggiornamento-degli-indicatori-del-sistema-informativo-a-misura-di-comune/>

phenomena substantially alter the urban structure and have a significant impact on social and economic ties in the area.

Several studies indicate a significant reduction in retail and wholesale activities, contrasted by growth in accommodation and catering activities (Confcommercio, 2024). The pandemic and high energy prices have accelerated this decline, although local commerce remains vital for urban liveability (Frago, 2021). Particularly affected by the commercial desertification are the inner and mountain areas (Clerici, 2025).

In Italy, over the past few decades, several significant events have had a profound impact on the retail sector's structure. The liberalisation of the commercial sector in 1998 accelerated the closure of several small retail outlets, undermining territorial cohesion, and the economic crisis of 2008 called into question the pillars of advanced capitalism, affecting the commercial sector and central and suburban urban spaces. The decline in consumption and changing spending habits have led to the closure of commercial activities, especially in city centres, often replaced by large commercial chains, such as outlets and suburban shopping centres, contributing to the crisis of traditional stores.

Commercial homogenisation, through the spread of franchising and fast fashion, has made the commercial offer less diversified, reducing the attractiveness of urban centres, while gentrification has transformed urban spaces, often excluding traditional and local commercial activities.

At the social level, we are witnessing a weakening of social and community ties, which encourages degradation and insecurity in central urban areas. The neighbourhood commercial activities provide the local population not only with an endowment of goods and services, but also generate “urbanity”, in the sense that they offer opportunities for interaction, aggregation and collective time (Tumini, 2024).

Using official statistics, this study examines changes in the number of retail units across Italian municipalities between 2014 and 2022 through percentage variation analysis. A subsequent multivariate approach explores the correlation between this decline and selected socio-demographic and geographical factors.

2. Data and methodology

The creation of statistical registers has profoundly transformed the methodology of producing official statistics. Sample surveys now play a renewed role in validating and supplementing archival sources. Business statistics were the first domain to extensively use administrative data, which contributed to the development of business statistical archives. As a result, official statistics offer comprehensive tools for analysing the production system by economic activity. However, to effectively capture the phenomenon at a territorial level and inform policy decisions, it is advisable to integrate the data from statistical archives with additional sources

accessible to policymakers. The statistical sources on companies used in this work are:

- the Statistical Archive on active enterprises (ASIA Enterprise), which considers the enterprise as the unit of observation for economic activity (5-digit NACE);
- the statistical archive on local units (ASIA-UL), which has the local unit as its unit of observation, and which is therefore better suited to territorial analyses;
- the Frame-SBS: structural statistics and the territorial structural statistics, based on the integration of administrative and statistical sources, provide a detailed overview of enterprises' economic variables, with a focus on financial statement data, associating economic variables with each local enterprise/unit.

The classification of economic activities enables the distinct identification of retail trade, both specialised and non-specialised, at the fifth digit of the NACE code, according to the type of commercial establishment. Enterprise structure variables were analysed using a Poisson model in conjunction with municipal data and indicators derived from the 'A misura di comune' indicator system.

The model, developed using 2022 municipal data, seeks to identify the factors associated with a variation within the sector *Retail sale in non-specialised stores* (NACE 47.1). The dependent variable is the number of local units (UL) in the sector in 2022. To model incidence rates rather than absolute counts, we included an offset term in the Poisson regression. Specifically, the logarithm of the number of UL in 2014 was incorporated as an offset, with its coefficient constrained to 1. This specification ensures that the estimated coefficients reflect changes in the rate of UL (and commercial desertification) per unit of baseline exposure, rather than changes in raw counts. By doing so, the model accounts for structural differences across municipalities, allowing for more accurate comparisons and a clearer interpretation of the covariates' effects.

The independent variables, qualitative and quantitative, refer to:

- population structure
- production system
- well-being of the population
- characteristics of the municipalities.

3. Results

The following section presents a multi-scalar analysis of retail transformations in Italy, observing the two time points, 2014 and 2022. It begins with a descriptive overview of employment and unit size across retail subsectors, then explores regional disparities in workforce distribution, structural shifts within non-specialised formats, and finally examines municipal-level patterns through both spatial mapping and regression modelling.

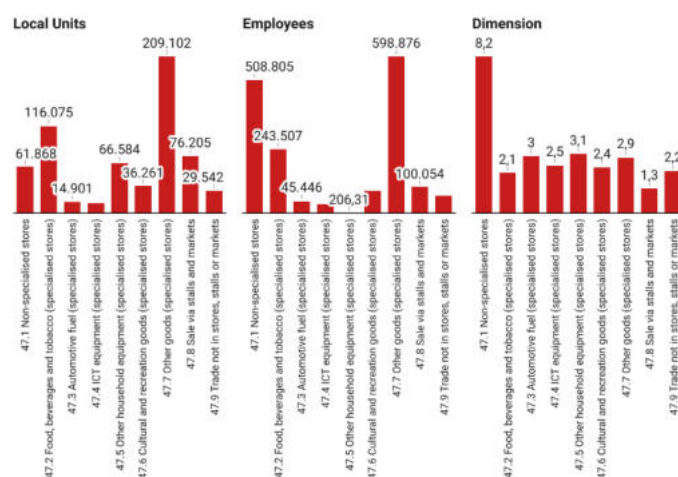
3.1 Descriptive analysis - distribution of employed ULs and average size

Retail trade represents a particularly significant component of Italy's production system. In 2022, it encompassed over 600,000 local units, accounting for 12% of the national total, and employed nearly two million individuals, corresponding to 10.4% of the total workforce.

It is the sub-sector of retail trade in specialised stores (NACE 47.7) that has the highest number of local units, followed by food stores (47.2). The largest number of employees is in the retail trade in specialised and non-specialised stores (47.7 and 47.1).

On average, local units within the retail trade sector employ three individuals. The non-specialised store sub-sector (47.1) comprises the largest establishments, whereas the food, beverages and tobacco sub-sector (47.2) is characterised by the smallest operational size (Figure 1).

Figure 1 – ULs and employees' distribution in retail trade. Year 2022.



Source: Authors' elaborations on Istat data. Created with Datawrapper.

Between 2014 and 2022, the sector has undergone profound transformations: small ULs shrink in favour of large ones, shops specialising in food and ICT have recorded an increase in terms of both ULs and employees, as well as trade non-stores (NACE 47.9), fundamentally e-commerce, which has recorded a rise of 72.5% of ULs and 56.4% of employees (Table 1).

Table 1 – *Percentage changes UL and employees in retail trade by subsector and class of employees. 2022 over 2014.*

NACE 3-DIGIT	CLASS OF EMPLOYEES									
	0-5		6-9		10-19		20+		Total	
	UL	Empl	UL	Empl	UL	Empl	UL	Empl	UL	Empl
47.1 Retail sale in non-specialised stores	-21.1	-19.6	6.1	6.6	16.4	17.3	27.0	12.0	-12.2	5.6
47.2 Retail sale of food, beverages and tobacco in specialised stores	0.9	2.7	53.1	54.8	69.4	72.2	107.2	81.9	2.5	10.5
47.3 Retail sale of automotive fuel in specialised stores	-31.5	-30.0	-2.4	-0.9	16.5	19.1	53.6	78.9	-28.4	-16.7
47.4 Retail sale of information and communication equipment in specialised stores	9.1	9.5	33.5	31.6	31.6	30.3	30.4	30.7	10.6	15.9
47.5 Retail sale of other household equipment in specialised stores	-19.2	-15.0	19.3	20.3	22.9	24.7	13.4	25.6	-16.5	-0.3
47.6 Retail sale of cultural and recreation goods in specialised stores	-24.5	-23.3	-3.6	-4.2	6.8	10.3	52.6	59.9	-23.2	-9.6
47.7 Retail sale of other goods in specialised stores	-16.3	-13.4	14.0	14.9	28.3	28.1	55.3	71.3	-13.4	1.7
47.8 Retail sale via stalls and markets	-18.6	-19.8	14.5	15.5	41.2	43.0	225.0	167.4	-18.4	-18.4
47.9 Retail trade not in stores, stalls or markets	73.0	52.9	74.4	76.7	58.6	59.9	53.1	56.3	72.5	56.4
RETAIL TRADE	-12.7	-11.5	15.9	16.6	24.1	24.8	33.8	25.0	-10.3	2.6

Source: Authors' elaborations on Istat data.

3.2 Regional-level analysis of changes in employee class distribution, 2014–2022

Building on the descriptive analysis conducted at the national level, a territorial examination proves valuable in highlighting regional disparities. Between 2014 and 2022, small non-specialised stores (NACE 47.1) declined across all regions except Lazio, whereas larger establishments increased throughout the country, with a more pronounced growth in the Southern regions. Small local units experienced a 20% reduction in employment, with the steepest losses (exceeding 30%) recorded in Molise, Marche and Umbria. Large ULs register a 12% increase in employees, with the largest increase in Campania (+81%) and Puglia (+48%).

Between 2014 and 2022, the food retail sub-sector (47.2) recorded positive developments, with increases in both the number of local units and employees, particularly among smaller establishments. Significant territorial differences emerged, with small stores maintaining their presence in Southern regions while declining in the North-East. In terms of employment, Basilicata and Lazio registered the highest growth, at 14% and 13%, respectively. Large-scale food retailers expanded across all regions, except Lazio.

Conversely, the household equipment retail sub-sector (47.5) experienced a general decline in both employment and the number of local units, most notably among small stores. The expansion of major retail chains appears to have significantly contributed to the decline of smaller outlets offering furniture, home essentials, and do-it-yourself supplies. Notable employment gains, exceeding 50%, were observed in Calabria, Sicilia and Lazio.

The cultural and recreational goods sub-sector (47.6), including books and sporting equipment, also witnessed a contraction of small businesses in favour of large retailers. The most substantial reductions in small outlets occurred in northern regions, while employment in large establishments doubled in Puglia, Calabria, Sardegna, Trentino and Umbria.

3.3 Structural shifts in non-specialised retail formats

One of the most significant transformations is related to non-specialised trade. At the national level, between 2014 and 2022, there is a crisis in hypermarkets ($>2,500$ m²), which lose more than 10% of employees; on the other hand, there is an increase in ULs and supermarket employees (>400 m² and $<2,500$ m²), which increase by 20% and 18% respectively. Discount stores, department stores and non-specialised appliance stores also increase.

Minimarkets experienced the most pronounced decline during the period under consideration, with a reduction of nearly 30% in employment and a loss of approximately 40% of local units (Table 2).

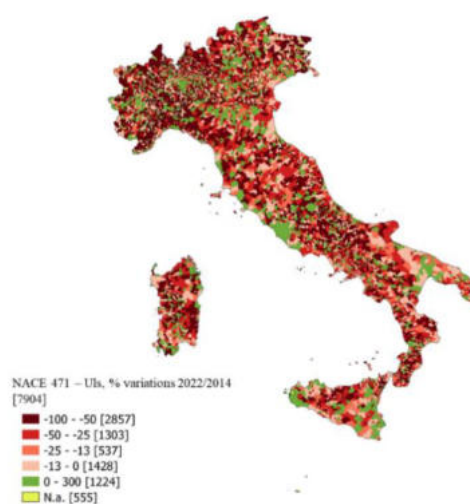
Table 2 – Percentage changes UL and employees in retail trade in non-specialised stores by subsector. 2022 over 2014.

NACE 5-DIGIT	Local Units	Employees
47111 – Hypermarkets	-0,2	-10,9
47112 – Supermarkets	19,2	17,6
47113 - Discount food stores	6,0	36,7
47114 - Minimarkets and other non-specialized miscellaneous food stores	-41,1	-28,7
47115 - Retail sale of frozen foods	0,3	22,0
47191 - Department stores	88,0	7,4
47192 - Retail sale in non-specialized stores of computers, peripherals, telecommunications equipment, audio and video consumer electronics, household appliances	27,8	20,4
47199 - Emporiums and other non-specialized stores of various non-food products	120,3	151,2
TOTAL	-12,2	5,6

Source: Authors' elaborations on Istat data.

3.4 Municipal-level analysis

Focusing once again on the non-specialised retail trade sector, a widespread decline in local units is evident at the municipal level. In contrast, increases in local units are generally concentrated along coastal areas and within major urban agglomerations, such as Rome (Figure 2).

Figure 2 – Retail sale in non-specialised stores. Percentage changes in ULs. 2022 compared to 2014.

Source: Authors' elaborations on Istat data.

Once the data on enterprises and local units had been restructured at the municipal level, a Poisson regression model was developed to identify the factors associated with changes in ULs within the non-specialised retail trade sector (NACE 47.1) between the two time points.

Building on the descriptive patterns observed across regions and store sizes, the following covariates were selected to capture demographic, economic and spatial heterogeneity (Table 3).

Table 3 – *List of covariates and acronyms.*

Covariates	Acronyms
Population changes between 2014 and 2022, %	popchg_14_22
Old-age index, 2022	oldage_idx
<i>Ratio between the population aged 65 and over and the population aged 0-14, multiplied by 100</i>	
Average taxable income per taxpayer, 2022, euros	tax_income
Population density, 2022, people/km ²	pop_density
Municipality in an inland area	inland_muni
<i>1: central areas; 0 = inner areas</i>	
Travel time to the nearest hub, minutes	time_to_hub
Change in sector employment between 2014 and 2022, %	empchg_sector
Value added per employee, 2022, euros	va_sector

We estimated a Poisson regression model to examine the territorial determinants of the number of local units (UL) in sector 47.1 in 2022, using the logarithm of UL in 2014 as an offset to model incidence rates rather than absolute counts (Cameron and Trivedi, 2013; Long & Freese, 2014). This specification allows for the interpretation of coefficients in terms of changes in the expected rate of UL per unit of baseline exposure, controlling for structural differences across municipalities. The model is statistically significant overall (LR $\chi^2(8) = 2052.80$, $p < 0.001$), with a pseudo R^2 of 0.0715, indicating a modest but meaningful explanatory power for a count-based specification. As expected in count-based models, the pseudo R^2 value is relatively low and should not be interpreted in the same way as in linear regression. Instead, model adequacy is better assessed through the global significance test, with the likelihood ratio chi-squared statistic (LR χ^2) providing a more reliable measure of overall model fit (Table 4).

All covariates included in the model are statistically significant at the 1% level. Recent population growth is positively associated with the rate of UL, suggesting that municipalities experiencing demographic expansion tend to retain or attract more commercial activity. In contrast, the old-age index exhibits a negative effect, indicating that demographic ageing may be linked to commercial contraction. Socio-economic conditions also play a significant role: higher per capita tax income and greater population density are both positively associated with UL rates, reflecting

the influence of economic vitality and urban concentration. Accessibility factors show penalising effects, with municipalities located farther from urban hubs exhibiting lower rates of UL. Of relevance is the variable *inland_muni*: it is a binary indicator where 1 corresponds to central areas and 0 to inner areas. The negative and statistically significant coefficient (-0.079 , $p < 0.001$) implies that, holding other factors constant, municipalities classified as central areas exhibit a lower expected rate of local units (ULs) in the non-specialised retail sector (NACE 47.1) compared to inner areas. Since the reference category is inner areas (coded as 0), the negative sign indicates that central areas are associated with a relative disadvantage in terms of UL presence.

Table 4 – *Parameter estimates from the generalized linear model with Poisson distribution and log link function.*

Covariates	Coefficient	St.Err.	t-value	p-value
popchg_14_22	0.009986	0.001	7.76	0.000
oldage_idx	-0.000224	0.000	-2.71	0.007
tax_income	0.000012	0.000	10.08	0.000
pop_density	0.000027	0.000	10.69	0.000
inland_muni	-0.078965	0.015	-5.30	0.000
time_to_hub	-0.003517	0.000	-9.54	0.000
empchg_sector	0.000529	0.000	23.05	0.000
va_sector	0.000003	0.000	8.98	0.000
_intercept	-0.307953	0.032	-9.49	0.000
log_UL_2014	1 (offset)			
Mean dependent var	9.953	SD dependent var		55.368
Pseudo r-squared	0.071	Number of obs		6200
Chi-square	2052.797	Prob > chi2		0.000
Akaike crit. (AIC)	26690.636	Bayesian crit. (BIC)		26751.227

Source: Authors' elaborations on Istat data.

This result challenges conventional assumptions about retail concentration in central zones and suggests that inner areas—often considered structurally weaker—may display unexpected dynamism or resilience in maintaining retail activity. Such findings underscore the importance of revisiting territorial classifications when designing place-based commercial policies.

Finally, sectoral dynamics are strongly predictive: both employment change and value added in the sector are positively associated with the outcome, confirming the relevance of economic performance indicators in explaining territorial variation. The constant term is negative and statistically significant, as expected in log-linear count models.

Overall, the results highlight the interplay between demographic, economic, and spatial factors in shaping the geography of commercial presence and support the use of exposure-adjusted models for territorial analysis.

4. Conclusions and policy implications

Between 2014 and 2022, the Italian retail sector underwent a profound transformation marked by the decline of small-scale retail units and the simultaneous expansion of larger commercial formats. This shift, consistent with broader international trends, has seen large-scale distribution (GDO) consolidate its dominance, often acting as a “category killer” by enlarging sales areas and concentrating market power. While traditional sub-sectors experienced significant setbacks, specialised food and ICT retailers demonstrated greater resilience, and the growth of e-commerce continued unabated. A central paradox emerges from the analysis: despite the contraction in the number of local units (ULs), employment in the sector increased, suggesting a reconfiguration of retail structures rather than a net loss of jobs.

This evolution reflects deeper demographic, economic, and spatial dynamics. The steady reduction in the number of Labour Market Areas signals a growing concentration of activity in metropolitan centres, reinforcing their attractiveness and reshaping territorial balances. Within the non-specialised retail trade sector (NACE 47.1), the contrast is particularly stark: hypermarkets registered sharp employment losses, while supermarkets expanded both in number and workforce. Minimarkets experienced the steepest decline, yet discount stores, department stores, and appliance retailers gained ground. The overall stability in employment figures is largely attributable to the transition of former micro-enterprise owners into wage employment within larger retail structures, indicating a shift in occupational status rather than a disappearance of labour.

Municipal-level changes in ULs show statistically significant associations with selected socio-economic and geographic variables, although no causal inference is drawn. Interestingly, inland areas—often marginalised in previous development models—display unexpected dynamism in retail growth. Demographic factors, such as population ageing, contribute to stable demand, while higher taxable income and improved accessibility, measured by reduced travel times to urban hubs, further support retail activity. Sectoral indicators, including employment change and value added, also reinforce commercial vitality, underscoring the importance of economic performance in shaping territorial outcomes.

Environmental considerations could add further complexity. The expansion of large-scale retail formats entails increased land consumption and a reliance on private transportation, raising concerns about sustainability. In contrast, neighbourhood shops offer environmental advantages by integrating into existing

urban fabrics and supporting soft mobility modes such as walking and cycling. This divergence highlights the importance of environmentally conscious planning in shaping the future of retail, in line with the priorities of the United Nations' 2030 Agenda, particularly Goal 11 on sustainable cities and communities (OECD, 2020).

The Poisson regression results offer clear policy insights for addressing commercial desertification. The positive association between recent population growth and UL rates suggests that demographic vitality is a key enabler of retail resilience. Conversely, the negative effects linked to ageing populations and peripheral location point to the need for targeted interventions in structurally disadvantaged areas. Municipalities with limited accessibility and weaker sectoral dynamics may require tailored support measures, including incentives for business retention, improved connectivity to urban hubs, and strategic alignment of local development plans with sector-specific trends. The strong predictive power of employment change and value added further highlights the importance of integrating labour market intelligence and economic indicators into regional programming. Overall, the findings support a place-based approach to commercial policy (Barca, 2009), one that recognises and responds to demographic, economic, and spatial asymmetries to promote inclusive and sustainable territorial development.

Addressing the decline of small retailers requires a multifaceted strategy that involves coordinated action between public institutions and private stakeholders. Several Italian regions have introduced economic incentives to sustain local commerce, including support for complementary services such as home delivery. Initiatives like the "Cities" project, led by Confcommercio and ANCI, promote urban regeneration by revitalising historic shops through collaborative efforts between business communities and local governments. In some urban contexts, shop owners have formed commercial districts, fostering a shared identity and enhancing the attractiveness of retail environments through events and improved offerings. Digitalisation programmes further empower small shops to compete in a changing market, enabling them to establish an online presence and adopt omnichannel strategies. At the municipal level, regulatory frameworks are being revised to protect neighbourhood retail, recognising its role as a public interest service and a pillar of social cohesion.

As Zanderighi and Orsi (2020) emphasise, fostering the resilience of proximity-based commerce requires a holistic approach that transcends economic efficiency. What emerges is the need for a balanced model that strengthens urban liveability while supporting the positive externalities generated by local retail ecosystems. Considering demographic transitions, environmental pressures, and digital transformation, the future of retail lies in strategies that combine competitiveness with inclusivity and sustainability. Neighbourhood retail should be recognised not

only as an economic actor, but as a form of social infrastructure essential to urban cohesion.

References

- ANQUEZ M.C. 1993. L'offensive des hard-discounts en France (Hard discounters in France). *Bulletin de l'Association de Géographes Français*, Vol. 70, No.3, pp. 248-259.
- BARCA F. 2009. Agenda for a Reformed Cohesion Policy. European Communities Brussels, Brussels.
- CAMERON A. C., TRIVEDI P. K. 2013. *Regression Analysis of Count Data*. 2nd ed. New York: Cambridge University Press.
- CIRELLI C. 2016. Le nuove geografie del consumo, tra crisi e resilienza. *Geotema*, n.51/2016.
- CLERICI M.A. 2025. Mountain Areas and the Growing Scarcity of Essential Services: The Evolution of Retail Business Density in Mountain Municipalities in Lombardy (Italy), 2001-2021. *European Countryside*, Vol. 17, No.1, pp. 47-69.
- CONFCOMMERCIO 2024. *Demografia d'impresa nelle città italiane*. 9° edizione. Roma: Ufficio Studi Confcommercio.
- FRAGO L. 2021. Impact of COVID-19 Pandemic on Retail Structure in Barcelona: From Tourism-Phobia to the Desertification of City Center. *Sustainability*, Vol. 13, No.15: 8215.
- HUBBARD P. 2018. Retail gentrification. In LEES L. and PHILLIPS M. (Eds.) *Handbook of Gentrification Studies*, Edward Elgar Publishing Online, pp. 294-309.
- LONG J. S., FREESE J. 2014. *Regression Models for Categorical Dependent Variables Using Stata*. 3rd ed. College Station, TX: Stata Press.
- OECD 2020. *A Territorial Approach to the Sustainable Development Goals: Synthesis report*, OECD Urban Policy Reviews, OECD Publishing, Paris.
- TUMINI L. 2024. About the Distribution of Daily Services and Commercial Opportunities. In PUCCI P. and VECCHIO G. (Eds). *Questioning Proximity - Opportunities and Challenges for Urban Planning and Mobility Policies*, Springer, pp. 91-101.
- ZANDERIGHI L., ORSI L. 2020. Commercio di vicinato e resilienza. *Micro & Macro marketing*, Vol. 29, No. 2, pp. 377-394.

Agata Maria Madia CARUCCI, Istat, carucci@istat.it

Annamaria FIORE, ARTI, a.fiore@arti.puglia.it

Valeria MARZOCCA, Istat, valeria.marzocca@istat.it

Roberto Antonello PALUMBO, Istat, palumbo@istat.it

**OECD PMR INDICATORS ON PROFESSIONAL SERVICES:
TOP PERFORMANCES OR OUTLIERS?
THE INHOMOGENEITY OF THE CIVIL LAW NOTARIES'
CLUSTER MAY BIAS THE ASSESSMENT ON THE
ADMINISTRATION OF THE JUSTICE¹**

Claudio Ceccarelli, Antonio Cappiello

Abstract. The article passes in review the PMR indicators on notary regulation underscoring that the inhomogeneity of the cluster produces a large gap between minimum and maximum values. If we only consider “civil law notaries”, we can obtain more genuine picture of the reality. Since notaries exercise public functions within the administration of the justice (public good), they need a high level of regulation which is indeed empirically observed in the more homogeneous adjusted distribution (considering only notaries with comparable functions). In the case of notaries, in order to overcome market failure, higher regulation would be needed to ensure higher protection for the average consumer. The analysis of the legislative framework of Sweden, USA, Costa Rica and Israel clearly shows the inconsistency of the PMR notarial cluster as well incompatibilities with the OECD definitions of the notarial profession. Once sharpened the frontiers of the sample, excluding units belonging to a different distribution, notaries presents homogenous higher distribution of the PMR “regulatory score”. The inverse relation between regulation (PMR) and “cost” and the positive correlation between PMR score and quality (Cappiello 2022) in conjunction with the EXCAS study on the better performances of the civil law notaries countries compared to countries using different systems (World Bank indicators of the property transfers of the civil law notaries, are used to make a comparison among countries), it seems to confirm the paternalistic need of the adoption of a civil law notary system. The analysis of the homogenous cluster of civil law notaries completely reverses the benchmark thresholds of the OECD PMR indexes. Contrary to the OECD PMR general vision that “less regulated is better”, the top five PMR average score (countries with lowest notarial regulation) is in fact associated with high average costs, while the highest five PMR average score (countries with highest notarial regulation) is associated with low average costs for the consumer. Therefore, if a country presents a notarial PMR value above the OECD AVG (a level of notarial regulation above the OECD average), it would be empirically considered an advantage (because it produces lower cost, efficiency and higher quality) rather than a signal for deregulation as actually proposed by OECD.

¹ The views and opinions expressed are those of the authors and do not necessarily reflect the views or positions of the entities they represent.

1. Introduction

Since 1998, the OECD Product Market Regulation (PMR) indicators have measured the degree of regulation in key sectors of the economy, including selected professional services that constitute important intermediate inputs in national productivity systems. Among these professions are lawyers, accountants, architects, engineers, real estate agents, and notaries, classified according to ISIC² definitions (see Table 1). PMR scores range from 0 (lowest regulation) to 6 (highest regulation) and are intended to assess the extent to which regulation may hinder competition, under the assumption that lower regulatory intensity is generally associated with better market outcomes. While this assumption may hold for purely market-oriented services, it is more problematic when applied to professions exercising public functions³. This paper focuses on the notarial profession and argues that the PMR assessment is biased by the inhomogeneity of the notarial cluster. In particular, the inclusion of systems based on “notaries public” alongside civil law notaries leads to misleading benchmarks⁴ and policy implications.

We show that, once the sample is restricted to countries adopting civil law notaries with comparable functions, the distribution of PMR scores becomes homogeneous and the interpretation of regulation is substantially reversed.

2. Notaries, Market Failure, and Public Goods

Civil law notaries are integral components of the administration of justice. They are public officers entrusted with the *ex ante* control of legality in legally sensitive transactions, most notably real estate transfers. Their function is to ensure legal certainty⁵, protect weaker parties, and prevent negative externalities such as

² The International standard industrial classification of all economic activities, abbreviated as ISIC, is a standard United Nations Statistics Division (UNSD) classification of economic activities arranged so that entities can be classified according to the activity they carry out.

³ Cappiello, A. OECD PMR indicators for professional services. Civil law notaries as ‘public good’: efficiency and legal protection need higher regulation, *RIEDS - Rivista Italiana di Economia, Demografia e Statistica - The Italian Journal of Economic, Demographic and Statistical Studies*, 2022, vol. 76, issue 3, 179-190

⁴ European Commission and OECD (2022). Assessment of the links between the European National Recovery and Resilience Plan and OECD PMR indicators.

⁵ Directive (EU) 2018/958 of the European Parliament and of the Council, of 28 June 2018, relating to a test of proportionality before the adoption of a new regulation of the professions, excludes the notary profession from its scope of application, in the light of the consideration that the requirements for entry and exercise of the same are proportional and justified by the public function that characterizes it. Indeed, Article 2 of the directive in question limits its scope of application only to professional activities falling within the scope of directive 2005/36/EC. The latter, in the text amended by Directive 2013/55/EU (see art. 1, point 2.b) of the European Parliament, in turn

litigation, fraud, and enforcement failures. As such, notarial services cannot be analysed as ordinary market services governed by pure competition. From an economic perspective, notarial activity addresses classic forms of market failure, including information asymmetry and contractual incompleteness. This explains why civil law notaries are subject to a high and relatively uniform level of regulation across countries adopting this institutional model. Empirically, OECD PMR data show that civil law notaries exhibit high regulatory scores (mean around 4.5 on a 0–6 scale), reflecting their public mandate rather than inefficiency or rent-seeking behaviour.

Table 1 – *OECD definitions of the professions analysed by the PME indicator.*

Lawyers (included in ISIC 4.0 6910 class) are professionals that usually provide: 1) legal representation of one party's interest against another party before courts and other judicial bodies; 2) advice and representation in civil cases; 3) advice and representation in criminal cases; 4) advice and representation in connection with labour disputes, and general counselling and advising, preparation of legal documents (including deeds, wills and trusts).
Notaries (included in ISIC 4.0 6910 class) are professionals that usually confer authenticity on legal deeds, contracts, oaths and other legal documents. The following options may apply: 1) an independent professional who charges fees to its clients (like in several European and Latin American countries); 2) a public employee, who offers its services in a public office and is paid as public employees. Those who receive his/her services may be asked to pay a fee, but this fee would accrue to the public office and not directly to the employee (like in some Nordic countries); 3) a lawyer who also offer notarial services, usually Administering oaths and certifying legal documents, after obtaining an additional qualification (like in the UK). In case 2 and 3 the OECD would consider that notary is not an independent profession for the purpose of PMR analysis.
Accountants (included in ISIC 4.0 6920 class) are professionals that can prepare financial accounts for firms, handle payrolls, reconcile firms' books at year end, and prepare tax returns for firms and individuals
Architects (included in ISIC 7110 class) are professionals that usually plan, design, and supervise the construction, restauration and refurbishment of buildings. They can also perform urban planning and landscape architecture.
Civil engineers (included in ISIC 7110 class) are professionals that usually plan, design, and supervise the construction, refurbishment and maintenance of buildings, as well as roads, bridges, dams, and the like.
Real estate agents (included in ISIC 4.0 6820 class) are professionals that usually arrange the selling, letting and/or management of real estate properties (e.g. houses, flats, building, shops).

Source: OECD 2023, *Definitions and instructions for the PMR questionnaire*.

3. OECD Definitions and Cluster Inhomogeneity

According to OECD definitions, notaries may operate under three different institutional arrangements: (i) independent professionals exercising a public function and charging regulated fees; (ii) public employees providing notarial services within public offices; and (iii) lawyers who perform limited notarial acts as an ancillary activity. For PMR purposes, only the first category should be considered an

excludes the profession of notary from its scope of application: article 2 of the “*Directive 2005/36/EC is amended as follows: .. this Directive shall not apply to notaries who are appointed by an official act of government.*”

independent profession. Beyond this formal classification, a substantive distinction must be drawn between civil law notaries and notaries public. Civil law notaries, recognized by the International Union of Notaries (UINL), are delegated by the State to perform legality controls with full evidentiary and enforceable effects. By contrast, notaries public—typical of common law systems—mainly certify signatures or copies and do not provide legal advice or control the substance of transactions. The inclusion of countries such as the United States, Sweden, and Israel in the PMR notarial cluster introduces units belonging to a different institutional population. In these countries, notarial functions are either minimal, ancillary to the legal profession, or purely administrative. Their inclusion artificially lowers the PMR average and inflates the dispersion of scores. In the USA the “notary public” is not providing legal advice or supervising crucial processes connected with the property transfers (activity normally carried out by lawyers). For instance, in New York (USA), anyone having a high school degree can become a notary public after paying 15\$ and passing a multiple-choice test of the duration of 1 hour concerning a booklet on notary public licence law⁶. As concerns Texas (NY and Texas are the representative States considered by the PMR to calculate the USA average⁷), on the portal of the Secretary of the State contains a “warning” specifying (in English and Spanish) that a “notary public” is not a “notario” (civil law notary) and “he is not authorised to practice law” neither to “give legal advice or prepare legal documents”⁸. Moreover, to become notary in Texas you do not need to pass any examinations⁹, you are only required to pay \$95.95 to get an authorisation to practice¹⁰. In Sweden, according to the law on Notary Public (SFS-nummer 1982:327 Förordning om notarius publicus¹¹), the activity of the notary seems related mainly to the certification in limited fields (certification of signatures, witness about

⁶ See information on the official website of state of New York (<https://dos.ny.gov/notary-public>)

⁷ See USA in the PMR table scores (OECD 2018)

⁸ Notice from the Secretary of the State of Texas (<https://www.sos.state.tx.us/statdoc/notary-public.shtml>) Notario Público? Not in Texas! 1) A notary public is not a *notario*; 2) A notary public is not authorized to practice law. 3) A notary public may not give legal advice or prepare legal documents; 4) A notary public may not charge a fee for preparation of immigration documents or represent someone in immigration matters. Please report any notaries public disobeying these rules to the Office of the Secretary of State.

⁹ FAQ American Association of Notaries (<https://www.texasnotary.com/notary-faqs/notary-course-and-testing#category-title>) “Do I need to take an exam or a notary course?: Notaries are not required to take a course or pass a test to become a Texas notary. However, for the notary's protection, training is highly recommended.

¹⁰ In the portal of Texas notaries is also specified that, to become a notary in Texas, you only need to pay \$95.95 and “you must: 1) Be 18 years of age or older; 2) Be a legal resident of the State of Texas; 3) Have no criminal convictions or felonies.” Source: <https://www.texasnotary.com/how-to-become-a-texas-notary>

sealing and closing of storage rooms, lottery certification and confirmation of certain powers of representation). The Swedish notary may also certify translations “to the extent that his language skills permit”. The typical services offered by the Swedish notaries¹² seem to have the *notary public*’s characteristics (mainly authentication of signatures and linguistic skills). The Swedish law does not foresee any notarial legality control for the purposes of the real estate transfer or other crucial activities usually delegated by the State to civil law notaries. The official website of the Stockholm municipality provides the following indications of the main services of *Notarius publicus*: 1) verifying signatures, copies, translations, and other data concerning the content in various documents; 2) witnessing when storage rooms are opened or closed, or when seals are put in place or are broken; 3) supervising lottery draws; 4) confirming that someone is qualified to do certain things, or that someone has the competence or capacity to represent someone else. As concerns Israel, in order to become a notary it is necessary, among other requirements, to be a member of the Israel Bar Association and have 10 years of work experience as a lawyer (see criteria 2 and 3 of Notary Licensing Department).¹³ Leaving apart the assessment concerning the notarial functions which, except some legal competences on the matrimonial agreements, seems anyway closer to those of the Anglo-Saxon “notary public”¹⁴ (Israeli notaries are not considered civil law notaries by the UINL), the

¹² Our most common services are...: 1) Legalisation of a signature on a document; 2) Legalisation of two signatures on a document Attestation/Affidavit/Spanish and French Power of Attorney (one signature); 3) Legalisation of the name and authorisation of an authorised signatory on a document; 4) Legalisation of the names and authorisation of two authorised signatories on a document; 5) Legalisation of a photocopy (on presentation of the original) 6) Apostille.

¹³ Israeli Ministry of Justice (Regulation of Professions Division, Notary licensing department) “To apply you must meet all the following criteria: 1) Be an Israeli citizen or have Israeli permanent residence status; 2) Be a member of the Israel Bar Association; 3) Have 10 years work experience as a lawyer; 4) Participate in a notary training course; 5) Have a criminal record check. The notary licensing committee will check if there are criminal investigations or proceedings against you; 6) Have a disciplinary complaints-history check”.

¹⁴ של נכונותו לאשר (3); לכך מוסמך היה, זולתו בשם, מסמך על שהחתום לאשר (2); מסמך על חתימה לאמת (1) הנוטריונים לחוק 7 סעיף 14 נכונותה לאשר (7); חי פלוני שאדם לאשר (6); אחרת והצהרה תצהיר ולאשר לקבל (5); מסמך תרגום של נכונותו לאשר (4); מסמך העתק נוטריין בידי הפעולה עשיית או כשהעריכה אחרת פעולה בו לעשות או מסמך לערוך (9); סחיר מסמך של העדה לערוך (8); מצאי רשימת של אחר דין פי על ציבורי נוטריין של בסמכות להשתמש (10); אחר מסמך פי על או, חוץ מדינת של דין לרבות, דין פי על מותרת או דרושה (11) לבצע רשאי נוטריין שרק פעולות. הנישואין לפני שנכרת, זוג בני בין ממון הסכם לאמת (11) English translation: Section 7 of the Notaries Law 1976-“to verify a signature on a document; (2) to confirm that the signatory of a document, on behalf of another, was authorized to do so; (3) confirm the correctness of a copy of a document; (4) to confirm the correctness of a document translation; (5) accept and approve an affidavit and other statement; (6) to confirm that a certain person is alive; (7) to confirm the correctness of an inventory list; (8) to make the witness of a negotiable document; (9) Edit a document or perform another action on it when editing or performing the action by a notary is required or permitted by law, including the law of a foreign country, or by another document; (10) use the authority of a notary public according to another law; (11) To verify a financial

exercise of the notarial function is accessory to that of lawyer and therefore the Israeli notaries, according to OECD definitions (par. 1), should not be included in the PMR notarial cluster. A different consideration would deserve Costa Rican notaries. In this case, the observation does not concern their functions (they provide services typical of civil law notaries) but the inconsistency with the OECD definition (see par. 1). In fact, even if Costa Rican notaries perform typical activities of civil law notaries and are part of the Latin Notaries International Union, they are required (in order to exercise as a notary) to be lawyers with at least two years of incorporation in the National Bar Association¹⁵. Therefore, we are within the case of “lawyers exercising the notarial profession” and this would be inconsistent with the OECD definitions. Even in this case, according to the OECD definitions, the PMR notarial cluster should not include the score of Costa Rica because within the case of “lawyers who also offer notarial services”¹⁶.

4. Outliers and Sample Adjustment

An exploratory data analysis of PMR scores confirms the presence of significant outliers in the notarial distribution. Countries such as the United States and Sweden display extremely low PMR scores that are not comparable with those of civil law notaries.

Costa Rica, although adopting a Latin-type notarial system, also raises consistency issues with OECD definitions because the notarial function is legally reserved to lawyers. Applying standard statistical tools, such as Tukey’s fences based on the interquartile range, these countries fall clearly outside the lower bounds of the civil law notarial distribution. Once these units are excluded, the remaining sample exhibits a much narrower dispersion, with a reduced gap between minimum and maximum values and a substantially higher average score. This adjustment has

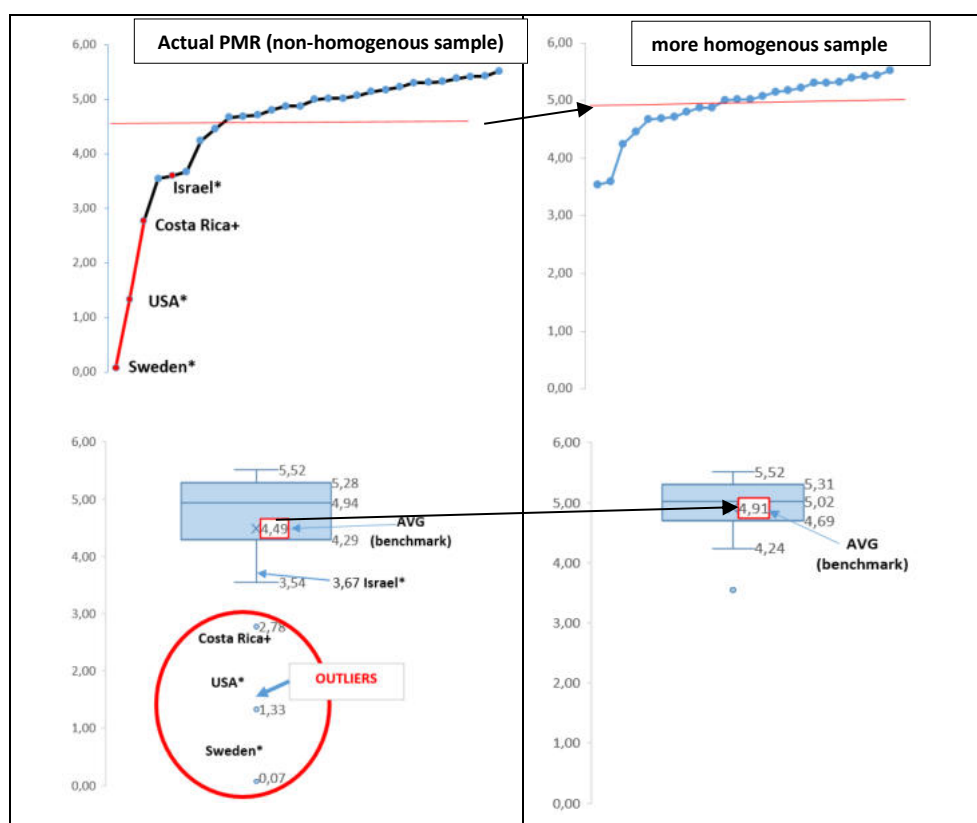
agreement between spouses, made before the marriage. Actions that only a notary may perform. (<https://main.knesset.gov.il/>)

¹⁵ Among the requirements to be a notary public in Costa Rica: “They must have a law degree and must be incorporated into the Costa Rica Bar Association for at least two years” (Codigo notarial: CAPÍTULO II, Requisitos e impedimentos para ejercer el notariado público. Artículo 3.- Requisitos. Para ser notario público y ejercer como tal, deben reunirse los siguientes requisitos: *..omissis..*: c) Ser licenciado en Derecho, con el postgrado en Derecho Notarial y Registral, graduado de una universidad reconocida por las autoridades educativas competentes; además, haber estado incorporado al Colegio de Abogados de Costa Rica al menos durante dos años y, con la misma antelación, haber solicitado la habilitación para ejercer el cargo.

¹⁶ As indicated at pag. 3 point 2 of the instructions for PMR “*in case a lawyer who also offer notarial services..*” OECD claims that “*..notary is not an independent profession for the purpose of this questionnaire. All answers for the previous update would be marked as sector does not exist ..*”

important implications for interpretation. In the homogeneous sample, the PMR mean increases from about 4.5 to nearly 5, and the standard deviation is more than halved. This indicates that high regulation is a structural and consistent feature of civil law notarial systems rather than an anomaly.

Figure 1 – Notarial PMR score: actual PMR vs more homogeneous sample (OECD countries)



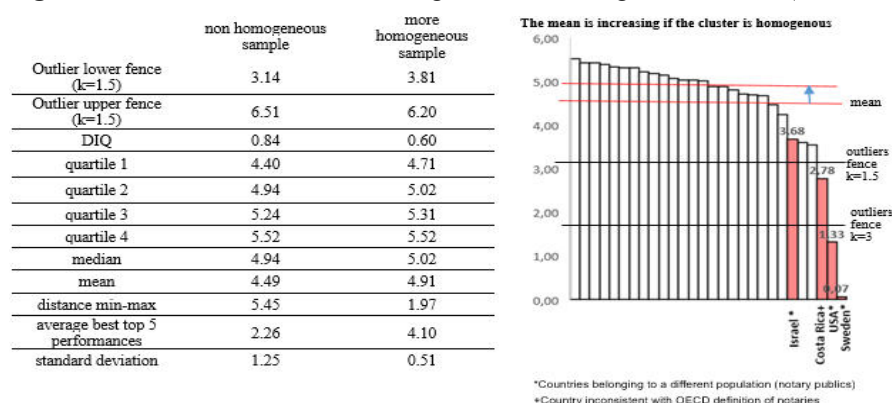
Source: elaboration on OECD countries - *OECD PMR indicator 2018* Notes: (*) units belonging to “public notaries” distribution” (Israel is belonging to a different distribution also by OECD definition) (+) unit belonging to a different distribution by OECD definition

5. Mean versus Median in PMR Interpretation

The OECD commonly uses the arithmetic mean PMR score as a benchmark to identify sectors or countries that are “over-regulated” and therefore candidates for reform. However, in the presence of outliers, the mean becomes a misleading

indicator. It is evident that the adjustment of the sample (eliminating outliers and units coming from a different distribution) will make the results closer to the empirical context. In fact, after the adjustment, the top 5 best performing average will increase from 2.2 to 4.1 (almost the double) and the gap between the maximum and minimum value will reduce from 5.4 to 1.9 (see table in Figure 2).

Figure 2 – Distribution values: inhomogeneous vs homogenous clusters (OECD countries)



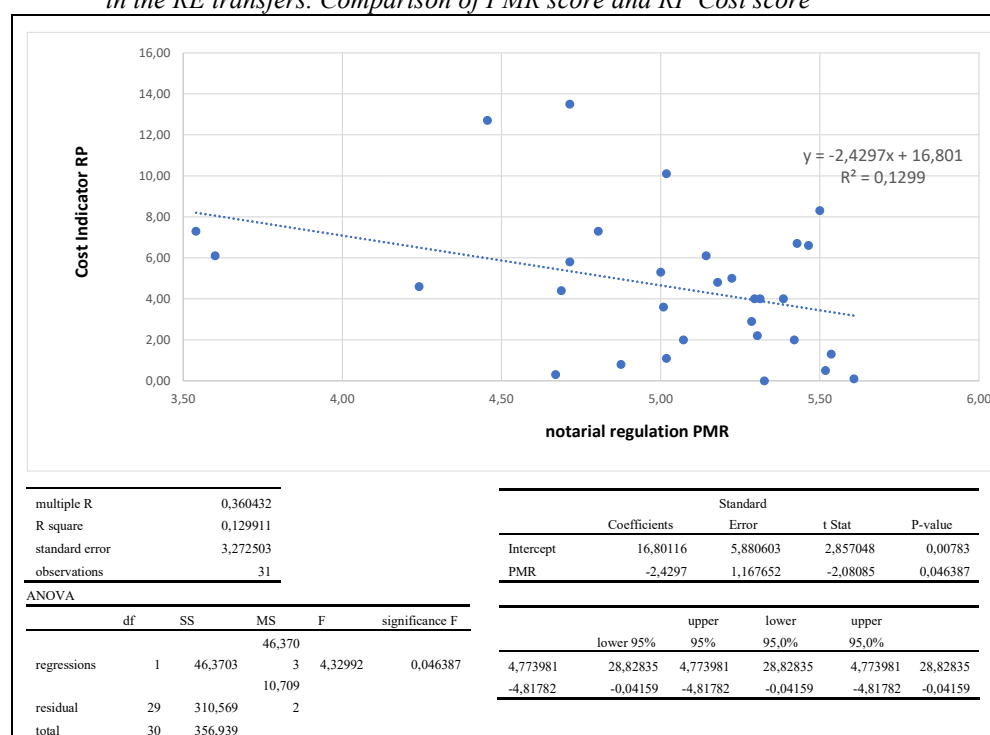
Source: elaboration on OECD countries - PMR indicator 2018

In the notarial case, the median provides a more appropriate measure of central tendency. The median PMR score is systematically higher than the mean, reflecting the fact that the majority of civil law notarial systems cluster around high regulatory values. Using the median as a benchmark would lead to a more accurate interpretation of regulatory needs in the administration of justice and would avoid policy recommendations driven by non-comparable cases.

6. Regulation and Costs: Empirical Evidence

Contrary to the standard PMR narrative, empirical evidence shows an inverse relationship between the level of notarial regulation and the cost of real estate transfers borne by consumers (Figure 4 and 5). Using World Bank Registering Property indicators and PMR data for countries adopting civil law notaries, higher PMR scores are associated with lower transaction costs, shorter completion times, and higher quality outcomes.

Figure 4 – Countries (also including non-OECD countries) adopting civil law notaries in the RE transfers. Comparison of PMR score and RP Cost score



Source: World Bank and PMR indicator 2018

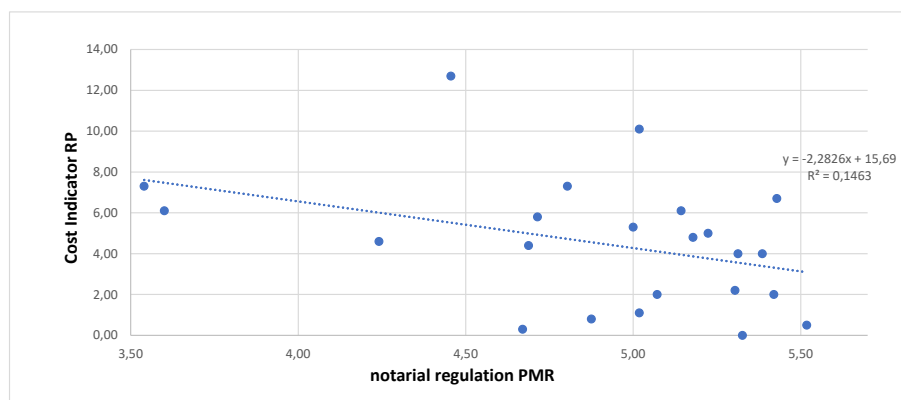
Table 1 – Countries* (analysed by PMR and adopting notaries in RE transactions) divided into clusters according to the RP Cost indicator of the DB report

cluster	OECD and non OECD countries		
		Cost RP	(level of regulation)
Cluster 1 C1 countries where CO < 3	MEDIAN C1	1,10	5,30
	AVERAGE C1	1,20	5,24
	ST.D C1	0,92	0,28
Cluster 2 C2 countries where 3 ≤ CO < 6,5	MEDIAN C2	4,70	5,08
	AVERAGE C2	4,81	4,90
	SD C2	0,83	0,50
Cluster 3 C3 countries where CO ≥ 6,5	MEDIAN C3	7,80	4,91
	AVERAGE C3	9,06	4,87
	ST.D C3	2,56	0,62

index	OECD countries		PMR notaries
MEDIAN C1	0,95		5,19
AVERAGE C1	1,11		5,15
ST.D C1	0,80		0,27
MEDIAN C2	4,90		5,07
AVERAGE C2	5,01		4,85
SD C2	0,76		0,53
MEDIAN C3	7,30		4,80
AVERAGE C3	8,82		4,65
ST.D C3	2,27		0,64

Source: World Bank and PMR indicator 2018 * including non OECD countries (analysed by OECD PMR).

Figure 5 – OECD Countries adopting civil law notaries in the RE transfers. Comparison of PMR score and RP Cost score.



Source: World Bank and PMR indicator 2018.

Table 2 – Inverse relation between Notarial PMR and RE consumer costs (OECD countries).

Indexes of the OECD PMR in the more homogeneous sample (Empirical evidence: PMR correlation with RE consumer costs) *	Consumer cost	PMR notarial regulation (min 0; max 6)	OECD PMR actual benchmark
AVG lowest 5 PMR scores (less regulated countries)	6.20 ↑	4.10 ↓	2.26 (AVG PMR top 5 best performances) According to the actual OECD PMR scheme, low level of regulation is supposed to have (without empirical evidence) benefits in terms of cost and quality of the notarial services
AVG highest 5 PMR score (more regulated countries)	2.64 ↓	5.42 ↑	5.42 (worst performances, see above comments about the top 5 best performances)
lowest PMR score (less regulated country)	7.30 ↑	3.54 ↓	0.07 (best performance, see above comments about the top 5 best performances)
highest score (more regulated country)	0.50 ↓	5.52 ↑	5.52 (worst performance, see above comments about the top 5 best performances)
Average PMR score According to the empirical analysis, if a country is above this OECD AVG, it produces better performances in terms of lower costs and better quality for the consumers)	4.41	4.91	4.49 (threshold for reforms) According to the actual OECD PMR scheme, if a country has a score above the OECD AVG, it is considered too regulated and is encouraged to deregulate

*Further analysis show negative trend of PMR correlation also with time and procedures to complete a Real estate transfer and a positive correlation with the “quality of the real estate transfers” (see Cappiello, 2022).

Regression analyses confirm a statistically significant negative correlation between PMR scores and consumer costs. When countries are grouped according to cost clusters, those with higher levels of regulation systematically display lower average costs. Conversely, countries with lower regulatory scores tend to exhibit higher transaction costs. This evidence completely reverses the OECD benchmark logic.

The evidence illustrated in table 2 completely reverses the OECD benchmark logic. In the homogeneous civil law notarial cluster, the average of the five least regulated countries corresponds to high consumer costs, while the average of the five most regulated countries corresponds to low costs. Being above the PMR average thus appears to be an advantage rather than a signal of inefficiency.

7. Policy Implications

The misinterpretation of PMR scores in the notarial sector stems from a failure to distinguish between regulation that restricts competition for private gain and regulation that enables the provision of public goods. Civil law notaries operate as institutional safeguards, internalising transaction risks and reducing downstream social costs. Using competition-based indicators without accounting for functional differences leads to distorted reform agendas. In the case of notaries, deregulation inspired by PMR benchmarks could undermine legal certainty, increase litigation, and ultimately raise total transaction costs.

8. Conclusions

This paper has shown that the OECD PMR assessment of notarial regulation is biased by the inhomogeneity of the underlying cluster. The inclusion of notaries public and systems inconsistent with OECD definitions produces misleading averages and benchmarks. Once the analysis is restricted to civil law notaries with comparable functions, PMR scores display a homogeneous distribution characterised by high regulatory levels. Empirical evidence demonstrates an inverse relationship between regulation and consumer costs in real estate transactions, as well as a positive association between regulation and quality. These findings challenge the assumption that “less regulation is always better” and suggest that, in the presence of market failure and public goods, higher regulation may enhance efficiency and consumer welfare. For civil law notaries, regulation should therefore be interpreted as an institutional necessity rather than a distortion. Evaluation frameworks should be refined to reflect the specific role of professions operating

within the administration of justice, avoiding inappropriate comparisons and misguided policy recommendations.

References

- CECCARELLI C, GIORGI G. M., GUANDALINI A. 2012. Estimator with Sampling Constraints and Their Effects. *Working Paper*, University of Rome La Sapienza.
- CAPPIELLO A. 2022. OECD PMR indicators for professional services. Civil law notaries as ‘public good’: efficiency and legal protection need higher regulation.n *Rivista Italiana di Economia, Demografia e Statistica*, 78, No. 3, pp. 179-189.
- CAPPIELLO A. 2021. OECD PMR indicators for professional services: are civil law notaries different? *OECD workshop on regulatory barriers to competition in professional services*, 18-19 November, Paris.
- CAPPIELLO A. 2014. World Bank Doing Business Project and the Statistical Methods based on Ranks: the Paradox of the Time Indicator. *Rivista Italiana di Economia, Demografia e Statistica*, Vol. 68, No. 1, pp. 79-86.
- KAPSTEIN E. 1999. Distributive Justice as an International Public Good in Global Public Goods: International Cooperation in the 21st Century, Inge Kaul (ed.) et al. OECD 2018, Product Market Regulation Indicators. Paris.
- WORLD BANK 2018. Doing Business Report. Washington D.C..
- STIGLITZ J., ROSENGARD J. 2015. *Economics of the Public Sector*. Norton.
- TUKEY J. W. 1977. *Exploratory Data Analysis*. Addison-Wesley.

Claudio CECCARELLI, Italian National Institute of Statistics ISTAT
clceccar@istat.it
Antonio CAPPIELLO, Senior Economist CNN economics@live.co.uk

SOCIETÀ E RIVISTA ADERENTI AL SISTEMA ISDS
ISSN ASSEGNATO: 0035-6832
E-ISSN ASSEGNATO: 3103-1757

Direttore Responsabile: CHIARA GIGLIARANO

Iscrizione della Rivista al Tribunale di Roma del 5 dicembre 1950 N. 1864



Associazione all'Unione Stampa Periodica Italiana

TRIMESTRALE

La copertina è stata ideata e realizzata da Pardini, Apostoli, Maggi p.a.m.@tin.it – Roma

Stampato da CLEUP sc
“Coop. Libreria Editrice Università di Padova”
Via G. Belzoni, 118/3 – Padova (Tel. 049/650261)
www.cleup.it

ATTIVITÀ DELLA SOCIETÀ

RIUNIONI SCIENTIFICHE

- XXXVII La mobilità dei fattori produttivi nell'area del Mediterraneo (Palermo, 15-17 giugno 2000).
- XXXVIII Qualità dell'informazione statistica e strategie di programmazione a livello locale (Arcavacata di Rende, 10-12 maggio 2001).
- XXXIX L'Europa in trasformazione (Siena, 20-22 maggio 2002).
- XL Implicazioni demografiche, economiche e sociali dello sviluppo sostenibile (Bari, 15-17 maggio 2003).
- XLI Sviluppo economico e sociale e ulteriori ampliamenti dell'Unione Europea (Torino, 20-22 maggio 2004).
- XLII Sistemi urbani e riorganizzazione del territorio (Lucca, 19-21 maggio 2005).
- XLIII Mobilità delle risorse nel bacino del Mediterraneo e globalizzazione (Palermo, 25-27 maggio 2006).
- XLIV Impresa, lavoro e territorio nel quadro dei processi di localizzazione e trasformazione economica (Teramo 24-26 maggio 2007).
- XLV Geopolitica del Mediterraneo (Bari, 29-31 maggio 2008).
- XLVI Povertà ed esclusione sociale (Firenze 28-30 maggio 2009).
- XLVII Un mondo in movimento: approccio multidisciplinare ai fenomeni migratori (Milano 27-29 maggio 2010).
- XLVIII 150 anni di Statistica per lo sviluppo del territorio: 1861-2011. (Roma 26-28 maggio 2011).
- XLIX Mobilità e sviluppo: il ruolo del turismo. (San Benedetto del Tronto, 24-26 maggio 2012).
- L Trasformazioni economiche e sociali agli inizi del terzo millennio: analisi e prospettive (Università Europea di Roma, 29-31 maggio 2013).
- LI Popolazione, sviluppo e ambiente: il caso del Mediterraneo (Università Federico II di Napoli, 29-31 maggio 2014).
- LII Le dinamiche economiche e sociali in tempo di crisi (Università Politecnica delle Marche, 28-30 maggio 2015).
- LIII Mutamento economico e tendenze socio-demografiche tra sfide e opportunità (Università degli Studi Internazionali di Roma, 26-28 maggio 2016).
- LIV Mobilità territoriale, sociale ed economica: modelli e metodi di analisi (Università degli Studi Internazionali di Catania, 25-26 maggio 2017).
- LV Coesione sociale, welfare e sviluppo equo e sostenibile (Università degli Studi dell'Insubria, Varese 24-25 maggio 2018).
- LVI Benessere e Territorio: Metodi e Strategie (Università Politecnica delle Marche, Ascoli Piceno 23-24 maggio 2019).

- LVIII Tra marginalità e sviluppo. La sfida della sostenibilità in una prospettiva mediterranea (Università LUMSA, Palermo, 26-27 maggio 2022).
- LIX Aspetti economici e sociali dell'invecchiamento demografico (Università degli Studi di Napoli Federico II Napoli, 25-26 maggio 2023).
- LX Salute, ambiente e disuguaglianze: istituzioni, imprese e società (Università degli studi di Milano – Bicocca & LIUC - Università Cattaneo, Milano & Castellanza (VA), 22-24 maggio 2024).
- LXI Povertà e disuguaglianze: popolazioni e territori nell'era delle transizioni (Istituto Nazionale di Statistica e Università degli Studi di Roma Tre, Roma, 28-30 maggio 2025).