VOLUME LXXIX – N. 4 OTTOBRE – DICEMBRE 2025

RIVISTA ITALIANA DI ECONOMIA DEMOGRAFIA E STATISTICA

Volume stampato grazie al contributo liberale della Banca d'Italia (anno 2024)

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VOLUME FUORI COMMERCIO

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WELL-BEING: A BETA-DISTRIBUTION-BASED APPROACH

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Abstract. In recent years, there has been growing attention to evaluating well-being at local level. Along this line, since 2013, the Italian Institute of Statistics (ISTAT) annually releases a dashboard of indicators to measure the so-called Equitable and Sustainable Well-Being (BES) for Italy, its Macro-area (NUTS-1) and regions (NUTS-2). More recently, the ISTAT provides BES indicators at local level (NUTS-3), related the 107 Italian provinces and metropolitan cities.
The aim of the paper is to provide a more in-depth analysis of territorial inequalities and divergences across the Italian provinces. Specifically, the paper represents the first attempt to synthetize the main domain of BES (economic, social and environmental among others) through the parameters underlying the Beta distribution of the multidimensional well-being. The parameters - mode and concentration- associated with the Beta distribution and used as a proxy of territorial disparities identify a high degree of heterogeneity not only between the Northern and Southern Italian provinces, but also among adjacent provinces.

1. Introduction

In recent years, there has been considerable interest among researchers and policymakers in assessing well-being. Traditionally, per capita Gross Domestic Product (GDP) has been used as an indicator of societal well-being, but it has limitations as it mainly measures the economic aspect of a country and does not fully capture overall welfare. Initiatives like the European Commission's "Going beyond GDP" and influential reports (Kolm, 1977; Atkinson *et al.*, 1982; Stiglitz, 2009) have highlighted that income alone cannot adequately represent the complexity of well-being.

Research has shown that well-being includes more than just material wealth, encompassing subjective elements such as perceptions of living standards (Ivaldi *et al.*, 2016; Bleys *et al.*, 2012; Noll, 2002; Sen, 1980).

As a result, it is widely recognized that measuring well-being requires consideration of both monetary and non-monetary factors.

For instance, the OECD suggests that well-being assessments should cover aspects like employment, housing, health, work-life balance, education, social connections, civic engagement, governance, environment, personal security, and subjective well-being.

Well-being is essentially a “complex system” composed of numerous components (Greco *et al.*, 2019). In the literature, two approaches address the multidimensionality of well-being: the composite index approach and the dashboard of indicators approach (see Hoffmann *et al*., 2008).

While, a dashboard provides a detailed array of single indicators across various dimensions of well-being, a composite index consolidates information from several dimensions into a single value.

The benefits of composite indices are clear as they provide a unidimensional measurement of well-being (Mazziotta and Pareto, 2016). True to its nature, a composite index is usually built to ‘tell a story’. It is, thus, ideally suited to identify and bring attention to a possibly latent phenomenon (Kuc-Czarnecka *et al*., 2020).

In this context, following Polinesi *et al.* (2024) we consider the multidimensional well-being as a Beta-distributed random variable within the interval (0,1), characterized by unknown parameters α and β.

It is well known that concave beta distributions, with shape parameters greater than 1, can be parametrized in terms of mode and concentration. We use this parametrization to compute a non-compensatory composite indicator (see Mazziotta and Pareto, 2018 for details).

The composite indicator is calculated for each province and for the years 2019 and 2022, capturing changes in multidimensional well-being over time, particularly before and after the onset of the Covid-19 pandemic.

The aim is to deepen understanding of the spatial distribution of the multidimensional well-being index at the local level in Italy, with a focus on Italian provinces. This insight can assist policymakers in directing resources to the most disadvantaged areas.

Moreover, we introduce a new measure, the Bivariate Beta Distribution Impact (BBDI for short) measure. This metric evaluates the contribution of individual regions (or provinces) to overall well-being, offering a new perspective on local disparities.

These two levels of analysis reveal that the traditional Italian North vs. South divide is clear.

The proposed approach lies within the framework of composite indicator representing a novelty in the literature, since to the best of our knowledge, this is the first time that multidimensional well-being is evaluated by means of a family of probability function.

Indeed, few papers on applying beta distribution focus exclusively on poverty and inequality measures (see for example Chotikapanich *et al*., 2012; Anderson *et al*., 2014; De Nicolò *et al.*, 2024).

The remainder of the paper is organized as follows. Section 2 introduces data and methodology used to construct the composite index of well-being for Italian provinces. It also discusses the measure to evaluate the regional contribution on Italian well-being. Section 3 illustrates the empirical results. Finally, Section 4 draws some conclusions.

Table 1 – *List of the selected elementary indicators and their corresponding pillar*.

Pillar	Indicator	Unit
Economic well-being	Employment rate (20-64 years old)	Percentage
	Youth employment rate (15-29 years old)	Percentage
	Average annual per capita income (pensions)	Euro
	Mobility of graduates (25-39 years old)	For 1,000 inhab.
	Non-partecipation rate	Percentage
Social well-being	Life expectancy at birth	Years
	Children who benefted of early childhood services	Percentage
	Participation in the school system of children	Percentage
	People with at least upper secondary education	Percentage
	People having completed tertiary education	Percentage
	Transition to university	Cohort specific rate
	Participation in long-life learning	Percentage
	Non-profit organizations	For 10,000 inhab.
	Women's political representation in municipalities	Percentage
	Young people's political representation	Percentage
	Municipalities: collection capacity	Percentage
	Hospital beds in high-care wards	For 10,000 inhab.
	Employees in cultural enterprises	Percentage
	Public transport network	Seat-*km* per capita
	Hospital beds	For 10,000 inhabitants
	Age-standardized avoidable mortality rate	For 10,000 inhab.
	Age-standardised cancer mortality rate	For 10,000 inhab.
	Age-standardised mortality rate for dementia	For 10,000 inhab.
	NEET	Percentage
	Inadequate numerical competence	Percentage
	Inadequate literacy skills competence	Percentage
Environmental well-being	Availability of urban greenery	m^2 per capita
	Municipal waste separately collected	Percentage
	Electricity from renewable sources	Percentage
	Landfll of urban waste	Percentage
	Consecutive dry days	Days
	Municipal waste produced	*Kg* per capita
	Density and importance of musems' heritage	Per 100 km^2
	Agritourism businesses	Per 100 km^2
	Density of historic greenery	Per 100 m^2

2. Data and methods

In 2022, as part of the "BES at local level" project, ISTAT published a set of 70 elementary indicators across 11 domains to describe the well-being of the 107 Italian provinces.

For our study, we use available data from the years 2019 and 2022 to monitor the well-being of these territories and belonging region over time. Specifically, the analysis involves 40 elementary indicators described in Table 1.

Let us go into the details of our framework. We consider a complex phenomenon and a cross-sectional dataset of variables (or indicators), $X_1, X_2, \ldots, X_k$, observable over a population of n units. We denote the values of the variables observed across the n units as x^i_j, where i = 1, 2, …, n and j = 1, 2, ..., k.

We model the multidimensional well-being as a Beta distributed random variable with support in the interval (0,1). To this end, we normalize the variables x^i_j according to the min-max approach.

Specifically, these scaled variables are defined as:

$$z_j^i = \frac{x_j^i - \min_i\left(x_j^i\right)}{\underset{i}{\mathrm{m}}\left(x_j^i\right) - \min_i\left(x_j^i\right)}, i = 1,2, \ldots, n,\ j = 1,2, \ldots, k. \tag{1}$$

If the j-th indicator has negative polarity, the complement of z_j^i with respect to 1 is computed[1]. This normalization procedure ensures that all indicators are positively correlated with the phenomenon we aim to measure.

Let z_j^i the realizations of $Z \sim Beta(\alpha, \beta)$, where $Beta(\alpha, \beta)$ denotes the Beta distribution of unknown parameters α, β > 0. The probability density function of Z is:

$$f(z, \alpha, \beta) = \frac{z^{\alpha-1}(1-z)^{\beta-1}}{B(\alpha,\beta)},\ 0 < z < 1, \tag{2}$$

where $B(\alpha, \beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha,\beta)}$ and Γ is the Gamma function.

The shape of the Beta distribution varies with parameters α and β. For example, when both parameters are greater than 1, the distribution can be reparametrized in terms of the mode ω (i.e., the most likely value of the distribution) and concentration κ (i.e., absence of variability). Formally:

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[1] The polarity represents the sign of the relation between the indicator and the phenomenon to be measured. We have a positive polarity if the individual indicator represents a dimension considered positive, that is, increasing variations of the indicator correspond to positive variations of the phenomenon. Similarly, we have a negative polarity if it represents a dimension considered negative.

$$0 < \omega = \frac{\alpha-1}{\alpha+\beta-2} < 1 \tag{3}$$

$$2 < k = \alpha + \beta < +\infty \tag{4}$$

This parameterization provides a more intuitive understanding compared to the original parameters[2].

The parameters of the well-being distribution are estimated at unit level, by applying the maximum likelihood approach to the scaled variables associated z_j^i, and the parameters of well-being α and β are then obtained by computing the sample mean of all estimates at unit levels.

Consequently, we have:

$$\alpha = \frac{1}{n}\sum_{i=1}^{n} \alpha_i, \tag{5}$$

$$\beta = \frac{1}{n}\sum_{i=1}^{n} \beta_i. \tag{6}$$

Thus, the unit-level parameters are weighted averages of their population-level counterparts. Notably, values of α and β estimated in Eqs. (5) and (6) closely align with those obtained through the maximum likelihood approach at the overall level, ensuring the robustness of the results[3].

In the following analysis, we examine variations in both mode and concentration by individually excluding each unit to assess its impact on well-being across Italy.
Specifically, we first estimate the parameters α and β of the Beta distribution associated with the overall population made by all units, then we estimate the parameters α_i^* and β_i^* of the Beta distribution associated with the population obtained eliminating the i-th unit from the overall population.
Therefore, the Bidimensional Beta Distribution Impact measure (BBDI measure for short) for each unit i can be defined as the two-dimensional vector containing the variation associated with mode and concentration, as follows:

$$\left[\frac{\omega-\omega_i^*}{\omega_i^*}; \frac{k-k_i^*}{k_i^*}\right], \quad i=1,2,...,n, \tag{7}$$

where ω_i^* and k_i^* are computed using Eqs. (5), (6) with α_i^* and β_i^*.

[2] We refer to Nadarajah and Kotz (2007) for a review of the properties and the variations of Beta distributions as well as their relationship to other distributions.
[3] The difference between the parameters obtained through sample mean and maximum likelihood estimation is 0.06 for the value of α (1.75 vs 1.81) and 0.02 for the value of β (1.50 vs 1.52).

Then, the non-compensatory composite index of well-being is computed for the units over the study period. Formally, the composite index for the i-th unit is defined as:

$$I_i = \omega_i - \frac{1}{k_i}, \quad \text{i=,2,...,n,} \tag{8}$$

where $\frac{1}{k_i}$ represents the penalty due to the dispersion level, i.e. the extent to which the values of the elementary indicators deviate from the mode. Notably, as $k_i \rightarrow \infty$ (indicating maximum concentration) the value of the index depends solely on ω_i.

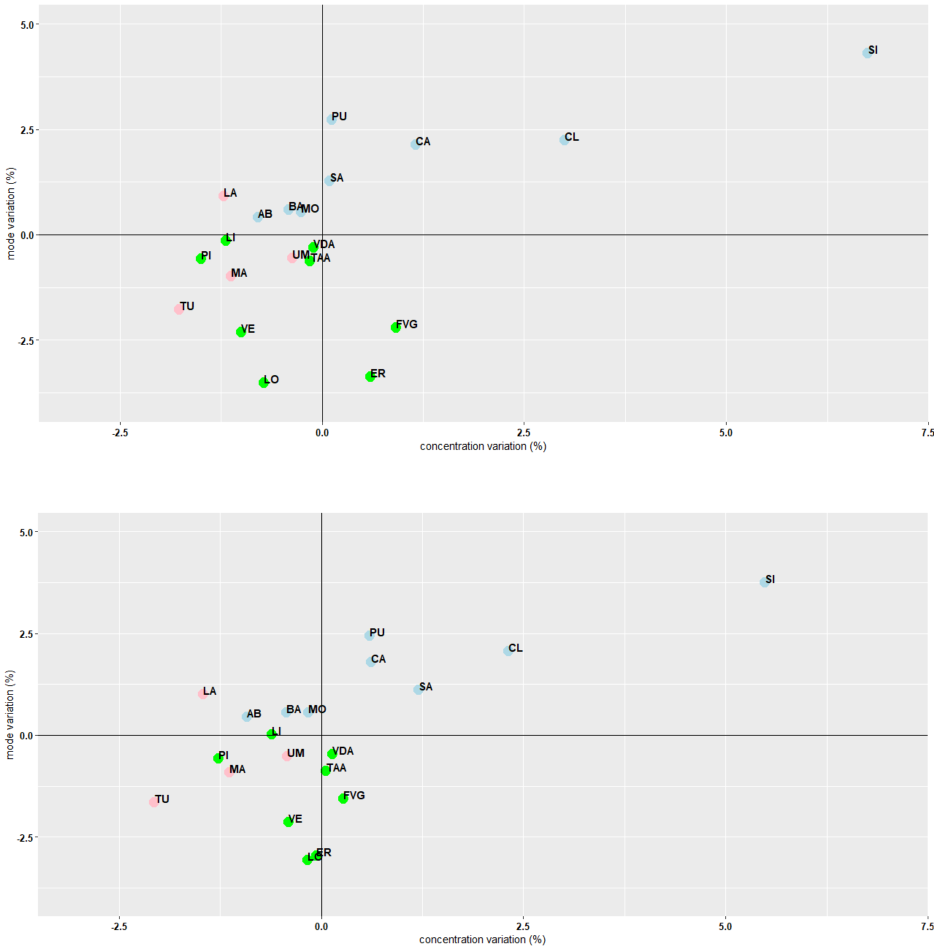
The quantity in (5) ranges between -1/2 and 1. It assigns -1/2 to the unit i associated with minimum concentration, k_i = 2, and mode equal 0 (i.e., the worst case) and 1 when the concentration is maximum, $k_i \rightarrow \infty$, and mode equal 1 (i.e., the best case).

Therefore, Eq. (8) as outlined in Mazziotta and Pareto (2016) decomposes the score of each i-th unit in two parts: mode level (ω_i) and penalty $\left(\frac{1}{k_i}\right)$. The penalty is a function of the indicators' dispersion in relation to the mode value and it is used to penalize the units. The aim is to reward units that, while having the same mode, exhibit greater balance among the indicator values.

3. Results

In this section, we present the results for changes in mode and concentration, as well as the well-being composite index defined in Eq. (8), separately for the two years considered. First, following Eq. (7), we compute the variation in mode and concentration at the regional level (Figure 1) and the variation in mode at the provincial level (Figure 2). Finally, we illustrate the spatial distribution of the well-being index across provinces (Figure 3).

Figure 1 – *Mode and concentration variation by eliminating each region at a time for the years 2019 (top) and 2022 (bottom). Colours indicate Italian macro-areas: South (light-blue), pink (Centre) and green (North).*



Note from Figure 1 that the Southern provinces - Puglia, Sardinia, Campania, Calabria and Sicily - if removed from the analysis of multidimensional well-being, would lead to a concentration of Italian multidimensional well-being at higher levels as they are associated with positive variation of mode and concentration (first quadrant). Conversely, Northern provinces contribute positively to Italian well-being (fourth quadrant). For simplicity, relatively to provinces we show only the mode variation (Figure 2).

Figure 2 – *Spatial distribution of mode variation for the years 2019 (left) and 2022 (right). Green (red) colour indicate positive (negative) impact on Italian well-being.*

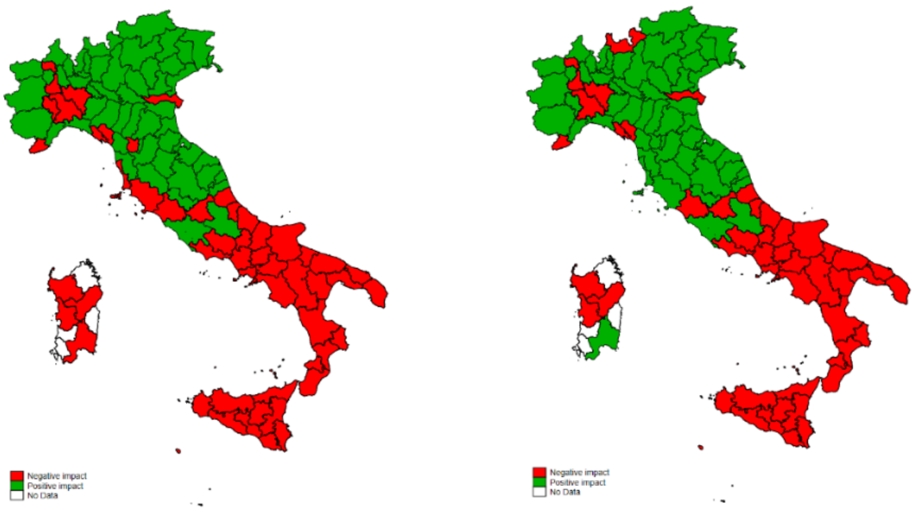


Figure 2 highlights that, from 2019 to 2022, the number of provinces experiencing a positive variation in mode increases. However, a clear divide between the North and South persists, with some exceptions observed in Lombardy.

Figure 3 – *Spatial distribution of well-being for the years 2019 (left) and 2022 (right). Darker colors indicate higher level of well-being.*

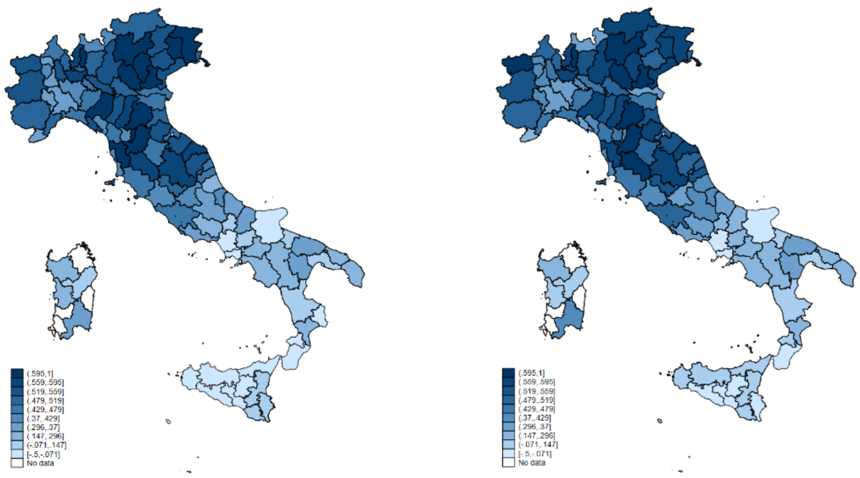


Figure 3 illustrates a geographical representation of how the multidimensional well-being index is distributed across the Italian provinces over the years 2019 and 2022. Its values are plotted following a colour scale with darker colours representing higher levels of well-being. A distinct divide between northern and southern provinces is evident, with a few notable exceptions.

Overall, the well-being index shows a slight increase in 2022 compared to 2019, potentially reflecting the impact of social protection policies aimed at supporting the most vulnerable populations during the pandemic (Polinesi *et al.*, 2023).

Table 2 – *Ranking of Italian provinces based on the value of the composite index for the years 2019 and 2022 with brackets indicating the change in position over time.*

Worst ten		Top ten	
2019	2022	2019	2022
Crotone	Crotone	Trieste	Trieste
Enna	Enna	Firenze	Firenze
Agrigento	Sud Sarde (92)	Prato (54)	Trento
Napoli	Agrigento	Bologna	Lecco
Caltanissetta	Foggia (96)	Pordenone (14)	Padova
Trapani (94)	Napoli	Lecco	Bologna
Vibo Valentia (89)	Caltanissetta	Verona	Verona
Messina (93)	Siracusa (95)	Parma (15)	Aosta (24)
Palermo (97)	Reggio Calabria	Trento	Siena (14)
Reggio Calabria	Caserta (97)	Padova	Udine (12)

Table 2 presents the rankings of the ten best and worst provinces based on their well-being levels, highlighting a clear divide between the North and South. In the lower part of the rankings, despite minor changes in positions, the bottom ten provinces remain largely consistent across the two years considered.

Conducting a territorial analysis of well-being is crucial for identifying the geographical areas most in need and for better directing available economic resources.

4. Conclusions

This paper contributes to the analysis of well-being across Italian provinces and regions by modeling multidimensional well-being as a Beta-distributed random variable. It develops a multidimensional index to track well-being over time, focusing on two key measures: mode and concentration.

The findings indicate that Southern provinces experience greater losses in well-being, as reflected by lower composite index values, and that Southern regions have a negative impact on overall Italian well-being.

While the aggregate index reveals no significant differences in well-being levels before and after the pandemic, further analysis of individual pillars or specific indicators within these pillars could yield different insights. Future research could explore these dimensions in greater detail.

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HEALTH, WELL-BEING AND QUALITY OF LIFE SATISFACTION: GENDER DIFFERENCES IN ITALIAN REGIONS[1].

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Abstract. Gender differences are an inherent part of human existence. However, beyond biological disparities, social structures have historically established gender-based roles, distinct societal functions, and varying social status across genders. The gender gap affects everyone: our families, communities, workplaces, societies and this influenced women health, well-being and quality of life. The EU has made significant progress in terms of gender equality in recent decades. A European-level tool that monitors disparities between men and women in different member countries is the Gender Equality Index, developed by the European Institute for Gender Equality (EIGE) in 2013. Starting from the analysis proposed by EIGE, the aim of this work is to represent gender differences in Italian regions in 3 domains: Health, Well-being and Quality of life. Using a multisource approach, simple indicators, both objective and subjective, were chosen for each domain. A total of 14 indicators were calculated, starting from Multipurpose survey on households "Aspects of daily life", Life tables and Multipurpose Survey: time use (all by Istat). The analyses were carried out with a model based on the use of multivariate analysis techniques and the construction of synthetic indices, one for each domain, capable of providing an overall view, which cannot be obtained by considering individual elements separately. The results show for Quality life satisfaction and Health a gap in favour of men, except for some territorial differences; instead, women reveal a better lifestyle, so the results of Well-being domain are to the advantage of them.

1. Introduction

Gender is an integral component of every aspect of the economic, social, daily and private lives of individuals and societies, and of the different roles ascribed by society to men and women. There is an increasing tendency worldwide to define quantifiable targets for equality and to measure each country's distance from them.

No country in the world has achieved gender equality yet, and international studies show that closing the gender gap will still take a long time, especially in some

[1] Authors contributions: Daniela Fusco paragraph 4; Paola Giordano paragraph 1 and Abstract; Maria A. Liguori paragraph 3 and related subparagraphs; Margherita M. Pagliuca paragraph 2 and related subparagraphs.

parts of the world where gender differences are still highly marked. The long and tremendous experience of COVID-19 has further prolonged this process; it has slowed down the reduction of gender gaps, more in some domains than in others, showing the fragility of the results already achieved, the weakness of gender policies, and the need to reinforce them (Di Bella *et al*., 2023).

According to the World Health Organization, despite living on average longer than men, women spend 25% more of their lives in poor health: activity limitations are particularly present in women's additional years of life. In the EU, men live on average 82% of their years without disability, while this percentage is lower among women, at 78%. Compared to men, older women score significantly lower on most indicators of subjective well-being (WHO, 2016).

Currently, on average in Europe, women's hourly wages in the EU are 16 percent lower than men's, pensions are 30.1 percent lower, and the difference between female and male employment rates is 11.6 percent (EC, 2020). Policy interest in achieving gender equality has become manifest at the European level with the 2020-2025 strategy, which sets out policy goals and actions to make concrete progress on gender equality in member states.

Over the last century, the issue of gender equality has become increasingly central to the political agenda of national and local governments, international organizations, and social movements. The European Union has been shown to be particularly sensitive to this issue, as evidenced by numerous documents. In 2013, the European Institute for Gender Equality has developed a tool that monitors disparities between men and women in different member countries, the so called Gender Equality Index.

In 2023, with 68.2 points out of 100, Italy ranks 13th in the EU on the Gender Equality Index. Its score is 2.0 points below the score for the EU as a whole. Since 2010, Italy’s score has increased by 14.9 points, which is the largest increase in overall score among all the Member States, resulting in the biggest rise in the ranking by eight places. This change occurred mainly due to improvements in the domain of power (+ 37.5 points). In any case, according to this Index, except for health, where Italy ranks 9th among all member states, and power, in all domains of the index Italy's performance is lower than in Europe (on average) (EIGE, 2023).

Moreover, Gender equality represents n. 5 of SDGs goals: achieve gender equality and empower all women and girls. Gender equality by 2030 requires urgent action to eliminate the many root causes of discrimination that still curtail women’s rights in private and public spheres. The study of gaps cannot be separated from an analysis that highlights the differences that characterize different geographical areas of the country.

Given the scope of analysis, the effects of which also depend on policymakers at both the national and local levels, it is important to focus on the regional geographic level to understand what gender inequality looks like in Italy today. What is more, it is believed that the still persistent lack of official studies emphasizing this spatial level makes it necessary to fill this gap. Starting from the domains proposed by the GEI, integrated with some of the indicators of the Sustainable Development Goals (SDGs), in order to measure the changes in gender inequalities with the arrival of the pandemic and how they differ in the Italian regions (Fusco *et al*., 2023), this work intends to identify a measurement of the phenomenon, from 2018 to 2021, in 3 domains: Health, Well-being and Quality of life satisfaction.

2. Methodology

2.1. Data

The aim of this work is to analyse gender differences in Italian regions in three domains: Health, Well-being and Quality of life satisfaction. Each domain is the synthesis of a set of elementary indicators (Fusco *et al*., 2023). Developing a synthetic measure is a challenging process that necessitates making a multitude of crucial decisions across conceptual, analytical, and empirical dimensions.

For each domain, a survey of sources was carried out in order to identify the most suitable indicators to represent the phenomenon. All the analysed data come from institutional surveys[2].

Therefore, the elementary indicators were chosen on the basis of data availability of statistical data at regional level; data timeliness to ensure an adequate time comparison; thematic appropriateness feasibility (the availability of obtaining and processing updated data in a simple way has been taken into account). The analysis was based on the last 5 years (from 2018 to 2022).

This analysis highlights how overall indicators vary between gender and over time, providing a detailed picture of gender differences in various domains.

2.2. Method

In order to synthesize each domain in a single composite index, we use a formative measurement model that is the indicators are considered as causing the gender gap (rather than being caused by it, such as in the reflective approach), so,

[2] The sources used for this study are: Istat, Multipurpose survey on households “Aspects of daily life”; Istat, Life tables; Istat, Multipurpose Survey: time use.

the correlations between basic indicators are not very relevant. According to this approach, indicators are not interchangeable.

Gender equality is based on the existence of a gender role, so the aim of the indicators is to establish the relative situation of men and women and the changes that have occurred at different moments in time. Therefore, In line with previous studies (e.g., Bericat, 2012; Klasen, 2006; Cascella *et al.,* 2022) we didn't use absolute levels of indicators, but we have calculated female-to male ratios (R), because they can be interpreted as a measure of the gender gap. The ratios measure the level attained by women in relation to the status attained by men in this way it is possible to capture the different forms of inequality rather than the single levels. A value R = 1 indicates perfect parity; a value 0 < R<1 indicates inequality favourable to men; and a value R > 1 indicates inequality favourable to women (Permanyer, 2010; Bericat, 2012).

Until now, some examples of indices that have used ratios are the Gender Equality Index developed by European Institute for Gender Equality (EIGE) and the Extended Regional Gender Gaps Index (eRGGI) (Cascella *et al*., 2022).

We apply the Adjusted Mazziotta–Pareto Index (AMPI) which allows spatial and time comparisons across units to be made. The AMPI is a non-compensatory (or partially compensatory) composite index that allows comparability of the data across units and over time (Mazziotta and Pareto, 2016). It is used by the Italian National Institute of Statistics for measuring ‘‘Equitable and Sustainable Well-being’’ in Italy. It is based on a non-linear function which, starting from the arithmetic mean, introduces a penalty for the units with unbalanced values of the indicators. Individual indicators are normalized by a re-scaling according to two ‘goalposts’, i.e., a minimum and a maximum value which represent the possible range of each variable for all time periods and for all units. Such type of normalization allows to perform absolute comparisons over time.

Given the original matrix X_{ij}, where i=1,...,n are the units of analysis (the Italian regions) and j=1,..,m are the basic indicators, we calculate the normalized matrix $R = \{r_{ij}\}$ as follows:

$$r_{ij} = \frac{(x_{ij} - MIN_{x_j})}{(MAX_{x_j} - MIN_{x_j})} * 60 + 70 \qquad (1)$$

where x_{ij} is the value of the indicator j in the unit i and MIN_{x_j} and MAX_{x_j} are the “goalposts” for the indicator j. If the indicator j has negative ‘polarity’, the complement of (1) with respect to 200 is calculated. To facilitate the interpretation of results, the ‘goalposts’ can be fixed so that 100 represents a reference value (e.g., we set the value of Italy equal to 1 in 2018). A simple procedure for setting the 'goalposts' is the following.

Let INF_{x_j} and SUP_{x_j} be respectively the overall minimum and the maximum values of indicator j across all regions and all time periods considered, and REF_{x_j} be the reference value for indicator j. Then the "goalposts" are defined as:

$$\begin{cases} MIN_{x_j} = REF_{x_j} - \Delta \\ MAX_{x_j} = REF_{x_j} + \Delta \end{cases}$$

where $\Delta = (SUP_{x_j} - INF_{x_j})/2$. The normalized values will fall approximately in the range (70; 130), where 100 represents the reference value.

Denoting with M_{r_j}, S_{r_j} and cv_i respectively, the mean, standard deviation and coefficient of variation (S_{r_j}/M_{r_j}) of the normalized values of the unit i, the generalized form of AMPI is given by:

$$AMPI_i^{+/-} = M_{r_j} \pm S_{r_j} cv_i \tag{2}$$

The sign ± depends on the type of phenomenon considered and, therefore, on the direction of the elementary indicators: if the composite index is 'positive', i.e., increasing values of the index correspond to positive variations of the phenomenon then $AMPI^-$ is used; on the contrary, if the composite index is 'negative', i.e., increasing values of the index correspond to negative variations of the phenomenon, then $AMPI^+$ is used. The AMPI decomposes the score of each unit in two parts: mean level (M_{r_j}) and penalty $(S_{r_j} cv_i)$. The penalty is a function of the indicators' variability in relation to the mean value ('horizontal variability') and it is used to penalize the units. The aim is to reward the units that, mean being equal, have a greater balance among the indicators values.

3. Results

The three selected domains (Quality of Life Satisfaction, Well-being and Health) were explained through 14 indicators.

The values of indicators and indices for each domain will be presented in the following paragraphs.

3.1. Domain Quality of life satisfaction

In the area of Quality of life satisfaction, all national indicators for men exceed those for women. The indicators in which the greatest gender differences are recorded are Positive judgement of future perspectives and Leisure time satisfaction; the lowest differences are recorded in Satisfaction with family relations indicator.

In 2021, due to a probable COVID-19 effect, Leisure time satisfaction, Satisfaction with family relations, and Satisfaction with friends relations worsen, both for men and women (Table 1).

Table 1 – *Indicators of Quality of life satisfaction. Values for Italy by gender and by years (2018-2022).*

year	Positive judgement of future perspectives		Leisure time satisfaction		Life satisfaction		Satisfaction with friends relations		Satisfaction with family relations	
	female	male	female	male	female	male	female	male	female	male
2018	27,2	31	64,6	68	40,1	42,8	22,8	23,7	33,1	33,4
2019	28,3	32	66,3	69,9	42	44,6	22	24,1	32,8	34
2020	26,9	30,5	67,5	71	43,1	45,5	21,9	23	32,7	33,2
2021	30	34	54,3	59	44,3	47,7	18	19,4	31,1	32,1
2022	27,9	31,1	63,5	67,9	44,9	47,7	20,5	22,7	31,9	33,3

Table notes: authors' elaboration

The synthetic index values in Table 2 show a different situation between regions and years. Although for this domain, the orientation of the indicators is in favour of males: almost all values have an index value below 100.

The only two exceptions are Molise and Valle d'Aosta in 2021. In Molise, females report higher satisfaction than males in terms of Positive judgment of future perspectives, Satisfaction with friendships, and Life satisfaction. In Valle d'Aosta, this trend is observed for Positive judgment of future perspectives and Life satisfaction.

Table 2 – *Regional synthetic Index of Quality of life satisfaction. Years 2018-2022.*

Index	**2018**	**2019**	**2020**	**2021**	**2022**
Piemonte	92,0	95,0	87,6	92,6	87,7
Valle d'Aosta/Vallée d'Aoste	87,2	94,3	86,6	103,6	88,0
Lombardia	95,7	92,1	89,4	78,4	88,7
Trentino-Alto Adige/Südtirol	97,8	94,2	93,7	94,7	97,5
Veneto	90,9	82,5	95,5	88,6	81,3
Friuli-Venezia Giulia	82,7	95,1	86,6	79,4	86,0
Liguria	87,4	92,4	89,5	85,9	88,9
Emilia-Romagna	91,2	86,5	92,9	91,9	94,6
Toscana	88,3	92,9	88,8	89,6	86,0
Umbria	72,7	77,0	84,7	88,7	89,7
Marche	89,8	87,0	98,4	88,1	83,7
Lazio	87,0	87,4	92,9	85,2	87,0
Abruzzo	81,2	84,0	85,8	93,3	83,6
Molise	89,5	76,0	84,1	101,3	72,0
Campania	92,0	83,9	92,0	86,4	84,7
Puglia	80,7	88,9	82,1	92,7	89,8
Basilicata	91,6	89,5	89,2	63,8	67,3
Calabria	86,1	88,8	89,3	91,1	90,9
Sicilia	86,8	82,4	86,3	83,2	85,9
Sardegna	76,8	87,1	85,1	81,8	94,3

Table notes: authors' elaboration

In 2022, no region achieves parity in this domain. The highest value of the index is that of Trentino-Alto Adige (97.5), the lowest that of Basilicata (67.3).

3.2. Domain Health

As expected, the Health domain is very linked to the Covid-19 pandemic: in 2020 Life expectancy at birth decreased, especially for females; Mental health index worsened in 2021 and Healthy life expectancy at birth worsened for females and the following year for males. As Table 3 shows, the indicators in which there are the greatest gender differences in favour of men are the Mental Health Index and Healthy life expectancy at birth, while Life expectancy at birth is consistently higher.

Table 3 – *Indicators of Health. Values for Italy by gender and by years (2018-2022).*

year	Mental health index		Life expectancy without limitations at age 65		Life expectancy at birth		Healthy life expectancy at birth	
	female	male	female	male	female	male	female	male
2018	66,2	69,6	9,8	10	85,2	80,8	57,6	59,4
2019	66,6	70,3	9,8	10,2	85,4	81,1	57,6	59,8
2020	66,5	71,2	9,7	9,5	84,5	79,8	60,1	61,9
2021	66	70,9	9,6	9,9	84,8	80,3	59,3	61,9
2022	67	71	9,9	10,2	84,8	80,5	59,1	61,2

Table notes: authors' elaboration

As Table 4 shows, all index values are around 100 and show low variability over the years. The synthetic index does not show a significant disparity until 2022; the disparity has probably increased due to the worsening of the health status, especially of women, after COVID-19.

Table 4 – *Regional synthetic Index of Health. Years 2018-2022.*

Index	**2018**	**2019**	**2020**	**2021**	**2022**
Piemonte	83,1	91,2	80,5	86,4	92,5
Valle d'Aosta/Vallée d'Aoste	70,7	98,8	96,0	100,9	85,5
Lombardia	98,6	88,5	90,1	85,0	92,5
Trentino-Alto Adige/Südtirol	101,8	103,9	100,1	98,7	94,3
Veneto	96,4	90,4	93,1	83,5	93,6
Friuli-Venezia Giulia	89,4	102,4	97,1	82,5	89,5
Liguria	85,3	96,1	80,4	98,6	91,3
Emilia-Romagna	94,6	87,8	91,1	85,3	89,5
Toscana	88,5	91,8	93,8	89,1	90,9
Umbria	85,8	76,7	79,3	75,3	88,5
Marche	89,1	98,0	95,3	74,6	88,2
Lazio	94,7	85,2	95,2	87,5	89,3
Abruzzo	87,0	93,1	94,0	95,4	94,2
Molise	82,4	85,0	87,1	87,8	71,3
Campania	101,7	102,5	99,1	88,0	83,5
Puglia	89,1	86,5	96,0	96,9	95,9
Basilicata	97,9	82,5	96,8	83,2	81,4
Calabria	101,8	82,0	78,2	95,2	94,3
Sicilia	86,0	89,5	91,0	86,8	92,6
Sardegna	81,4	86,7	72,7	87,4	90,6

Table notes: authors' elaboration

In 2022 there was a general worsening of women's health conditions, which caused a reduction in the synthetic index. The highest value of the index, which is below parity, is recorded in Puglia (95.9), the lowest in Molise (71.3).

3.3. Domain Well-being

In Italy, in the domain of Well-being, if Sedentariness behaviour is excluded, women behave better: they follow a diet and are more fit, drink less alcohol and smoke less (Table 5). With the exception of the Smoking indicator, gender differences have decreased over the years.

Table 5 – *Indicators of Well-being. Values for Italy by gender and by years (2018-2022).*

year	Adequate nutrition		Alcohol consumption		Overweight or obesity		Smoking		Sedentariness	
	female	male	female	male	female	male	female	male	female	male
2018	22,4	16,6	9,5	24,3	35,8	54,3	15,6	23,4	38,9	32,4
2019	20,1	15,1	9,5	22,3	36,4	53,9	15,2	22,5	38,3	32,6
2020	21,2	16	10,2	23,6	37,3	54,9	15,8	22,5	37,6	31,2
2021	19,9	15,2	9,2	20,5	35,7	53,6	16,0	23,1	34,6	30,3
2022	19,0	14,4	9,6	21,8	36,0	53,4	16,3	24,2	38,8	33,7

Table notes: authors' elaboration

As Table 6 shows, in all the years considered and, in all the regions, the synthetic index is above 100. In Liguria and Sardegna the situation has improved over time, while it has worsened in Basilicata, mainly due to a reduction in the Adequate nutrition indicator.

Table 6 – *Regional synthetic Index of Well-being. Years 2018-2022.*

Index	2018	2019	2020	2021	2022
Piemonte	115,0	120,9	118,8	123,6	121,6
Valle d'Aosta/Vallée d'Aoste	119,8	128,3	124,4	108,7	122,6
Lombardia	118,5	121,3	110,8	117,8	117,5
Trentino-Alto Adige/Südtirol	123,4	127,2	119,0	127,5	121,2
Veneto	119,5	120,6	120,4	125,1	119,3
Friuli-Venezia Giulia	112,5	123,4	108,0	113,6	109,8
Liguria	117,5	125,8	118,0	120,0	125,8
Emilia-Romagna	116,9	118,0	115,7	120,0	117,7
Toscana	113,6	122,7	116,7	122,2	118,0
Umbria	124,1	116,0	117,7	124,0	117,5
Marche	120,3	113,6	119,6	115,2	117,9
Lazio	118,8	111,5	118,6	115,6	118,0
Abruzzo	115,2	123,3	128,7	121,7	123,1
Molise	115,8	119,9	130,5	128,7	125,1
Campania	119,0	116,4	110,4	118,1	118,4
Puglia	117,4	118,7	111,9	120,9	124,2
Basilicata	129,1	116,4	126,8	123,2	115,0
Calabria	125,1	115,1	118,1	115,7	118,8
Sicilia	122,8	117,4	120,4	116,8	119,0
Sardegna	126,6	121,0	129,2	122,9	130,3

Table notes: authors' elaboration

Even in 2022 the index values are all above 100: on average, females behave better in all areas of well-being. This means that the females have better lifestyles than the males, with the exception of the sedentary lifestyle, perhaps linked to less free time. The situation of the females, in 2022, is better in Sardegna and Liguria, worse in Basilicata and Friuli-Venezia Giulia.

4. Final remarks

Academics and policymakers increasingly highlight subjective well-being as a key indicator of societal performance, with some advocating for policies aimed at maximizing happiness (Layard, 2011). Well-being is closely linked to health and quality of life.

Blanchflower and Bryson (2024) argue that men have become happier and more satisfied with life than women since a period immediately preceding the COVID-19 pandemic, implying that women are less happy than men today, whether positive or negative affect metrics are used to capture well-being.

The evidence presented in the last paragraph is consistent with the proposal that women express a less satisfactory quality of life than men, on average, expressing lower perceptions of perspective and relationships. These perceptions worsen in the post-pandemic period. The paradox is that women, while expressing less satisfaction with quality of life and worse health, worsened after COVID-19, compared to men, have a higher life expectancy. This could be due to well-being, in the sense of lifestyle, which is good for having a long life. The findings show that, on average, women are more proactive about disease prevention and adopt healthier lifestyles than men, yet they tend to have poorer overall health.

Women's health status is also influenced by the sociocultural context. In Italy, women still bear the greatest burden of family care. In addition, there remain gender differences in the world of work (access, pay, career opportunities) that can influence the state of women's mental and physical well-being.

Of course, in Italy there are many important regional differences in the aspects considered in this research, so regional monitoring is necessary. The results for the three domains showed that the construction of a regional ranking, alongside the reading of the individual domains, could be an important informational input for monitoring the issues over time.

This would be useful for policy makers considering our nation's programmatic choices in the context of the national strategy for gender equality.

Acknowledgements

The authors would like to thank Cira Acampora and Matteo Potenzieri for their support in data quality control.

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A PROPOSAL FOR A COMPOSITE INDEX TO MEASURE DISTRESS IN MARGINALIZED MUNICIPALITIES[1]

Valeria Quondamstefano, Mariangela Verrascina

Abstract. Over the years, the scientific community has increasingly emphasized the need to adopt a multidimensional approach to analyse and measure inequalities. This approach recognizes that inequalities are complex and multifaceted phenomena, involving interconnected components that span various dimensions. In the context of the proposed study, thanks to the availability of results from the Permanent Census of Population and Housing and information derived from other Istat sources, comprehensive analyses have been conducted on all municipalities across the national territory, utilizing data collected in the year 2021. These insights covered a range of factors including territorial characteristics, environmental conditions, demographic dynamics, and socio-economic indicators. Additionally, specific attention has been directed towards gender disparities, with the inclusion of variables that shed light on differential experiences and opportunities among diverse groups. Furthermore, some indicators have been tailored to account specific age groups, such as young adults and the elderly. Finally, the composite index Adjusted Mazziotta-Pareto Index (AMPI) and the Chisquared Automatic Interaction Detector (CHAID) have been calculated.
Subsequently, the study has been focused on municipalities that can be considered more disadvantaged in terms of access to basic public services (Inner Areas), in order to determine if similar trends occur throughout the national territory or if belonging to certain geographical areas represents an additional penalizing factor.

1. Introduction

Italy has approximately 7,900 municipalities, of which 5,532 have fewer than 5,000 inhabitants, and of these 2,007 have fewer than 1,000 inhabitants while only 25 municipalities having more than 150,000 inhabitants. The population, which is distributed differently throughout the territory, also has different characteristics: municipalities have extremely varied demographic, social and economic structures, depending on their size and population density too.

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[1] Sections are attributed as follows: sections 4, 5, 6 and 7 to Valeria Quondamstefano, sections 1, 2 and 3 to Mariangela Verrascina.

It is well known that the great territorial differentiation in Italy in terms of size of municipalities, altitude zone, degree of urbanisation, presence and accessibility of services leads to forms of discomfort for Italian municipalities and consequently also for the population living there. Smaller and peripheral territories, especially those that have been experiencing depopulation phenomena in recent years, due to the emigration of young people, and the ageing of the resident population, and which therefore have particular demographic structures, are at a disadvantage (Istat, 2024).

This work presents a proposal to measure some disparities in marginal Italian municipalities through a synthesis of some structural measures of the population and some characteristics of the Italian territory in order to identify the level of distress. The demographic and socio-economic characteristics of the resident population in each municipality of the national territory are derived from data collected in the year 2021 by the Permanent Population Census. The other information is derived from statistics that Istat makes available, such as the Areas at risk of landslides[2].

2. Classification of Municipalities based on Inner Areas

When analysing aspects that may show disparities between municipalities, one cannot disregard the classification of the Italian territory according to the Inner Areas geography. This classification first identifies municipalities with characteristics of pole, inter-municipal pole or belt depending on the availability and accessibility of certain essential services (in particular mobility, education and health) or if they are not far from these; the rest of the municipalities are classified as Inner Areas, i.e. territories of the country that are further away from the centres offering the three types of services. The distance to the supply of essential services is calculated in terms of travel time; as travel time increases, so does the potential difficulty in accessing services.

The definition of Inner Areas dates back to 2014, when the Department for Economic Development and Cohesion (DPS), now named Agency for Territorial Cohesion, launched a ‘National Strategy for Inner Areas’ (SNAI) as part of the strategic options for the programming of 2014-2020 EU funds (Dipartimento per lo sviluppo e la coesione economica, 2014). For the 2021-2027 programming cycle, the 2014 Inner Areas Map was revised, at the end of 2019, to consider the updated presence of services. More advanced and accurate distance calculation techniques have also been introduced (Istat, 2022).

[2] Indicator obtained by processing data from Ispra and Istat. The data come from the IFFI (Inventory of landslide phenomena in Italy) project. For the numerator, data come from the National mosaic Ispra of the Landslide Hazard Areas of the Hydrogeological Structure Plan (PAI). The area of municipalities (surveyed on 1st January of each year) was used for the denominator (source Istat).

In the 'Pole' municipalities and those that form an 'Inter-municipal Pole' all three services considered are present; 'Belt' municipalities are those for which the distance (in road travel minutes) to the nearest pole is less than 27 minutes. Inner areas are subdivided according to the highest travel time: thus, for times between 27 and 41 minutes the municipalities are classified as 'Intermediate', between 41 and 67 minutes as 'Peripheral', above 67 minutes as 'Ultraperipheral'.

The set of Poles, Inter-municipal Poles and Belt municipalities are referred to as 'Centre Areas' or 'Centres', while the set of Intermediate, Peripheral and Ultraperipheral municipalities identify the 'Inner Areas'.

The municipalities in the Inner Areas are 3,834 (48.51 percent) out of the total 7,903 municipalities existing in Italy in 2021 and have less than a quarter of the total population (13,397,431 out of 59,030,133, i.e. 22.69 percent)). Predominantly, the municipalities in the Inner Areas are mountainous or hilly and are characterised by problems of depopulation, demographic ageing and reduced employment. The Inner Areas are also characterised by the high vulnerability of the territory on which they insist, influenced by their geomorphology (Istat, 2020).

3. Individual Indicators

The interpretation of situations of inequality between Italian municipalities is carried out using some simple and non-redundant indicators representing demographic and socio-economic characteristics of the resident population in the municipality. Some indicators are calculated by gender, in order to analyse whether differential experiences and opportunities can lead to results showing disparities. Finally, an indicator on the morphology of the territory was considered, which represents the level of vulnerability/fragility of the municipalities and which may generate disparities. Specifically, the indicators calculated are:

A. *Proportion of population aged 0-17 years (percentage)* calculated as the ratio of the population aged under 18 to the total resident population per hundred inhabitants;
B. *Dependency ratio (percentage)* calculated as the ratio of the sum of the population aged under 20 and over 65 and the working age population (20-64) per hundred inhabitants;
C. *Proportion of the population aged 25-29 with an educational qualification below lower secondary education* calculated as the ratio of the population aged 25-29 with an educational qualification below lower secondary education to the population of that age group per hundred inhabitants (proxy for the school drop-out rate);

D. *Incidence of employed women aged 20-29 on employed men aged 20-29* calculated as the ratio of employed women aged 20-29 to employed men of the same age group per hundred inhabitants;
E. *Share of women aged 20-64 who receive no income or are housewives* calculated as the ratio of the female population aged 20-64 who receive no income or are housewives to all the women of the same age group per hundred inhabitants;
F. *Areas at risk of landslides (percentage)* calculated as the ratio of land areas covered by high and very high risk of landslides to municipal area.

The indicators described are calculated with the results of the 2021 edition of the Permanent Census of Population and Housing (Istat, 2022). The data on the area at risk of landslides have 2020 as a reference period. The territory taken into account refers to the municipalities existing in 2021.

4. Methodology

4.1. Composite indices

The methodology of composite indices in statistics is a technique used to summarize information from multiple variables into a single indicator. This approach is particularly useful in situations where it is necessary to condense a large amount of data into a more manageable and interpretable form. Composite indices are widely used in economics, sociology, epidemiology, and other disciplines to measure complex phenomena such as economic well-being, quality of life, public health, and more (OCSE, 2008).

4.2. Adjusted Mazziotta-Pareto Index

To synthesize individual indicators into a single, cohesive measure, this work used the Adjusted Mazziotta-Pareto Index (AMPI), a partially non-compensatory composite index designed to standardize individual indicators at a reference time point. This standardization process ensures that the indicators are independent of their original units of measure (De Muro *et al.*, 2011). By assigning equal weights to all individual indicators, the AMPI facilitates absolute time comparisons (Mazziotta and Pareto, 2016). The AMPI introduces a re-scaling mechanism for individual indicators, setting them within a range of 70 to 130. This re-scaling is based on two ‘goalposts’: a minimum and a maximum value that define the potential range of each variable across all time periods and units. These goalposts help ensure that the indicators are comparable over time by providing a consistent framework for measurement. While this approach allows for the aggregation of data with different variabilities, it does come with certain trade-offs. Specifically, aggregating indicators with inherently different variabilities can introduce some level of distortion. However, the normalization process mitigates this issue by aligning the indicators within the same range, thereby reducing variability disparities. As a result, the normalized indicators exhibit much more similar variability compared to their original forms, enhancing the overall reliability and interpretability of the composite index (Mazziotta and Pareto, 2013). Furthermore, the AMPI's methodology supports the creation of a robust and versatile tool for various applications.

4.3. Chi-Squared Automatic Interaction Detector

The method of sorting municipalities by the Adjusted Mazziotta-Pareto Index (AMPI) is indeed intriguing and provides valuable insights into the phenomenon being studied. However, a more systematic approach is necessary to classify municipalities while considering the distress composite indicator in relation to various covariates. In this context, an effective classification method is the Chi-squared Automatic Interaction Detector (CHAID) (Kass, 1980). This multiple tree statistics algorithm allows for the rapid and efficient visualization of data, creating segments and profiles based on the results. CHAID works by repeatedly splitting the dataset into mutually exclusive subgroups that share similar characteristics with respect to the dependent variable, AMPI in this case. It examines the relationships between the dependent variable and each of the independent variables, selecting the best splits based on statistical significance. This process results in a decision tree that highlights the most influential factors and their interactions. Specifically, in this approach, the AMPI serves as the dependent variable. The independent variables include administrative subdivisions (such as Geographical area, Region, Province/Metropolitan City), geographic characteristics (Altitude zone), demographic characteristics (Degree of urbanisation[3]) and National Strategy for Inner Areas. By using CHAID, municipalities can be systematically classified in a way that takes into account the multidimensional nature of disparities and related covariates. This classification can reveal underlying patterns and trends, providing a more nuanced understanding of how various factors contribute to the composite indicator across different municipalities. This approach not only enhances the interpretability of the data but also aids in identifying key areas for targeted interventions and policymaking. In summary, while the AMPI provides a valuable measure for sorting municipalities, incorporating a systematic classification method like CHAID enriches the analysis. By considering administrative, geographic, and demographic variables, CHAID enables a comprehensive understanding of the

[3] For the classification of the Degree of urbanisation, the Eurostat definition is followed (Eurostat, 2019).

factors influencing the distress composite indicator, facilitating informed decision-making and effective policy development.

5. Main results

Table 1 shows the best 10 Italian municipalities according to the AMPI ranking. Nine municipalities of these are in the North-East, in the province of Bolzano/Bozen and one in North-West, in the province of Pavia. These municipalities have AMPI values between 93.45 and 94.21.

Table 1 – *The best 10 Italian municipalities according to the AMPI ranking – Year 2021.*

AREA	REGION	PROVINCE / METROPOLITAN CITY	MUNICIPALITY	AMPI	N°
North-East	Trentino-Alto Adige / Südtirol	Bolzano/Bozen	Velturno/Feldthurns	93.45	1
North-East	Trentino-Alto Adige / Südtirol	Bolzano/Bozen	Lauregno/Laurein	93.59	2
North-West	Lombardia	Pavia	Rognano	93.65	3
North-East	Trentino-Alto Adige / Südtirol	Bolzano/Bozen	Falzes/Pfalzen	93.76	4
North-East	Trentino-Alto Adige / Südtirol	Bolzano/Bozen	Luson/Lüsen	93.77	5
North-East	Trentino-Alto Adige / Südtirol	Bolzano/Bozen	Verano/Vöran	93.99	6
North-East	Trentino-Alto Adige / Südtirol	Bolzano/Bozen	Villandro/Villanders	94.02	7
North-East	Trentino-Alto Adige / Südtirol	Bolzano/Bozen	Terento/Terenten	94.10	8
North-East	Trentino-Alto Adige / Südtirol	Bolzano/Bozen	Perca/Percha	94.17	9
North-East	Trentino-Alto Adige / Südtirol	Bolzano/Bozen	Senale-San Felice/Unsere Liebe Frau im Walde-St. Felix	94.21	10

Source: Elaborations on data from Permanent Population Census, Istat

Table 2 shows the 10 worst municipalities according to the AMPI ranking: 7 are in the South, 2 in the North-West and 1 in the Centre. The AMPI values range from 122.83 to 114.81. Between the best (Feldthurns/Feldthurns) and the worst municipality (Bisegna) there are 29.38 AMPI points.

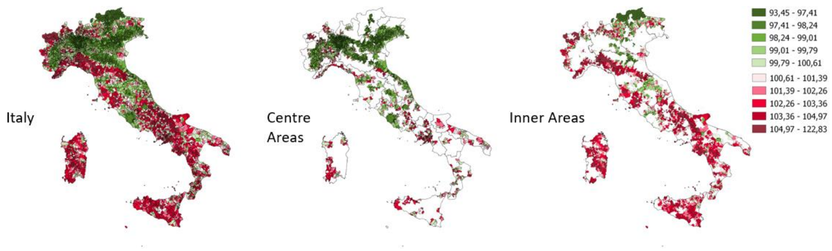
Table 2 – *The worst 10 Italian municipalities according to the AMPI ranking – Year 2021.*

AREA	REGION	PROVINCE / METROPOLITAN CITY	MUNICIPALITY	AMPI	N°
South	Abruzzo	Chieti	Roio del Sangro	122.83	7,903
North-West	Valle d'Aosta/Vallée d'Aoste	Valle d'Aosta/Vallée d'Aoste	Rhêmes-Notre-Dame	118.90	7,902
Centre	Lazio	Roma	Roccagiovine	118.11	7,901
North-West	Valle d'Aosta/Vallée d'Aoste	Valle d'Aosta/Vallée d'Aoste	Ollomont	117.12	7,900
South	Puglia	Foggia	Celle di San Vito	116.71	7,899
South	Campania	Avellino	Montaguto	115.89	7,898
South	Abruzzo	Chieti	Montebello sul Sangro	115.54	7,897
South	Abruzzo	Chieti	Colledimacine	115.11	7,896
South	Campania	Salerno	Cetara	114.82	7,895
South	Abruzzo	L'Aquila	Bisegna	114.81	7,894

Source: Elaborations on data from Permanent Population Census, Istat

Taking Italy as the basis for our composite index, Figure 1 shows the 7,903 Italian municipalities in 2021 ranked according to AMPI values.

Figure 1 – *AMPI ranking of municipalities: Italy, Centre Areas and Inner Areas - Year 2021.*



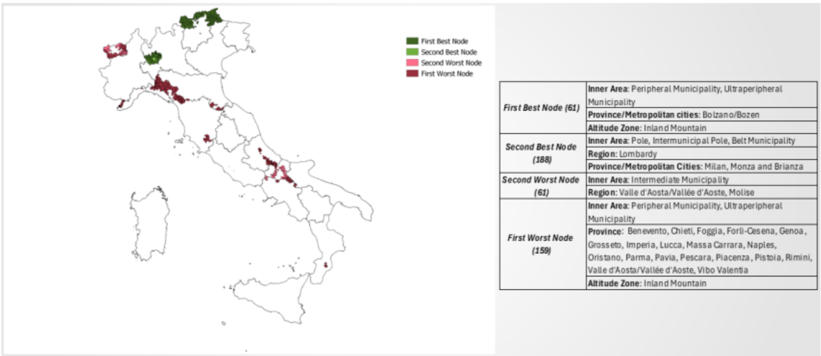
Source: Elaborations on data from Permanent Population Census, Istat.

Specifically, the maps refer to Italian municipalities as a whole, municipalities in Centre Areas and municipalities in Inner Areas. The map highlights with a dark green colour those municipalities with a low level of distress. As the intensity of the green colour becomes lighter, the phenomenon increases in intensity, until it changes to shades of red. The darker the colour, the higher the level of distress in those areas. It can be seen that in the Centre Areas there are municipalities with AMPI greater than 100 (i.e., territories with greater hardship than the Italian average) and in the Inner Areas there are municipalities with AMPI significantly lower than 100 (territories with less hardship than the Italian average). Keeping in mind that the Inner Areas are the most peripheral territories in the country in terms of access to basic public services, one would think that the territories in these areas would be the most critical ones.

The CHAID classification helps to test the veracity, or otherwise, of this idea. As mentioned above, the CHAID, using the composite AMPI index as the dependent variable and some administrative-geographic-demographic indicators as the independent variables, makes possible to identify some groups of municipalities with similar AMPI index values.

Figure 2 shows the results of the best and worst nodes.

Figure 2 – *CHAID: The best and the worst nodes - Year 2021.*



First Best Node (61)	**Inner Area**: Peripheral Municipality, Ultraperipheral Municipality
	Province/Metropolitan cities: Bolzano/Bozen
	Altitude Zone: Inland Mountain
Second Best Node (188)	**Inner Area**: Pole, Intermunicipal Pole, Belt Municipality
	Region: Lombardy
	Province/Metropolitan Cities: Milan, Monza and Brianza
Second Worst Node (61)	**Inner Area**: Intermediate Municipality
	Region: Valle d'Aosta/Vallée d'Aoste, Molise
First Worst Node (159)	**Inner Area**: Peripheral Municipality, Ultraperipheral Municipality
	Province: Benevento, Chieti, Foggia, Forlì-Cesena, Genoa, Grosseto, Imperia, Lucca, Massa Carrara, Naples, Oristano, Parma, Pavia, Pescara, Piacenza, Pistoia, Rimini, Valle d'Aosta/Vallée d'Aoste, Vibo Valentia
	Altitude Zone: Inland Mountain

Source: Elaborations on data from Permanent Population Census, Istat.

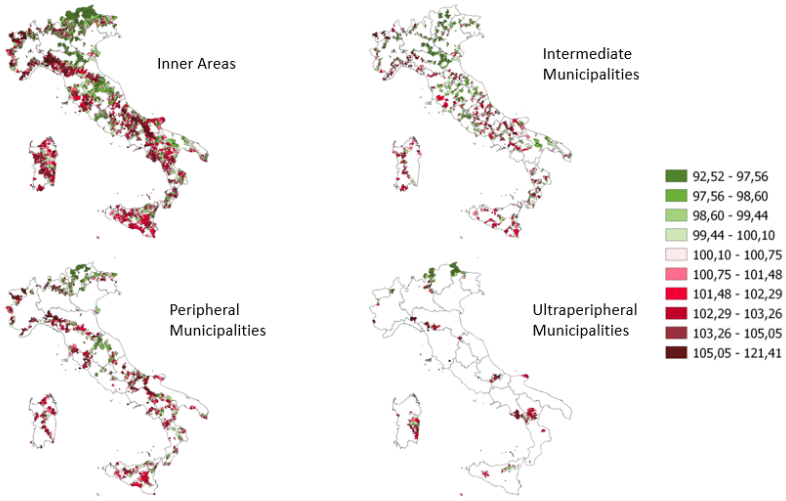
The best node is represented by 61 municipalities in the Peripheral and Ultraperipheral Areas of the province of Bolzano/Bozen with Inland Mountain altitude zone. This means that these very edge areas are actually the least deprived in Italy. The evidence from the data, therefore, is contrary to the initial assumptions. But this is unique, in fact if we look at the 2 worst nodes, we see that these are in Peripheral and Ultraperipheral Areas. The analysis at this point must necessarily continue with a focus on Inner Areas.

6. Focus on Inner Areas

Given the results generated by the classification trees, a focus was placed on the Inner Areas to understand which municipalities within this classification are actually the most on the margin. Inner Areas are divided into Intermediate, Peripheral and Ultraperipheral Municipality, according to the distance from a pole that plays the role of a centre of supply of fundamental services relating to education, mobility and health care[4].

Out of the 3,834 municipalities in the Inner Areas, the AMPI was again calculated (in this case the base, set equal to 100, is the average of the values of these municipalities). Figure 3 shows the new AMPI ranking.

Figure 3 – *AMPI ranking of Inner Areas, Intermediate Municipalities, Peripheral Municipalities and Ultraperipheral Municipalities - Year 2021.*



Source: Elaborations on data from Permanent Population Census, Istat.

It can be seen that in all subdivisions of the Inner Areas there are less disadvantaged and more disadvantaged municipalities than the average. In particular, in the Intermediate Municipalities fall 1,928 municipalities, of these 52.54 percent have a higher than average AMPI, indicating a more marginalized situation. In the Peripheral Municipalities there are 1,524 municipalities, of these 70.01 percent have a higher than average AMPI. Finally, 382 municipalities are classified as Ultraperipheral Municipalities, of these 71.99 percent have a higher-than-average AMPI. This shows how, even with exceptions (e.g., some municipalities in the province of Bolzano/Bozen), the farther a municipality is from a Pole, the more it

[4] Intermediate Municipality: if they are between 27 to 41 minutes' travel time away from a centre
Peripheral Municipality: if they are between 41 to 67 minutes' travel
Ultraperipheral Municipality: if they are more than 67 minutes' travel.

will tend to be on the fringes, i.e., at a disadvantage compared to others. Most likely the exceptions are due to better policies in the area (also in terms of tourist attraction), and it is precisely in this direction that politicians should aim.

As the final analysis, the work classified the municipalities in the Inner Areas according to Altitude Zone and Degree of Urbanization (Degurba). Altitude zone derives from the division of the national territory into homogeneous zones resulting from the aggregation of contiguous municipalities based on altimetric threshold values. In particular, the classification includes: Plain, Coastal Hill, Inland Hill, Coastal Mountain and Inland Mountain.

Degree of urbanisation is a classification that indicates the character of an area. Based on the share of the local population living in urban clusters and urban centres, it classifies Local Administrative Units (LAU or municipalities) into three types of area: Cities (densely populated areas), Towns and suburbs (intermediate density areas), Rural areas (thinly populated areas). Table 3 shows the percentage of Municipalities with AMPI >100 in Inner Areas per Altitude Zone and Degree of urbanisation (Degurba). The best situation in Towns and suburbs occurs in correspondence of Intermediate Municipalities on Inland Hill (22.56 percent), the worst in Peripheral Municipalities on Coastal Hill (75.00 percent). In Rural Areas the most critical situation occurs in Ultraperipheral Municipalities on Inland Hill (95.12 percent), while the best in Intermediate Municipalities on Plain (39.60 percent).

Table 3 – *Percentage of Municipalities with AMPI >100, Inner Areas per Altitude Zone and Degurba – Year 2021.*

Inner Areas	Intermediate Municipalities			Peripheral Municipalities			Ultraperipheral Municipalities		
Altitude Zone \ Degurba	Cities	Towns and suburbs	Rural areas	Cities	Towns and suburbs	Rural areas	Cities	Towns and suburbs	Rural areas
Plain	100,00	38,02	39,60	100,00	58,54	44,44	-	-	100,00
Coastal Hill	0,00	49,38	71,72	-	75,00	79,20	-	62,50	85,71
Inland Hill	0,00	22,56	63,45	-	55,10	83,61	-	100,00	95,12
Coastal Mountain	-	60,00	61,11	-	37,50	75,86	-	50,00	88,89
Inland Mountain	-	28,10	58,42	-	45,24	66,53	-	60,00	65,13

Source: Elaborations on data from Permanent Population Census, Istat.

7. Conclusions and Next Steps

The data collected from the Permanent Census of Population and Housing, also integrated with other sources, will allow for the annual analysis of the life histories of the population and will assist in the planning of specific local policies, facilitating the eventual identification of sub-populations (or territories) which are particularly vulnerable or in difficulty. This integration of the Permanent Census with additional data sources will provide a comprehensive overview of the population's dynamics over time. It will help identify trends and patterns in demographic changes, such as migration, aging, and socio-economic shifts. By understanding these life histories, policymakers can design and implement targeted interventions aimed at addressing specific needs and challenges within local communities. This detailed, data-driven approach ensures that resources are allocated efficiently and effectively to support the most vulnerable groups.

However, the analysis of individual indicators from census data does not provide an overall view. To achieve this, it is necessary to construct a composite indicator to measure multidimensionality and analyse the results. In our work, the analysis of the multidimensional hardship of municipalities indicated a clear surpassing of physical and administrative territorial boundaries: peripheral areas (for example, in the province of Bolzano/Bozen) can be less fragile than others located in centre areas. This means that if good and forward-looking policies are adopted, the situation in these territories can be significantly better than what geomorphological evidence might suggest.

Next steps of the analysis will concern:

- Comparison between the trend of Italians and that of foreigners resident in the area: This involves examining the demographic trends of both native and foreign populations. By comparing these trends, we can gain insights into migration patterns, integration levels, and potential socio-economic disparities. Understanding these differences is crucial for developing inclusive policies that cater to the diverse needs of both groups.
- Expand the set of individual indicators: To enrich the analysis, it is essential to incorporate a broader range of indicators. These could include economic factors (such as employment rates and income levels), social factors (such as education and health outcomes), and environmental factors (such as air quality and green spaces). Expanding the set of indicators provides a more holistic view of the factors influencing population dynamics and helps identify key areas for intervention.
- Study of disparities in Italian municipalities as a function of other spatial classifications (e.g., Local Employment Systems, Ecoregions): This step involves analysing disparities across different municipalities using various spatial classifications. Local Employment Systems and Ecoregions offer additional layers of context, highlighting regional economic and environmental characteristics. By studying these disparities, we can identify

specific local strengths and weaknesses, tailor policies to regional contexts, and promote balanced and sustainable development across the country.

These next steps will enhance our understanding of demographic changes and regional disparities, ultimately supporting the creation of more effective and equitable policies.

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SURVEYING HOMELESSNESS IN ROME, THE WAY TO THE FIRST NOTTE DELLA SOLIDARIETÀ[1]

Eugenia De Rosa, Vanessa Ioannoni, Francesca Scambia

Abstract. In 2023 the National Statistical Institute of Italy signed a collaboration agreement with the Department of Social Policies and Health of Roma Capitale in order to provide methodological support for the implementation of a survey of the homeless people in the city of Rome.
The survey is based on the Point in Time approach. It is a street-by-street count on a specific day and within a defined time frame. The *Notte della solidarietà* survey, carried out on the evening of 20 April 2024, counted people sleeping in the overnight shelters and on the streets, and by means of a short questionnaire it captured some of their basic characteristics.
Given the complexity from the organisational and methodological point of view, a pilot survey was carried out in 2023 in the Esquilino neighbourhood alone. Esquilino is considered to have a high concentration of homeless people due to the presence of the Termini railway station. Various aspects of the survey were tested: the content and type of questionnaire, the size and structure of the areas to be surveyed, and the volunteers' training. The aim of this paper is to illustrate how the experience of the pilot survey and its results led to design the methodological framework and organisational structure of the first *Notte della solidarietà* in the city of Rome.

1. Introduction

Homelessness is an increasing phenomenon that characterises urban city centres with different forms and emerging needs. Most researchers agree the main causes result from a complex interaction of individual factors, life events and structural (social and economic) factors (Herman, et al. (1997); Koegel, et al. (1995); Susser, et al. (1993).

Extreme poverty and social exclusion are among the concerns of the social services at municipal and national level in all the industrialised countries. Both at a national and European level the lack of comprehensive data does not allow for adequate monitoring and policies to tackle homelessness. Despite the volume of research into homelessness in the EU, the numbers of homelessness as well as deeper information on their characteristics are still unanswered questions.

[1] This article is the joint work of the authors, however paragraph 1, 4.1, 4.2, 4.4, 7 are written by Francesca Scambia, paragraphs 2,3 by Vanessa Ioannoni, paragraphs 4.3, 5, 6 by Eugenia De Rosa.

Difficulties in measuring homelessness lay in how to capture it but also in the lack of a definition on who is homeless, and which living conditions may lead to consider a person as a homeless. In Italy homeless people are not included in the statistics on poverty, and since a relevant portion of them have not civil registration they escape the Population and Housing Census surveys, falling in the area of the hard-to-reach populations.

In order to create a common framework, the European Typology of Homelessness and Housing exclusion (ETHOS) was developed by the European Federation of National Organisations Working with the Homeless (FEANTSA) in 2011. This classification, though not created for statistical purposes, based on a grid of indicators related to severe housing exclusion classifies homeless and severely marginalized people into 4 conceptual categories of severe housing exclusion.

Specific methods have been implemented to collect data on this population that is differently featured in different cities and countries. This is also why in Rome a pilot survey was the premise of a city survey on homelessness carried out in 2024. Also in other cities, namely Paris and New York the PIT counting has always been a progressive process that step by step included new areas of the city. Acquiring data and interviewing homeless people not only requires a knowledge of the target population, also the land morphology, the streets' map, the organization of shelters, the habits and concentration of the homeless population in the city are to be known in advance. The pilot survey enabled Istat researchers to detect the main methodological aspects to be matched with organizational issues in order to achieve better results in such a complex city as Rome is.

The aim of this paper is to provide an organised information on how the pilot survey in Rome led to the city survey and how the Istat team dealt with the critical issues of this kind of survey that involves a huge number of non-professional surveyors. This paper is structured as follows: paragraph 2 reports some of the experience of other cities where the PIT survey has been carried out; paragraph 3 describes the previous Istat experiences in studying homelessness; then a detailed account of how the survey areas, teams and tools were organised for the pilot survey is given (paragraph 4) together with some of the pilot's results, a focus on the de-briefing process follows in paragraph 5. Finally, a short description of the city survey conducted in 2024 and some concluding remarks are reported.

2. PIT Count: France, U.S.A., Canada

In France, the Point-in-Time (PIT) survey on homeless named the *Nuit de la Solidarit*é (Night of Solidarity), has been carried out for the first time in Paris in 2018. For the 7th edition, more than 2,000 volunteers and around fifty associations were deployed in the capital on the night of 25-26 January 2024 to better understand the profiles of the homeless and meet their needs. The survey was extended to 27 municipalities in the outskirts, where a further 618 people were counted. In 2023, the initiative brought together more than 2000 volunteers in Paris and 1400 in the 27 participating outlying towns, and involved 150 associations. The *Nuit de la Solidarité*, inspired by projects that have been running in other large cities, has spread to other areas of France.

In the United States, the PIT Count is an annual survey of homeless people carried out by local agencies called Continuums of Care (CoCs) on behalf of the United States Department of Housing and Urban Development (HUD). The Point-in-Time Count is a one-day count of sheltered and unsheltered homeless individuals and families across the United States carried out by the U.S. Department of Housing and Urban Development (HUD). The PIT consists of a count and a survey of homeless people, to get a sense of scale and to estimate the number of people in different sub-categories, such as homeless veterans or homeless youth.

In Canada data on homelessness are collected by communities and regions in core locations, thorough the point-in-time counts. Everyone Counts 2020-2022, the Third Nationally Coordinated Point-in-Time Counts (PIT) of homelessness in Canada took place between March 2020 and December 2022. The Point-in-Time Counts are a community-level measure of sheltered and unsheltered homelessness. It also provides a national picture of homelessness.

3. Istat experiences on surveying the homeless

The 2020 World Population and Housing Census Programme identified population and housing censuses as one of the primary sources of data for formulating, implementing and monitoring policies and programmes aimed at inclusive socioeconomic development and environmental sustainability. It, also, recognizes population and housing censuses as an important data source for the measurement of progress of the 2030 Agenda for Sustainable Development, with special attention to the situation of people by some personal characteristics (sex, age, race, ethnicity etc.) including people experiencing homelessness. However, some hard-to-reach demographic targets are exposed to a high risk of being undercounted in the Population and Housing Census. In order to identify these hard-to-reach populations, the Italian Permanent Census has relied on municipal registry data. Since 2021, an ad-hoc survey has been conducted, involving all Italian municipalities, it focuses on the three specific population segments, including those consisting of homeless people. The field of observation for the ad hoc survey in the registries on homeless people is limited to the component registered in the Population Register. It consists of homeless persons without a fixed abode who have taken up their domicile in the Municipality (Article 2, paragraph 3 of law 24 December 1954, no. 1228) and homeless persons without a fixed abode who are registered at a virtual address or at a real address belonging to an association or used by the municipality for the registration of homeless persons.

The field of observation, limited to the registered component of the population, does not ensure an exhaustive enumeration of the subgroups in question for the purpose of counting and defining the total homeless population.

The aggregate of homeless people registered in the Population Registry falls within the field of observation of the EU Regulation on primary and secondary homelessness. However, this register data also includes people registered as homeless for other reasons (e.g. due to work, circus performers, itinerant traders, or other reasons). Furthermore, homeless people who are not registered in the Population Registry remain outside the observation field of homeless people (for example, non-EU foreign homeless individuals without a valid residence permit or whose residence permit has not been renewed). (Ioannoni et Paluzzi, 2023)

Another important official data source on homeless is the national survey on soup kitchens and overnight shelters' services. The survey estimated the number of people who sleep in the street (or in overnight shelters) using an indirect sampling. The survey tried to estimate the homeless population, or rather a relevant part of it, in the places where the people go and receive the services they need.

The first targeted research that led to the official estimate of the number of homeless people at the national level was carried out by Istat in 2011 (Istat, 2014), by an agreement with the Ministero del Lavoro e delle Politiche Sociali, the Federazione Italiana degli Organismi per le Persone Senza Dimora (fio.PSD, the Italian Federation of Agencies for the Homeless) and the Italian Caritas (the charity agency of the Catholic Church). The survey on soup kitchens and overnight shelters tried to detect the homeless population, or rather a substantial part of it, in the places where the people go and receive the services they need; specifically, the centres where soup kitchens and night shelter services are provided have been considered (De Vitiis et al., 2014a and 2014b; Istat, 2014). The national survey carried out in soup kitchens and night shelters used a methodology based on indirect sampling. This theory is based on the idea of using statistical units - in this case, the services (meals and beds) provided in the soup kitchens and night shelters - as a basis for sampling, which are linked to the target population (the homeless people who use these services).

4. The PIT Pilot Survey in the Esquilino neighborhood

4.1 Areas and Teams

In the perspective of the city survey in 2024 a pilot was conducted on March 2023 following an agreement signed by Istat with Roma Capitale. The Point in Time method was chosen to be the most effective for studying this kind of hard-to-reach population considering other experiences. The survey was organised dividing the Esquilino neighbourhood into 24 areas of about 2/3 km walking distance. The survey included also an emergency overnight shelter located in front of the Termini central station hosting about 40 people. The whole neighbourhood was organised with one team for one area. Each team was composed by 3/5 volunteers trained to act as surveyors.

Before starting the survey, on the same evening a final session of training was held to emphasize the importance of the event and to stress the relevance of correctly filling out the questionnaire. After the session all the teams received a number of paper questionnaires, the Team Sheet and a list of what to do and what not to do, together with useful contacts in case of need or emergency.

Each team was organised assigning different tasks and roles, so that team members knew how to support their team. Roles were organised as follows: the team leader divided up the tasks, filled out the Team Sheet, collected the questionnaires at the end of the survey and addressed all critical issues; the guide showed the other team members the route to follow in the assigned area; the interviewer approached the homeless person on the road and proceeded with the observation-interview by providing answers to the interviewer; the compiler wrote in the questionnaire the information collected or observed.

The teams had to go to their assigned area walking through all its streets, checking also people sleeping in cars or tents. The perimeters which marked the area borders were divided according to the side, so that each team was aware of their task and competence.

4.2 The surveyors

The number of volunteers who registered for the event exceeded the request, and this was considered an encouraging evidence for larger surveys. About 200 volunteers, in their majority from associations committed to tackle extreme poverty together with medical students from the Tor Vergata University of Rome.

For a very challenging survey with non-professional surveyors and aimed at a hard-to-reach population, training played a crucial role. Istat designed the training and carried it out in two different sessions. The first was organised at the municipality premises and mainly addressed to the people in charge of associations to make them aware of the task and also to enable them to transfer information to their members. The associations were very much involved and interested in facilitating the phenomenon of homeless people to emerge. They directly know many situations of homeless people due to their weekly service in the street. Their skills in approaching homeless people is very helpful for the survey, however the idea they had of already knowing the topic influenced their behaviour not always focused on the aim of the survey.

That is why in the second meeting, before starting the survey, the training focused on: survey tools (questionnaire and Team Sheet), description of the activity to be carried out as surveyors (not as social operators)

Simple instructions on how filling out the questionnaire, also in the case of non-interaction with homeless people were provided.

Also instruction on what to do (i.e. Make sure to cover the entire assigned area/zone - Maintain an appropriate distance from the interlocutor), and what not to do (i.e. Do not request any documents and do not take photographs) were provided in a written paper after the training.

4.3 The questionnaire

For the pilot survey, an anonymous individual paper questionnaire was designed to be filled out by volunteer surveyors for each homeless adult person encountered in the assigned area or in the shelter. An electronic version of the questionnaire, implemented with the Survey Solutions App provided by the World Bank, was tested by the Istat researchers alone.

The questionnaire was divided into two main parts: the first part “Reserved to the surveyor" was to be completed exclusively by the surveyor before interaction with the homeless person; the second part “Information on the person collected or estimated by the surveyor" where information on the homeless person were collected also with the help and the interaction of the homeless person, after requesting the consent to answer the interview. There was also a final part for remarks by the surveyors' team.

The main information collected in the first part of the questionnaire (before the contact), were used to check the eligibility of the encountered person, to assess whether the person was homeless or not, and to collect data on the socio-economic profile of people who experience homelessness. Before starting a question was asked to know whether the person had been already interviewed that same evening, in order to avoid double count.

Surveyors were also required to indicate area, address and location/settlement of the encountered person, clothing and shelter, pets, presence of groups of people. The main part of the questionnaire collected information about gender, age, country of origin of the person, access to local social services.

In the case when the homeless person either decided or was unable to answer the question, the surveyor was required to make an assessment and provide an approximate information. The final part of the questionnaire to be completed by the surveyor covered information on whether the homeless person had valid documents or not. This information is not directly asked to the person. Finally there was a blank field where the surveyor and the whole team could write information on the health status, and more in general, the condition of the homeless person, clothing, and information about the interview such as questions with unreliable answers, the language use and so on.

Another survey tool is the Team Sheet to be filled in at the end of the survey by the supervisor of each team in order to provide information about the time (start and end of the field work), the number of members, information on how the team worked, suggestions and critical aspects that emerged during the field work.

4.4 Results by Gender and Country of Origin

The results of the PIT count was a total number of 168 homeless people including 133 sleeping in the street and 35 hosted in the emergency shelter.

The average age just over 40 (42.1), therefore we can say that people in the street are not too old and men in their majority (87%) (Fig.1). The largest group was composed by foreign people mainly coming from no-EU countries (Fig.2), and especially from Africa.

Figure 1 – *Percentage of homeless people by gender PIT 2023.*

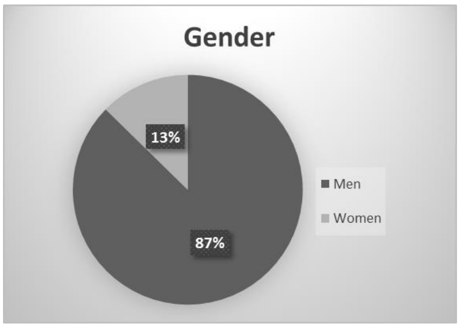
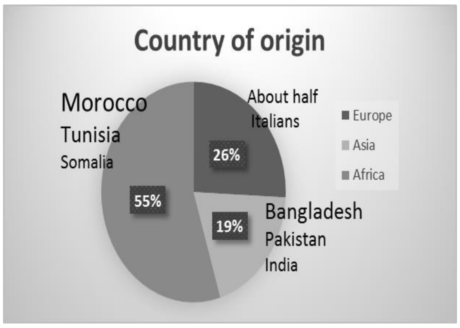


Figure 2 – *Percentage of homeless people by country of origin PIT 2023.*



5. From the pilot to the city survey design

In order to evaluate the pilot survey and draw useful information for the design of the final survey, a de-briefing process was designed.

An initial assessment of the pilot survey was carried out by the Istat team with a dedicated meeting immediately after the field work. For a more systematic assessment, the results of the questionnaire and remarks from the questionnaires and the team sheets were previously analysed. A de-briefing day with volunteer surveyors was also organized on 19 April 2023. A template was designed for a final assessment. The main considered aspects include: a) the questionnaire (questions to be added and removed, questions to be modified or whose purpose should be better clarified, additional response “modes”); b) organizational aspects and teamwork; c) the approach of surveyors with homeless people: different approaches by different teams in interacting and interviewing; the role of the supervisor, poor and scarce use the questionnaire blank field (Table 1).

As for the questionnaire, the structure worked well, both for the survey on the street and in the shelter; in many cases the respondents showed willingness to tell their story. This kind of reaction was somehow unexpected and led, for the final survey, to consider a new and longer version of the questionnaire both for the street and for the shelters. In this way the interview could capture more information, on the homeless’ working and health condition, on the services used and other interesting features.

A traditional methodological challenge involved the definition of poverty and homelessness (De Rosa, 2006) and the initial assessment of eligibility by the team of the person encountered “as homeless” because the instruction given were not always enough, besides the fact that this is indeed a difficult task. When a person is already prepared to sleep in the street, it is easier to understand that they are homeless, but when the person is walking or moving around, how can you know whether they are homeless or not? For this reason the need of including direct questions on eligibility in the questionnaire emerged. The assessment of indirect eligibility on the basis of observation and evaluation by surveyors alone showed its limits.

The analysis emphasised that final remarks are very important, even if not drafted by all teams/surveyors. For the final survey, the decision was made to expand the section of the questionnaire related to the remarks by surveyors and to structure them with some specific questions. Surveyors were encouraged to fill out this field receiving guidelines on the key issues.

The de-briefing highlighted that experimentation of the electronic questionnaire could work well: it is easy to use and friendly in the interaction with the respondent. So for the final survey, electronic questionnaire (app) was chosen as the survey technique for all, by providing a training module dedicated to this aspect and preparing a tutorial on its use. Several surveyors pointed out as critical aspect that maps were not always clear, so for the design of the final survey, more detailed maps, with further instructions, were developed, marking the all path to be walked for each team.

Training and team organization worked well: the presence of volunteers was very helpful in approaching the homeless while the presence of university students ensured good data collection. The mobilisation of students and local organisations for the pilot survey provided a positive answer on the feasibility of conducting this type of survey over a larger area of the city and the possibility of involving more citizens as volunteer surveyors. At the same time, we observed very different ways of working among teams. Training to transfer a more uniform approach emerged as a key issue for future surveys.

The training of non-professional surveyors is a crucial and critical issue. This finding is in line with the experience of other countries that have also adopted a point-in-time approach to investigate homelessness (Develtere, 2022). This led to consider for the final survey a more targeted training on the questionnaire for a more professional approach, and an increased care in the team composition by providing for each team at least one student, always keeping a gender balance.

Table 1 – *Main issues from the Pilot Survey PIT 2023 (Esquilino Area) and input for the design of the final Survey Design PIT 2024 (Rome).*

	Pilot Survey PIT 2023	*City Survey PIT 2024*
Eligibility	Initial eligibility by the team was not enough	Questions on eligibility also directly asked
Questionnaire	The questionnaire worked well. Willingness in many cases to provide more information	One single longer questionnaire the same version for the survey on the street and in the overnight shelters
Observations by surveyors	Final remarks are very important, but they were not included by all teams/surveyors	Encouraging remarks providing guidelines on key issues
Electronic questionnaire	Easy to use and friendly in the interaction with the respondent	Electronic questionnaire (app) as the survey technique, paper questionnaire in case of need only
Maps	Not always clear	More detailed maps, with further instructions
Training and Teams	Civil society interest and mobilization. The presence of volunteers was very helpful in approaching the homeless person but with very different ways among teams. Two short training sessions are not enough.	More targeted training on the questionnaire for a more professional approach and more attention in the team composition with at least one student and gender balance

6. Notte della solidarietà, Rome 2024

The pilot survey 2023 put the basis and the experience for the first *Notte della solidarietà* in the city of Rome, which took place on 20 April 2024. The cartographers of Roma Capitale designed the 338 areas to be surveyed in the city centre, and particularly within the railway ring plus some other interesting areas for the purpose. All the areas were grouped in 20 clusters which offered also a meeting point each. As for the Pilot survey each team was assigned one area to be surveyed.

The cluster coordinator was the reference person for all the team leaders of their cluster. An online platform was created for the registration of volunteers and team leaders. More than 1700 volunteer surveyors registered themselves to participate in the night survey. The volunteers had different affiliations, they belong to more than 100 associations and entities, and 6 Universities (800 university students) in addition to citizens who autonomously decided to participate. The teams were in charge of conducting the survey on the street, while a contemporary survey was conducted in 48 night shelters for a total number of 1300 estimated guests. The survey in the night shelters was carried out by the people in charge of running these facilities.

For the PIT 2024 a web questionnaire was prepared on the Survey Solutions platform provided by the World Bank. It is an easy to use and friendly tool suitable for a street survey also because it can be easily installed on the smartphone. All team leaders were in charge of using the app and save all the data. Some few paper questionnaires were provided for emergency cases only.

The training was organised by Istat starting with the Cluster coordinators and then with the team leaders. For the purpose two video tutorials were prepared: one on the questionnaire app, and one on the way to approach homeless people in the street and in the night shelters to properly conduct the interview.

During the evening and night of 20 April a control room was settled at the Campidoglio, where the proper entrance of data was monitored, several telephone lines were organised to give direct support to surveyors, as well as to people in the night shelters, in order to ensure a total coverage. The results of the survey were presented by a press conference and a press release on 24 June 2024 at the Campidoglio.

7. Conclusion

Surveying homelessness is still a challenge in all the big cities; the PIT Approach, though limited, is considered the most effective method by now.

It should be noticed that the PIT survey has to be adapted in each city according to the specific features of the territory and of the homeless people’s concentration and behaviour. In some cities homeless people are mainly in transit while travelling to other countries or cities, and are not stable in the area, while in other cases they are people who underwent difficult paths and have been living in the street for a long time. That is why pilot surveys are very helpful especially in this kind of surveys conducted with non-professional surveyors and targeting a phenomenon which is always changing and developing.

In the last years a deep reflection has been carried out on homelessness at European level, this led also to think about new services and solutions to solve or to deal with homelessness. Having comprehensive data on the phenomena is crucial to find solutions. Istat is preparing the PIT survey on homelessness in the 14 Italian metropolitan city municipalities for 2025. The experience of Rome 2024 keeps for Istat as a reference point for all the coming surveys of the same kind.

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ITALIAN OFFICIAL DEVELOPMENT ASSISTANCE (ODA): A TERRITORIAL PERSPECTIVE[1]

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Abstract. Official Development Assistance (ODA) promotes the economic development and welfare of developing countries. Its relevance has increased constantly since 1970 when the UN set the target of 0.7% of GNI for donor countries. This goal has been further reaffirmed by SDG 17.2 of the 2030 Agenda. In the last few years, there has been a growing strand of literature attempting to disentangle the development efforts of donor countries. Still, little emphasis has been put on the "local" dimension of aid on the donor side. This paper examines the flows of Italian Official ODA for project-based interventions and international scholarships, funded by local administrations and Italian public universities. Using OECD data, we examine the regional distribution, the sectoral allocation, the type of interventions, and the geographical orientation of ODA in the years 2019 and 2021. In addition, we carry out an exploratory econometric exercise to understand whether regional ODA flows follow a similar dynamic to that of trade flows between the recipient country and the region, using a simple gravity model. Results show that Italy's ODA is mostly concentrated in a few Regions and focuses on a limited number of key sectors, addressing specific countries. We discuss the implications of these findings for the coherence and effectiveness of the development cooperation policy.

1. Introduction

The development of local communities is a noble goal even if the ways to achieve it are complex. Yet ahead of the publication of the 2030 Agenda, the international community had taken some steps in the direction of rebalancing the dynamics of global development. This awareness has given rise to *Official Development Assistance* (ODA): the aid provided by developed countries to the least developed or to developing ones. The first international entity to formalize this exchange of resources was the Organization for Economic Co-operation and Development (OECD), which in 1961 established the Development Assistance Committee (DAC),

[1] The paper is the result of the common work of the authors. Armenise has written Section 5; Fiore has written Section 2; Giannelli has written Section 1; Guida has written Section 3; and Virga has written Section 4. Conclusions and future developments are by all the authors. The views expressed in the paper do not reflect those of the authors' affiliation institution.

gathering donor countries, and providing economic, financial, and technical assistance. Currently, ODA covers a multitude of resources including grants, loans, export credits, mixed credits, associated finance, private investment, etc. Moreover, the target of 0.7% of a country's Gross National Income (GNI) devoted to ODA was first agreed upon in 1970 and reaffirmed in the 2030 Agenda (Target 17.2). OECD yearly publishes ODA data on the national level; however, it is recognised that a localised approach is essential to translate SDGs into effective place-based actions. Therefore, the need to monitor the contribution of local entities to the 2030 Agenda requires observing indicators related to Target 17.2 at the regional level (Armenise, 2023; Lella and Oses-Eraso, 2023).

Indeed, there is a significant distinction between the source of funding, typically a state, and the channel through which ODA is delivered. ODA can be channelled through governments/ministries, non-governmental organizations or public-private partnerships, multilateral agencies, and international organizations (most frequently). Finally, part of ODA is channelled through the so-called "territorial entities" (e.g., states in a federal system, regions, municipalities, etc.), and public universities. As for Italy's ODA, by cross-checking OECD data and those provided by the Italian Ministry of Foreign Affairs and International Cooperation (MAECI), it has been possible to analyse the ODA channelled through territorial entities and public universities.

The focus of this research is to dig out the contribution of Italian territorial entities and public universities to development cooperation and to investigate potential patterns highlighting connections between local donor entities and recipient countries. The underlying idea is that local administrations and public universities play a crucial role in fostering development by leveraging their proximity to communities and understanding local needs. In this sense, they translate development policies into actions addressing specific territorial challenges. Another concept behind the study is that development cooperation itself may act as a booster for bilateral relations among donor and recipient territories, even if the cause-effect relationship in these dynamics requires further evidence and investigation.

The rest of the paper is structured as follows. Section 2 reviews the literature and outlines the theoretical background. Section 3 presents the data and methods. Section 4 introduces the descriptive results and Section 5 the empirical results. Finally, section 6 contains the preliminary conclusions and future developments.

2. Previous literature

To map the historical evolution of ODA, which has served as a benchmark for foreign aid in fostering development cooperation for half a century, the seminal reference is Hynes and Scott (2013); the authors present a comprehensive analysis of its trajectory and suggest potential refinements to the ODA framework to maintain its significance in the future.

The literature on ODA unfolds in various strands. Scholars have primarily concentrated on evaluating the effects of ODA on recipient countries, examining various development sectors. Lin Moe (2008) aims to investigate the relationship between ODA and human and educational development in countries in Southeast Asia between 1990 and 2004; Wang et al. (2021) estimate how ODA promote renewable energy development levels in developing countries; Wang et al. (2022) provides a better understanding of the effects of ODA on carbon emissions in 59 low-income and lower-middle-income countries. The QuODA, now in its fifth edition, serves as an extensive instrument for evaluating the quality of aid[2]. It assesses and benchmarks ODA providers across 17 quantitative indicators, organized into four distinct dimensions based on the concepts proposed by Birdsall et al. (2010). A new strand of literature has emerged since ODA became one of the targets of the 2030 Agenda (OECD, 2023). Yet, the body of literature analysing Italian ODA is not extensive. Venturi (2019) highlights the discrepancy between international laws and Italian priorities. Likewise, Paviotti and Fattibene (2023) argue that development cooperation, including ODA, is facing a pivotal moment in Italy.

To the best of our knowledge, no study has provided a comprehensive territorial breakdown of ODA from a single donor country.

3. Data and methods

The analyses presented in this paper are based on an elaboration of OECD-MAECI data on ODA flows managed by Italian local administrations and universities in 2019 and 2021.

Italian Regions and universities play a pivotal role in the country's development cooperation framework (Sistema Italia), emphasizing the importance of decentralized cooperation through aid delivered by local authorities.

Additionally, Italy actively fosters academic partnerships between Italian universities and institutions in developing countries, especially in Africa, the Balkans, and the Mediterranean. These partnerships encompass inter-university collaborations and training activities including specialized courses and master's programs, tailored to address the specific needs of participants.

[2] The Quality of Official Development Assistance (QuODA) is a tool developed by the Center for Global Development and the Brookings Institution to measure which donors provide “higher quality aid” and how they can improve. For more information: www.cgdev.org/topics/quoda.

The analysis in this study adopts the DAC-CRS methodology used by donors to report their aid flows to OECD. Specifically, the paper focuses on two prominent modalities of ODA flows: project-type interventions (C–C01) and international scholarships (E–E01, E02).

Project-type interventions (C-C01) refer to structured initiatives comprising coordinated inputs, activities, and outputs agreed upon with partner countries to achieve defined objectives or outcomes within a specified timeframe, budget, and geographical scope. Scholarships and student costs in donor countries (E) include scholarships/training in donor countries, financial aid awards for individual students, and contributions to trainees (E01), as well as indirect ("imputed") student costs of tuition in donor countries (E02)[3].

The thematic focus of the analysed ODA – referred to as "*Sector Code*" or *Purpose Code*"[4] by the OECD – is based on the specific economic or social sector that the aid intends to support, regardless of the type of goods or services provided by the donor. Contributions not easily attributed to specific sectors are classified as non-sector allocable aid.

As for the geographical distribution of the aid examined - termed "geographical aid allocations" by the OECD - ODA it is classified by income group (e.g., Least Developed Countries [LDC)], Other Low-Income Countries [Other LICs], Lower Middle-Income Countries [LMICs], Upper Middle-Income Countries [UMICs], unallocated areas, and More Advanced Developing Countries and Territories [MADCTS]), or by geographic regions (e.g., sub-Saharan Africa, South and Central Asia, other Asia and Oceania, Middle East and North Africa, Latin America and the Caribbean, Europe, and unspecified regions).

Finally, in this study, ODA flows managed by Italian local administrations and public universities have been grouped according to their respective administrative Regions.

[3] Other cooperation modalities included in the study though not significantly relevant in ODA flows include core contributions and pooled programmes (B); experts and other technical assistance (D); other in-donor expenditures (H); and administrative costs not included elsewhere (G, G01).

[4] In the Creditor Reporting System (CRS), data on the sector of destination are recorded using 5-digit purpose codes. The first three digits refer to the corresponding DAC sector or category. As a result, in the present study, the sector codes were merged into 11 categories based on their sectoral inclinations. The categories identified included: Education (111-114), Health (121-123, 130, 140), Civil Society & Peace (151-152), Social infrastructure & Transport (160), Energy (231-232), Business & Banking (240, 250), Agriculture, Forestry, Fishing & Environment (311-313, 410), Industry, Trade & Tourism (321, 323, 331, 332), Emergency & Disaster (520, 720, 730, 740), Administrative (910), Other (430, 998).

4. Descriptive results

In 2019, the total disbursement of Italian ODA channelled through local administrations and public universities amounted to over 40 million USD. As with 2021, most ODA flows were concentrated on scholarships and student costs in donor countries (E) and project-type interventions (C) (Table 1).

Table 1 – *Italian regions' ODA per cooperation modality. Years 2019 and 2021. Values in dollars (USD).*

Cooperation modality	2019	2021
B - Core contributions and pooled programmes and funds	4,478	0
C - Project-type interventions	11,599,167	10,176,833
D- Experts and other technical assistance	1,228,506	1,568,386
E - Scholarships and student costs in donor countries	27,783,990	42,710,576
G - Administrative costs not included elsewhere	0	938,266
H - Other in-donor expenditures	74,730	63,062
Total	40,690,871	55,457,123

Source: Authors' elaboration on OECD-MAECI data.

In 2019, the total ODA allocated to project-type interventions by Italian local entities and public universities amounted to 2.6% of Italy's overall ODA for this category (11,599,167 USD out of a total of 439,787,140 USD). Conversely, in the same year, ODA allocated by public universities for scholarships and training accounted for 80% of the total Italian ODA in this category (27,783,990 USD out of 34,727,371 USD).

By 2021, the allocation for project-type interventions had significantly declined, accounting for just 0.04% of the total ODA in this category (111,556 USD out of 272,077,365 USD). However, the allocation for scholarships and training via public universities rose substantially, constituting 98.9% of the total Italian ODA in this category (12,736,697 USD out of 12,871,023 USD).

In 2019, among the 17 Regions contributing to ODA flows (excluding Basilicata, Calabria, Lazio, and Aosta Valley), 10 Regions predominantly directed their efforts toward category E - Scholarships and student costs in donor countries. Notably, Liguria, Molise, Sicilia, Umbria, Marche, Emilia-Romagna, and Veneto flows were concentrated almost exclusively in category E, with the largest disbursement (in absolute terms) made by Emilia-Romagna (9,809,135 USD), Tuscany (6,731,484 USD), and Marche (4,283,272 USD), collectively amounting to 20,823,891 USD out of 27,783,990 USD.

For category C – Project-type interventions, ODA flows were prevalent in six Regions (Bolzano, Campania, Friuli-Venezia Giulia, Apulia, Sardinia, Trento), with Lombardy allocating half of its ODA to project-type interventions. Friuli-Venezia Giulia, Apulia, and Trento focused exclusively on category C, and Sardinia almost entirely. Bolzano and Trento collectively contributed 5,688,436 USD out of a total of 11,599,167 USD.

By 2021, the total ODA disbursement increased significantly, exceeding 55 million USD (+36.3%). Scholarships and student costs in donor countries (category E) remained the predominant focus in 11 of 17 Regions (excluding Basilicata, Lazio, Aosta Valley, and Liguria). Regions such as Umbria, Sicily, Molise, Marche, Calabria, and Abruzzo directed all their ODA flows exclusively to category E. In absolute terms, the largest contributions were from Veneto (15,032,985 USD) and Emilia Romagna (12,677,733 USD) out of a total of 42,710,576 USD. For project-type interventions (category C), ODA flows were concentrated in four Regions (Bolzano, Friuli-Venezia Giulia, Apulia, Sardinia), with Bolzano making the largest contribution of 2,335,239 USD out of a total of 10,176,833 USD for this category.

In terms of aid flows classified by recipient countries, in 2019, the majority of ODA was directed to the South of Sahara, with over 13 million USD allocated to this region. Excluding regional and unspecified allocations, the Middle East and North of Sahara followed, receiving 3,575,245 USD and 3,075,639 USD, respectively. While most Regions diversified their ODA allocations across multiple areas, certain Regions, including Sicily, Campania, Liguria, and Friuli-Venezia Giulia, concentrated their efforts on one or two specific geographical areas. The emphasis on the South of Sahara persisted in 2021, with ODA flows in this region totalling 11,738,296 USD. In contrast to 2019, South and Central Asia emerged as the second largest recipient region in 2021, with ODA disbursement reaching 8,197,445 USD, primarily from Emilia-Romagna and Veneto. Other notable recipient regions included the Middle East (4,959,076 USD) and Europe (4,612,618 USD). Although the general trend of regional diversification in ODA flows continued, exceptions were observed, such as Sicily exclusively focusing on the South of Sahara, and Molise concentrating solely in South America (Table 2).

Table 2 – *Italian regions' ODA per recipient countries. Years 2019 and 2021. Values in dollars (USD).*

Recipient countries	2019	2021
Africa	993,394	1,424,103
Asia	9,083	2,296,852
Caribbean & Central America	641,697	834,265
Europe	3,287,421	4,612,618
Far East Asia	2,824,050	2,064,865
Middle East	3,575,245	4,959,076
North of Sahara	3,075,639	3,090,822
Regional and Unspecified	5,784,560	13,996,449
South & Central Asia	5,076,143	8,197,445
South America	2,061,809	2,242,332
South of Sahara	13,361,830	11,738,296

Source: Authors' elaboration on OECD-MAECI data[5].

An alternative approach to examining the geographical allocation of ODA is to analyse the distribution across income groups as classified by the OECD. The data reveals that, excluding unallocated funds, Lower Middle-Income Countries received the highest ODA flows in both 2019 and 2021, amounting to 16,168,121 USD and 17,634,742 USD, respectively. This was followed by Upper Middle-Income Countries and Least Developed Countries, while Low-Income Countries received only a marginal share.

Digging out the ODA amounts channelled through local administrations and public universities individually, in 2019, local administrations accounted for approximately 10 million USD, while public universities received nearly three times that amount (29,866,823 USD). By 2021, the ODA flows from local administrations declined slightly to just over 8 million USD. In contrast, aid channelled through universities significantly increased, exceeding 45 million USD.

At the regional level, most regions demonstrated a specialization, predominantly focusing on either category C or category E. Notably, Tuscany, Piedmont, Lombardy, and Emilia Romagna were among the few Regions maintaining ODA flows in both categories throughout both years. A clear specialization pattern emerged: in some Regions, institutional donors were exclusively local administrations (e.g. Bolzano and Apulia), while in others, universities and research centres were the primary donors (e.g. Abruzzo, Calabria, Campania, Molise, Sicily, and Umbria).

[5] In the OECD classification for ODA flows, the region name "Africa" or “Asia” generally refers to the entire continent encompassing all its sub-regions. This distinction is important for accurately categorizing and analyzing aid distribution.

Finally, regarding sectoral allocation, the majority of ODA was concentrated in education accounting for 78% and 84% of total flows in the two years analysed, respectively, with a particular emphasis on post-secondary education. ODA flows in education constituted the largest share of total ODA at the local level in both years, increasing from just over 30 million USD in 2019 to more than 45 million USD in 2021. Following education at a considerable distance were the sectors of Health and Agriculture, Forestry, and Fishing & Environment (none exceeded 10-11% of the total in either year).

5. Empirical results

The descriptive heterogeneities emerging from these regional data can be explored using gravitational models (Tinbergen 1962, Anderson 1979, Eaton 2003, Anderson and Van Wincoop 2003). The reference equation for econometric analysis is derived from the log-linear formulation of the classic gravitational model, expressed as:

$$\ln(ODA_{y,i,j}) = a_1 \ln(Pop_{y,i}) + a_2 \ln(Pop_{y,j}) + a_3 \ln(GDPpc_{y,i}) + a_4 \ln(GDPpc_{y,j}) + a_6 \ln(dist_{i,j}) + X'_{iy}\delta_1 + Z'_{jy}\delta_2 + \varepsilon_{ijt} \quad (1)$$

where $ODA_{y,i,j}$ represents the official flow of development aid from Italian region *i* to country *j* in year *y* (2019-2021). The logarithm of the per capita gross domestic product (GDPpc) of the donor region is included as an index of the region's wealth level and its capacity to donate, while that of the recipient country indicates the level of need for aid. The logarithm of the population (Pop) of region *i* and country *j* is the other variable used to represent the mass of the origin and destination countries. Bilateral distance[6] $dist_{i,j}$ captures the transportation costs and cultural differences. The matrices X and Z contain controls for the donor region (X) and the recipient country (Z), respectively. In this specification, time-fixed effect variables are included to control for unobservables at the country level.

In addition to the standard controls in the specification of a gravitational model, such as contiguity and colonial relationships between the donor regions and the target country, controls were included considering the share of immigrants (ln_imm) from the recipient country in the donor region, and the impact of the recipient country on exports (ln_q_exp).

[6] The bilateral distance is measured as the Euclidean distance between the capital of region *i* and the capital of country *j*.

This specification allows us to evaluate whether these regional aid flows follow theoretical regularities, as highlighted in international trade by gravitational models, wherein they are determined by the mass variables related to the countries and their distance.

Table 3 presents the estimates of the gravitational model according to three OLS specifications[7]. As can be observed, the results in column III do not always show regression coefficients with the expected signs and significance, thus not fully confirming the presence of a gravitational effect in the development aid flow. In line with gravitational logic, distance (ln_dist) consistently shows always a negative and significant coefficient ($p < 0.01$), indicating that greater separation reduces sub-national ODA flows.

It is interesting to note the differing effects of demand and supply between the beneficiary and donor. Specifically, the coefficient for the population is positive and statistically significant only for the recipient country of the development aid and not for the donor region. On the other hand, the coefficient for per capita GDP is statistically significant and negative only for the donor country. This latter result also represents an important point of differentiation from traditional gravitational models, showing that as the per capita income of the donor region increases, the flow of development aid decreases. The export variable (ln_exp) is not significant, indicating that commercial interests are not a key driver of these sub-national flows. Conversely, the control variable for the proportion of immigrants (ln_imm) has a positive and statistically significant coefficient (at the 5% level) associated with ODA flows, suggesting that diaspora ties may favour development aid disbursements.

The R-squared is not too high, assuming a value of 0.11, only in the third specification.

[7] A Breusch–Pagan test led to reject the null hypothesis of homoskedastic errors. Accordingly, we re-estimated the model using robust standard errors. As expected, the magnitude and signs of the coefficients remained consistent, while the standard errors (and thus t-statistics) were adjusted to account for non-constant variance. We show in Table 3 only results with robust standard errors. We checked Variance Inflation Factors (VIF), which ranged from 1.46 to 3.39, with a mean of 1.96. These values lie well below the conventional thresholds (e.g., 5), indicating no serious multicollinearity concerns among the regressors. In addition, we conducted further diagnostic checks to verify the suitability of our model specification: a) we assessed the distribution of the residuals using a normality test (Jarque-Bera) and while strict normality is less critical with a sufficiently large sample, our results did not indicate significant departures from normality that would affect the validity of the estimates; b) as our dataset is cross-sectional (or short-panel), we do not expect strong autocorrelation, nevertheless we performed a Durbin-Watson test, and found no evidence of serial correlation condition.

Table 3 – *The gravity model for the Italian regional ODA – 2019-2021. OLS with Dependent Variable: ODA flows.*

VARIABLES	I	s.e.	II	s.e.	III	s.e.
ln_gdp_pc_i			-0.601***	(0.192)	-1.714***	(0.238)
ln_gdp_pc_j			0.00342	(0.0990)	-0.159	(0.184)
ln_pop_i			0.348***	(0.104)	-0.200	(0.129)
ln_pop_j			0.593***	(0.0674)	0.589***	(0.117)
ln_dist	-0.365***	(0.123)	-0.835***	(0.132)	-0.698***	(0.198)
ln_imm_i					0.226***	(0.0666)
ln_q_exp_j					-0.0738	(0.0889)
Constant	9.158***	-1.030	3.819**	-1.802	8.024***	-2.531
Observations	2,625		2,561		1,605	
R-squared	0.003		0.058		0.117	

Standard errors robust in parentheses.
**** p<0.01, ** p<0.05, * p<0.1*

Source: Authors' elaboration on OECD-MAECI data.

6. Conclusions and future developments

The analysis carried out in this preliminary work will allow a more detailed study of what territorial channelled ODA generate in terms of development for both the donor and recipient territories.

Through OECD-MAECI data, it has been possible to explore Italian local territories' contribution to 2030 Agenda. These data allow us to measure the development aid generated by a specific territory (Armenise, 2023; Lella and Oses-Eraso, 2023). In this sense, the analysis enables the identification of key donors in Italian Regions and provides some insights: the main territorial-based donors are universities and Region's administrations. The contribution to development is diversified; the beneficiary countries do not follow a common pattern, except for geographical distance; the projects and resources allocated to aid, although growing over the past three years, show limited temporal stability.

Indeed, there is a concentration of funds in a few Regions, suggesting a need for more diversified ODA flows. Understanding what drives different disbursement paths and why some Regions are less active in development cooperation is crucial for optimizing aid effectiveness and orienting development policies. Overall, the geographical allocation of ODA flows reveals a complex landscape of priorities. For a comprehensive understanding, rigorous research is essential to unravel the determinants influencing ODA channelled through local administrations. Factors such as geopolitical relations, economic dependencies, and historical ties wield significant influence. By delving into these dynamics, researchers can provide nuanced insights that empower policymakers to formulate ODA strategies that are more responsive and effective in addressing development needs. In addition, preliminary empirical results obtained by adopting a gravitational model indicate that local-based aid flows do not fully align with traditional gravitational models of international trade. These flows are not attracted to or generated by the classic mass variables used in these models. Therefore, it is likely that elements beyond economic size and wealth level, such as social, volunteer, or political relations, play a role in development aid.

Leveraging the available information, it may be insightful to investigate how these flows contribute to creating social capital, economic benefits, increased trade and movement of people. Delving deeper into these aspects can reveal new dynamics of development aid. Moreover, comparative analysis between regional ODA allocations and national-level priorities offers a refined perspective on the intersections between global and domestic developmental agendas.

It is undeniable that local actors act as an important bridge between higher government levels and grassroots efforts, making development cooperation more effective and contextually relevant.

In conclusion, a rigorous examination of the “local” dimension of international aid can contribute to informing evidence-based policymaking in ODA, advancing global and national efforts to achieve the objectives of the 2030 Agenda.

Acknowledgements

The authors would like to thank the participants of the LX Scientific Meeting of the Italian Society of Economics Demography and Statistics for their insightful comments.

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MEASUREMENT OF THE "FIGHT AGAINST CLIMATE CHANGE" OBJECTIVE: EVIDENCE FROM EUROPEAN COUNTRIES

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Abstract. Sustainability is a complex multidimensional framework to be evaluated and measurement tools play a crucial role in this challenge. The 2030 Agenda for Sustainable Development, adopted by all United Nations Member States in 2015, declines sustainability through 17 objectives (17 Sustainable Development Goals, SDGs), to reach by 2030. Among all Goals, here we focus on climate change, that is on Goal 13 "Take urgent action to combat climate change and its impacts". With the aim of better monitoring and evaluating sustainability levels of countries and how far they are from achieving their goals, the current study proposes the use of a modified version of the Wroclaw taxonomic method. The proposed index is used to aggregate indicators belonging to Goal 13 for 18 European countries in 2020 and 2021. The effectiveness of the proposed method is assessed by comparing results with the classical indices used for measuring SDG progress.

1. Introduction

The main global challenge of this century is achieving sustainability, which requires the creation of innovative methods to measure and monitor progress. To ensure that a sustainable development is both understood and implemented, the 2030 Agenda – an ambitious and transformative plan for People, Planet, and Prosperity – has been adopted by all United Nations Member States in 2015.

The 2030 Agenda embodies all facets of sustainable development, emphasizing its pillars: social inclusion, economic development, and environmental sustainability. It operates through the identification of 17 Sustainable Development Goals (SDGs), supported by 169 targets and 240 indicators (see Bartram *et al.*, 2018 for details).

Specifically, the 17 SDGs introduce crucial themes such as gender equality, protection of forests and oceans, promotion of peace and justice, fair work, urbanization and the fight against climate change (Biggeri *et al.*, 2019).

The United Nations propose various indicators to monitor progress towards the goals[1]. However, given the actual inability to standardize the measurement of the

[1] https://undocs.org/en/A/RES/70/1

SDGs across countries, they can measure the SDGs using their own methodologies and indicators which may be different from those provided by the United Nations.

The challenge for countries is to define the objectives along with their respective sub-targets and indicators to be achieved through national policies.

Here, we focus on environmental sustainability analysed into SDG 13, a Goal aiming at combating the climate crisis by promoting actions at different levels.

As stressed by Butera (2011), climate change is a multidimensional phenomenon and its impact should be investigated considering all the factors jointly. In fact, the worsening of a single environmental factor can trigger reactions on others and, consequently, amplify its negative effects. This indirect and interconnected nature, not only complicates efforts to identify and measure controlling variables, but also makes the prediction of its biological, socioeconomic, and physical impacts challenging.[2]

SDG 13 is outlined in the 2030 Agenda through 5 sub-targets assessing the risks of climate change, adaptation measures, its integration into policies for mitigation, and educational awareness efforts. In turn, the 5 sub-targets are declined by mean of 8 indicators.

However, despite several progress in most of the SDG, the United Nations' Sustainable Development Report 2022 (United Nations, 2022) attaches to the SDG 13 a “code red warning” meaning that almost all countries are very far from the achieving of the target. For instance, considering all countries, Energy-related CO2 emissions increased by 6% in 2021, reaching highest level ever; global temperatures have arisen reaching more extreme weather and, estimates suggest that medium- to large-scale disasters will increase by 40% from 2015 to 2030. Thus, it seems that the planet is on the brink of a climate catastrophe and progress towards SDG 13 are unsatisfactory.

Also in the European context, although the EU's overall progress towards the SDGs is favorable, advancement on SDG 13 is moderate and considerably trails behind progress on other environmental goals. In fact, moving from global to European context, the scenario is quite similar: there is a string decline in emissions during the COVID-19 pandemic, which, in parallel with the global context, sees significant increases in 2021 (Sachs *et al*., 2023). Thus, the current situation remains critical, characterized by significant economic losses and challenges in managing the increasingly serious impacts of climate change.

In this context, it becomes crucial the adoption of appropriate tools capable of measuring a multidimensional and complex phenomenon such as climate change.

[2] https://ec.europa.eu/eurostat/web/products-flagship-publications/w/ks-04-23-184

According to Bidarbakht-Nia (2020), there are at least three different methods to measure progress on SDG. All methods consist in the construction of a synthetic index aiming at reducing complex systems into lower-dimension space, and allowing the performance of an individual unit to be evaluated across space and time (Mazziotta and Pareto, 2013).

The first one, has been developed by Sachs et al. (2017). It is a composite indicator that uses the arithmetic mean to aggregate elementary variables, resulting in a final sustainability score for each country based on their performance across the SDGs. To normalize elementary variables, the minimum of considered values among units is subtracted to the current value and then divided by the difference between the target value and the above-mentioned minimum. In other words, the current value is compared to the worst performer. The index gives a measure of how close the country is to the target

The second one, developed by UNESCAP (Bidarbakht-Nia, 2017) computes the progress of a country respect to the values achieved in 2000. The overall index is the arithmetic mean of normalized indicators. Here, for a given country, the normalization is obtained by divided the difference between the current values and the value achieved in 2000 by the difference between the target value and the 2000s-value. In this way, the index is a sort of share of total progress that the country needs to make.

Finally, OECD (2017) monitors SDG achievement by computing the arithmetic average of normalized indicators. Here, for each country, the normalization of each indicator is obtained as the ratio between the difference of the current value and the target and, at the denominator, the standard deviation of current values computed across countries. The main advantage of such approach is that it accounts for distributions.

As described above, the three methods use the arithmetic mean as aggregation procedure and, this introduces a compensatory effect that does not fully reflect the multidimensional nature of SDG measurement.

To address this limitation, we propose a modified version of the Wroclaw Taxonomic Method (hereafter, WTM) (Florek et al., 1951). We compute a non-compensatory composite indicator for 18 European countries over the years 2020 and 2021.

The WTM indicator is computed as a normalized distance of each European country from an ideal unit, that is, the unit which achieves the best performance on all the indicators (see Silvio-Pomenta,1973; Schifini *et al.*, 1980; Mazziotta *et al.*, 2010 for details).

The idea behind this method is to account for the distance with respect to an ideal unit that is a synonymous of reference value or goalpost (Ermini *et al.*, 2023).

The main novelty is to consider the country-specific target levels as goalposts and the resulting composite indicator represents the mean distance from the "most achievable" climate goals.

The rest of the paper is organized as follow: Section 2 describes data and the main characteristics and properties of the modified version of WTM. Section 3 highlights the main results of the computation of the index, comparing with the simple arithmetic mean. Section 4 concludes.

2. Data and methods

The empirical analysis is based on four elementary indicators included in the SDG 13 provided by EUROSTAT[3] (Table 1), namely 1) Net greenhouse gas emissions expressed in units of CO2 (*EMI*); 2) Climate economic losses measured in euros per capita (*LOS*), 3) Percentage of population covered by the Covenant of Mayors for Climate & Energy signatories (*COV*) and 4) Percentage of renewable energy consumption on the gross final energy consumption according to the Renewable Energy Directive (*REN*).

The analysis is carried out for 18 European countries: Belgium (BE), Bulgaria (BG), Czech Republic (CZ), Germany (DE), Greece (GR), Spain (ES), France (FR), Italy (IT), Luxembourg (LU), Netherlands (NL), Austria (AT), Poland (PL), Portugal (PT), Romania (RO), Slovenia (SI), Slovakia (SK), Finland (FI), and Sweden (SE), over the years 2020 and 2021.

Table 1 reports the target values in the target country to capture the distance from achieving SDG 13. Along this line, for the variables *EMI* and *REN*, country target levels are obtained from the 2019 National Energy and Climate Plans (NECP 2019) and the Regulation on the Governance of the Energy Union 2018/1999/EU, respectively. Best theoretical scenarios are used for the variables *LOS* (0 euro) and *COV (100%)*.[4]

Looking at the original formulation, the starting point of the WTM method is the computation of the Euclidean distance between the j-th indicator z_{ij} $j \in \{1,..,k\}$ of the i-th statistical unit $i \in \{1, \dots, N\}$ from the ideal unit z_{oj}:

$$D_i = \sqrt{\sum_{j=1}^{k}\left(z_{ij} - z_{oj}\right)^2}. \tag{1}$$

[3] https://ec.europa.eu/eurostat/databrowser/explore/all/all_themes

[4] Data for the four variables and two years are available upon request.

The ideal unit is a hypothetical country which achieves the best performance on all the indicators. In this context, the ideal unit could be a vector with target values for each indicator.

Table 1 - *Target values of elementary indicators for 2020 and 2021.*

	Target			
	*EMI**	*COV**	*LOS**	*REN**
BE	-35	100	0	25
BG	0	100	0	27
CZ	-14	100	0	23
DE	-38	100	0	30
GR	-14	100	0	31
ES	-26	100	0	42
FR	-36	100	0	33
IT	-33	100	0	30
LU	-40	100	0	23
NL	-36	100	0	26
AT	-36	100	0	46
PL	-7	100	0	25
PT	-17	100	0	47
RO	-2	100	0	34
SI	-15	100	0	37
SK	-12	100	0	24
FI	-39	100	0	51
SE	-40	100	0	65

However, even if the definition of the 2030 Agenda (United Nations, 2015) makes it clear that targets are global in nature and universally applicable, the introduction of national targets is recommended. In fact, "*Targets are defined as aspirational and global, with each government setting its own national targets guided by the global level of ambition but taking into account national circumstances*" (United Nations, 2015, point 55).

Thus, each government should set its own targets, related to the global one, to stress the link between sustainable development. In this way, the definition of country-specific SDG targets implies their integration into the national strategic framework and stimulate a more efficient system of reporting and assessing the progress in achieving each relevant goal. In addition, the use of an own reference-point instead of a common one can be a useful instrument especially to evaluate the performance of a unit over time. This type of approach involving a unit-dependent point of view is not entirely new in the literature on the construction of composite indicators. Several scholars are introducing unit-dependent aggregation methods, Mauro et al. (2018) and and Biggeri et al. (2019) aggregate the indicators relative to different units with power means of different order.

Here, we modify the WTM to account for country-specific target levels, as follows:

$$D_i = \sqrt{\sum_{j=1}^{k}\left(z_{ij} - t_{ij}\right)^2}, \tag{2}$$

where t_{ij} represents the country-specific reference value.

We observe that, by definition, the distance between two points satisfies symmetry property. Therefore, the distance respect to the target gives the same results if a country exceeds or lacks a quantity c from the target since $[(t_{ij} - c) - t_{ij}]^2 = [(t_{ij} + c) - t_{ij}]^2$.

To address this issue, for all countries whose achievements exceed their respective targets, the value of the achievement is set equal to the target and, as a consequence, the distance is zero, that is:

$$z_{ij} = \begin{cases} t_{ij} & if\ z_{ij} \geq t_{ij} \\ z_{ij} & if\ z_{ij} < t_{ij} \end{cases} . \tag{3}$$

If the achievement of the target implies that the indicator value should be less than the target value, we simply modify Eq. (3), accordingly.

Finally, the Wroclaw indicator for each country i, can be computed as follows:

$$W_i = \frac{D_i}{d + 2\sigma(d)}. \tag{4}$$

Here the coefficient d is the arithmetic mean of all distances between each statistical unit i and the ideal unit and σ represents its standard deviation:

$$d = \frac{1}{n}\sum_{i=1}^{n} D_i \tag{5}$$

$$\sigma(d) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(D_i - d)^2}. \tag{6}$$

The index in Eq. (4) ranges from 0 to 1, where 1 represents the greatest distance from achieving climate goals (i.e., worst scenario) and 0 means the achievement of the goals (i.e., best scenario).

The use of the WTM allows for comparisons between spatial and temporal units. Furthermore, it is a highly dynamic model, as the inclusion of new units does not alter the values of the indices already calculated (Ermini *et al.*, 2023).

3. Empirical findings

The WTM composite index measures the distance from achieving climate goals established by SDG 13 for the European context. It should be noted that the best performances are related to countries with lower index values, and, therefore, values close to zero.

As first step, we apply Eq. (3) for variable *COV* and *REN*, whereas, in the case of *EMI* and *LOS* indicators, we use the reverse.

Table 2 reports the results of the computation of WTM, according to Eq. (2), (4) and (6).

In 2020, Portugal was closest to achieving climate goals with a score of 0.332, while Greece had the worst score at 0.964 (Table 2a). In 2021, Italy showed the best performance with a score of 0.243, while Belgium was furthest from achieving climate objectives with a score of 0.911 (Table 2b).

Table 2 – *Wroclaw index values by country for the year 2020 (left side) and 2021 (right side).*

(a)

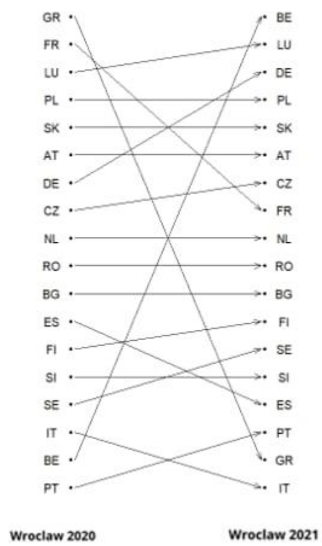
Country	WTM 2020
1. GR	0.964
2. FR	0.918
3. LU	0.893
4. PL	0.779
5. SK	0.741
6. AT	0.738
7. CZ	0.732
8. DE	0.725
9. NL	0.705
10. RO	0.651
11. BG	0.582
12. ES	0.524
13. FI	0.515
14. SI	0.489
15. SE	0.473
16. IT	0.456
17. BE	0.417
18. PT	0.332

(b)

Country	WTM 2021	Ranking in 2020
1. BE	0.911	17
2. LU	0.886	3
3. DE	0.822	8
4. PL	0.772	4
5. SK	0.732	5
6. AT	0.707	6
7. CZ	0.673	7
8. FR	0.670	2
9. NL	0.656	9
10. RO	0.601	10
11. BG	0.574	11
12. FI	0.491	13
13. SE	0.463	15
14. SI	0.458	14
15. ES	0.296	12
16. PT	0.278	18
17. GR	0.266	1
18. IT	0.243	16

Figure 1 depicts changes in country rankings over the two years 2020 (on the left) and 2021 (on the right). The countries are listed in descending order, with the first being the furthest from achieving climate goals and vice versa.

Figure 1 - *Ranking variation of Wroclaw index (2020 vs 2021).*



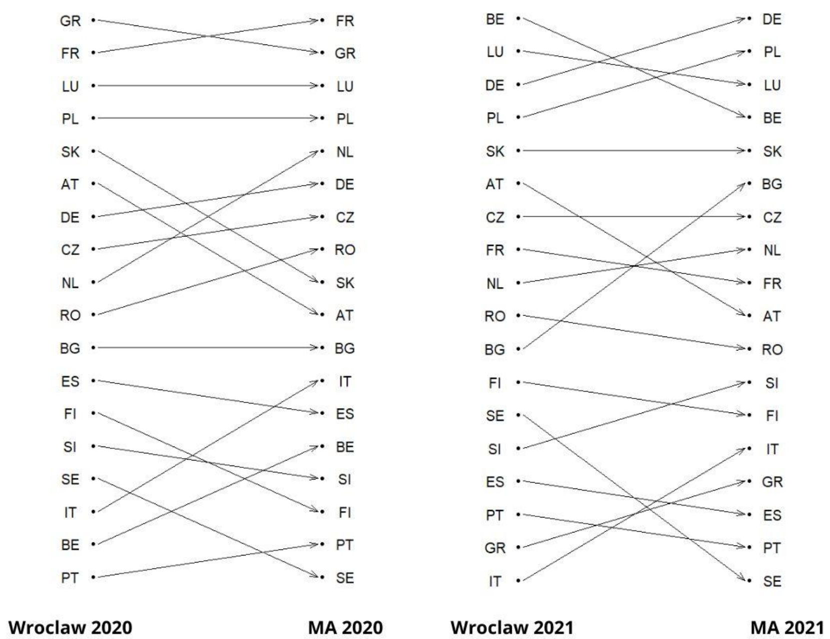
The WTM index reveals notable changes in the ranking from 2020 to 2021. Firstly, Greece moves from the last position to second place. Conversely, Belgium deviates significantly from its climate targets in 2021, becoming the country furthest from reaching them. These changes in the position deserve to be more in-depth investigated, looking at the specific policies adopted in the various countries over the years under analysis.

Countries showing substantial positive changes in the ranking include Italy, Spain and France. On the other hand, Germany and Belgium significantly worsen their positions, moving further away from achieving their objectives.

Poland, Slovakia, Austria, the Netherlands, Romania, Bulgaria, and Slovenia maintain their positions by slightly reducing their scores, thus getting closer to the established climate goals. In contrast, the Czech Republic, Luxembourg, Finland, and Sweden record a slight increase in their indices, leading to a drop in some positions in their ranking. For the Nordic countries, this decline can be attributed to the ambitious nature of their goals.

To ensure that this modified version of the WTM represents a significant contribution to measure the SDGs, the index obtained with this methodology is compared with the classical method used to compute SDG index, that is the arithmetic mean (MA). Although we are aware that AM has some disadvantages, first of all the compensability (perfect substitutability) among indicators since it assumes that the poor performance of one indicator can be completely compensated by the high performance of another. This can lead to misleading conclusions where high values in some indicators mask weaknesses in others. However, here we apply the AM, following Sachs et al. (2016) and Lafortune et al. (2018). More in detail, Sachs et al. (2016) propose as aggregation method for SDG indicators the AM for aggregation. Instead, Lafortune et al. (2018) apply to SDG indicators both the MA and the geometric mean obtaining quite similar rankings and for this reason they suggest using the MA to facilitate interpretation.

Figure 2 - *Ranking variation: Wroclaw Index vs Arithmetic Mean Index.*



The results are shown in Figure 2, listing countries in descending order from the worst to the best position. It is worth to note that the two indices yield different results when examining the ranking of countries. For example, Sweden, Finland, and Austria, among others, exhibit better overall performance associated with a higher MA index, despite still being far from achieving SDG 13.

Relying solely on the MA index could lead to misleading results for policymakers due to its compensatory effect, potentially causing them to decide not to intervene in countries where the achievement of sustainability remains distant.

4. Conclusions

Achieving sustainability is the major global challenge of this century, requiring innovative measurement methods. The 2030 Agenda, adopted by all UN Member States in 2015, outlines 17 Sustainable Development Goals (SDGs) with 169 targets and 240 indicators, covering social, economic, and environmental aspects. SDG 13 (Climate Action) aims to combat climate change through adaptation, mitigation, and awareness measures. Despite progress in some areas, the 2022 UN Sustainable Development Report issued a "code red warning" for SDG 13, as global CO_2 emissions hit record levels, temperatures continue to rise, and natural disasters are projected to increase by 40% between 2015 and 2030.

The simplest method to evaluate the achievement in SDG targets is the arithmetic mean that has the main disadvantage of hide poor performance in one indicator thanks to high performance of another.

To overcome compensability issues, this study proposes a modified Wroclaw Taxonomic Method (WTM) to compute a non-compensatory composite indicator for 18 European countries (2020–2021). The WTM method measures each country's normalized distance from an "ideal unit", representing the best possible performance across all indicators. Unlike traditional methods, this approach considers country-specific targets as reference points, offering a more realistic assessment to evaluate the country achievement of climate goal

However, this study has several limitations. The main issue is data availability, as SDG 13 for EU countries reports several missing values or missing country-specific targets that have reduced the number of analysed units. A further critical point concerns distance calculation from targets. In this study, when a country exceeded its target, it was assigned the target value, setting its distance to zero. However, this approach penalizes countries performing better than the benchmark. Future research should account for how much a country surpasses the target to provide a more comprehensive assessment and fairer rankings.

Since achieving sustainability is a global challenge, developing reliable and effective measurement methodologies remains crucial for understanding and addressing this multidimensional phenomenon.

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A MEASURE OF THE POTENTIAL POLLUTANT LOAD OF URBAN WASTEWATER

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Abstract. Water resource management is a crucial process for ensuring sustainable development and the achievement of the goals set by the 2030 Agenda. Preserving the integrity of ecosystems dependent on the water cycle over time is essential for achieving and maintaining collective, economic, and social well-being. As part of this context, this work aims to quantify the potential pollutant load of urban wastewater, generated at the municipal level and analyzing its distribution in the national territory. The tool adopted to achieve this goal is the estimation of Total Urban Equivalent Inhabitants (TUEI), a quantity that takes into account not only the resident population but also other categories of individuals contributing to the production of biodegradable pollutant loads, such as the tourism sector, commuter flows, industrial activities, accommodation, and catering establishments. The main contribution of the analysis is therefore to define the need for urban wastewater treatment from various pollution-generating sources, meeting the current needs of the Regions and the Ministry of Environment and Energy Security responding to European Urban Waste Water Treatment Directive. The estimation was produced for the year 2021, integrating information from multiple sources. Furthermore, different levels of territorial aggregation were considered. In particular, estimates in the domains of interest (municipal, provincial, regional) are obtained from data related to census sections. With this methodology, attempts were made to introduce elements useful for measuring TUEI and improving the assessment of pollutant loads, a complex topic that still presents critical elements in the availability and usability of sources and deserves further investigation.

1. Introduction and aim

Water is a key element for life and has always played a significant role in the social and economic development of society. It fosters prosperity by meeting essential needs, ensuring health, economic development, food and energy security. If water resources management infrastructure is properly developed, it can promote growth and prosperity by storing a reliable water supply and providing it to various economic sectors. Similarly, safe, accessible and well-functioning water supply and sanitation systems improve the quality of life for all citizens (UNESCO, 2024). In this regard, the focus of international institutions on the centrality of water in development processes is evidenced by the Sustainable Development Goals, collected in the ambitious Agenda 2030 program. A crucial aspect of this project is specifically dedicated to water resources and aims to ensure availability and sustainable management of water and sanitation for all. In this context, in order to get closer to achieving the aforementioned goals, it is essential to build a reliable estimate of the potential pollutant load generated in the territory to support decision-makers in designing appropriate treatment plants and minimising the percentage of untreated wastewater.

Wastewater carries numerous pollutants: biodegradable organic material, nutrients, bacteria and viruses, solvents, detergents, fats, oils, metals, micropollutants from pharmaceuticals and plastics, and other organic and inorganic substances derived from households and industries (Halleux, 2023). Therefore, adequate treatment of wastewater is vital to protect human and environmental health. Lack of sanitation can cause pollution of rivers, lakes, seas and drinking water, leading to diseases in humans (European Environment Agency, 2019) and limits in social development. The estimation of the potential pollutant load of a territory's wastewater is carried out by calculating a particular statistical measure, that of equivalent inhabitants. Equivalent inhabitants represent an estimate of the biodegradable organic load produced by domestic and economic activities. In detail, according to Directive 91/271/EEC concerning urban wastewater treatment, “one equivalent inhabitant (E.I.) is the biodegradable organic load having a 5-day biochemical oxygen demand (BOD_5) of 60 g of oxygen per day” (Directive 91/271/EEC). Estimating the number of equivalent inhabitants allows the assessment of the overall load on a territory.

In Italy, however, there is no nationally shared methodology for calculating equivalent inhabitants. Each region adopts its own methodology and communicates the result to central institutions, preventing comparisons between different geographical areas. The purpose of this work is therefore to propose a uniform and nationally shared methodology capable of quantifying the potential pollutant load of territories during the week of maximum plant load and providing initial indications on actions to be taken.

In the second paragraph, the methodology implemented for calculating Total Urban Equivalent Inhabitants (TUEI) will be described, providing information on the data sources used.

The third paragraph is devoted to the analysis of the results obtained through the application of the proposed method paying particular attention to the different TUEI components and the deviation from the loads manageable by the existing plants at the regional level.

Finally, advantages and disadvantages of the methodology will be reported in the last paragraph, but above all possible developments in order to better investigate a topic, central to the challenge towards sustainability in the coming years.

2. Methodology: sources and choices

In the TUEI estimation methodology proposed here, biodegradable pollutants in urban wastewater are considered. Therefore, wastewater produced by domestic and assimilated activities is considered, but also discharges from tourist, hotel, school and micro-enterprise activities that operate within urban centers and discharge into the sewer system, having qualitative characteristics equivalent to human metabolism or domestic activities (ISTAT, 2009). By integrating information derived from ISTAT surveys with additional elements from the scientific literature, the calculation is carried out with reference to the year 2021, examining the "maximum load" week, which is the week of the year with the highest pollutant load (in terms of flow rate or BOD_5 concentration). This week usually coincides with the period of maximum attendance.

The pollutant load component due to domestic activities is obtained by considering both the legal population surveyed in the territory and the present and nonresident population, i.e. individuals present in the municipality but having their usual residence in another municipality or abroad (ISTAT, 2023), as well as the amount of commuting worker and students. The reference source for the legal population is the *Censimento permanente della popolazione*. Since data for the present but non-resident population is not available for the year considered, it is estimated using a linear regression model between the resident population and the present but non-resident population from the last available year (2011)[1]. In these cases, each inhabitant constitutes a unit of equivalent population. To obtain information regarding commuting, the origin-destination matrix of 2011 is considered (ISTAT, 2011). The estimation of the relative pollutant load, subtracted from the departure municipality and added to the arrival municipality, does not refer to the entire day but to an estimated period of 8 hours for workers and 6 hours for students. The data obtained is then adjusted in proportion to the resident population in 2021.

Regarding the impact of the tourism and hotel sector, the number of beds available in accommodation facilities is supplemented by the potential population

[1] The regression model was constructed region by region. For Lazio, the capital Rome was excluded from the calculation of coefficients, while it was included to estimate the value of the municipality in 2021.

present for tourism or vacation in private dwellings and the contribution from discharges related to food service activities, bars, and their staff. The source for the number of beds is the ISTAT survey "Capacity of Accommodation Establishments," covering 2021, in which hotels, guesthouses, camping, vacation villages and private homes used on an entrepreneurial basis for seasonal rentals are examined (ISTAT, 2021). Beds in farmhouses and mountain lodges are excluded as they are usually located in areas not served by the sewerage system. The estimation of the pollutant load from restaurant and bar activities is derived by considering both the number of staff employed in these activities, obtained from the Asia archive for the year 2021, and the estimated number of place settings. An additional step involves weighting the territories based on their tourism vocation (ISTAT, 2022) a coefficient of 1 is assigned to territories with a higher tourism incidence, while a coefficient of 0.9 is assigned to the others. For estimating the potential population present for tourism or vacation in private homes, the number of unoccupied dwellings is considered, multiplied by the average number of people present in occupied dwellings recorded in the same municipality. Based on a pilot study, three different coefficients are applied to account for the fact that, on average, not all secondary homes are inhabited or used. These coefficients primarily account for demographic variation, as there is a strong correlation between lower occupancy in unoccupied dwellings and the demographic decline of the resident population.

Finally, when examining the contribution of economic activities, those that are more "water-demanding" are considered, meaning activities that use water in their production cycle and return it to the environment with modified qualitative characteristics compared to the initial state (Barbiero, 2003). Enterprises with more than six employees are excluded from the calculation because, in most cases, they do not use the public sewer system and have their own treatment systems. Specifically, for each municipality, the number of employees, distinguished by economic activity, was obtained from the Asia Archive of local units for 2020, and the relevant IRSA-CNR coefficient was applied[2]. These coefficients consider one equivalent inhabitant to be the amount of organic substance present in the daily domestic discharge, equivalent to 54 g of BOD_5 per person, while current regulations state that an equivalent inhabitant produces 60 g of BOD_5 per day. Therefore, a re-proportioning coefficient of 54/60 = 0.9 was applied. Additionally, to account for

[2] IRSA's Notebook 119 (ISSN 0390-6329), "The method of zonal coefficients for assessing potential industrial pollutant load in different territorial aggregations," was consulted, in which the "national" coefficients for converting inhabitant equivalent/addicted for hydro-demanding economic activities are given. The "zonal" coefficients are also reported in the notebook, but since some years have passed since the calculation of these coefficients, it was deemed more appropriate to use the national ones, which are valid from the point of view of their applicability throughout the country, considering Italy a homogeneous area from the economic point of view (Barbiero, 2003).

preliminary treatments before discharge into the public sewer system, a multiplicative coefficient of 0.2 was used, considering an 80% reduction in the pollutant load by the producers.

For a more detailed territorial analysis, the calculation of TUEI (Total Urban Equivalent Inhabitants) was also developed for census sections. Information on residents is provided by ISTAT for census sections, while all other factors were estimated for census sections with weights determined by the resident population. For the population present in private homes, weights were determined using data on unoccupied dwellings from the 2011 Census.

Table 1 - *Summary of the methodology adopted for the calculation of TUEI.*

COMPONENT	SOURCE (YEAR)	METHOD	COEFFICIENTS
Resident Population	Population Census (2021)		1 inhabitant = 1 E.I.
Present population but not resident	Population Census (2021)	Linear regression model between resident and present population in 2011.	1 inhabitant = 1 E.I.
Commuter population	Commuting Matrix (2011)		8/24 for work 6/24 for students
Potential population present in hotel facilities	Capacity of collective accommodation establishment (2021)	Beds in hotel facilities (excluding cottages and lodges).	Tourism vocation = 1 No-tourist = 0,9
Potential population present for tourism or holidays in private dwellings	Population Census (2011-2021)	Unoccupied dwelling, multiplied by the average number of people in the occupied dwelling.	Variation population 2021/11 • >0%= 0,7 •<0 >-10% =0,5 •<-10% = 0,3
Population equivalents related to restaurant and bar service activities	Business Register (ASIA, 2021)	1 employee = 12 place settings (Restaurant). 1 employee = 50 customers (Bar). Restaurants = E.I. for every 3 place and 3 employees. Bar = E.I. every 7 customers and 7 employees.	Tourism vocation = 1 No-tourist = 0,9
I.E to the most water-intensive micro-enterprises with less than six employees	Business Register (ASIA, 2020)	Employees in local industrial unit by IRSA CNR coefficients (with adjustment).	Reductions of pollutant load by producers = 80%

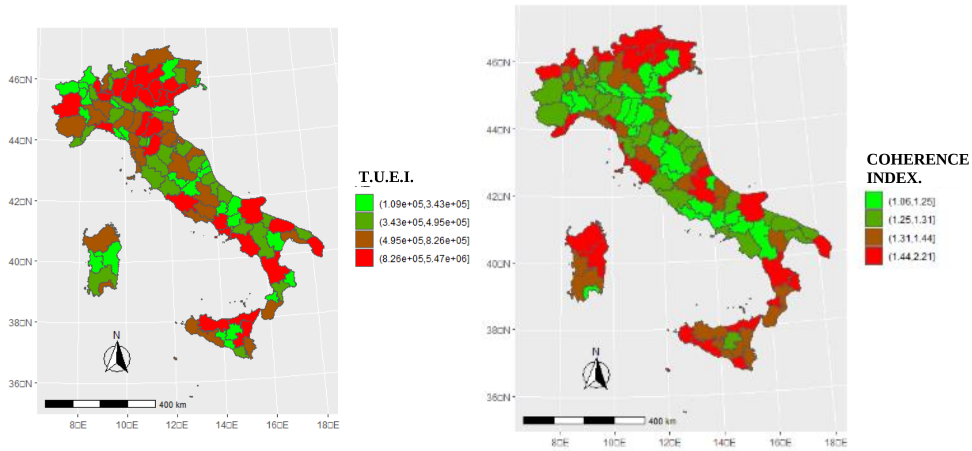
Once the TUEI for each census section was calculated, based on the sum of the previous variables, the density of TUEI per square kilometer for each census section was determined. It was decided not to include in the calculation of total urban equivalent inhabitants at the municipal level those sections where pollutant loads are not normally conveyed into the public sewer system, those with a TUEI/km² density of less than 1000.

3. Result: Descriptive analysis of TUEI and service coverage

In this section, a descriptive analysis is made of the results obtained from the estimation of TUEI considering the different components used. Next, the results of the TUEI at the provincial level are examined. In conclusion, a comparison is made between the actual purification capacities of plants at the regional level (Ramberti et al., 2022) and the maximum potential pollutant load estimated through the proposed methodology.

Figure 1 - *Provincial distribution of TUEI in absolute values (left) and consistency index (right). Colors refer to quartiles of the distributions.*

a) b)



As we can see in figure 1.a), there is a non-homogeneous distribution of the potential pollutant load of urban wastewater across the national territory. The areas with the highest presence of TUEI in absolute terms are, as expected, the metropolitan cities and the most populated provinces, but also provinces with historically significant tourism development and attractive capacities, such as coastal areas. Conversely, the inland areas of our peninsula, particularly the Apennine region and the Sardinian hinterland, which are less involved in major tourist routes and have fewer water-intensive industries, show a lower presence of equivalent inhabitants (E.I.).

In order to better assess the impact of the various components in the calculation of TUEI, particularly concerning the most significant component, the resident population, a consistency index was defined as follows:

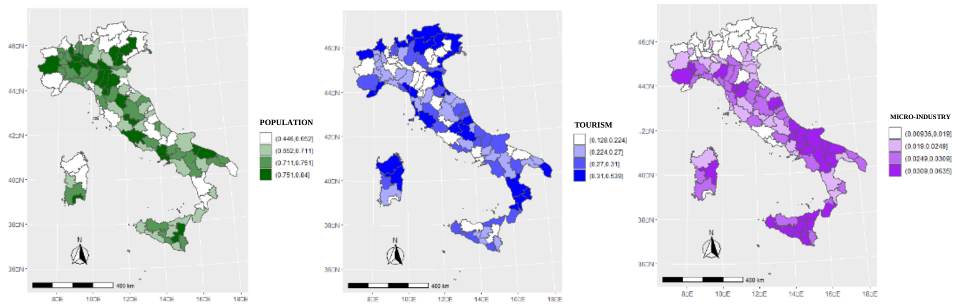
$$\textit{Coherence Index} = \frac{TUEI}{resident\ population}$$

This indicator always takes values greater than 1 since the estimate of TUEI is, in all cases, higher or at most equal to that of the resident population. The closer the indicator is to 1, the greater the coherence between TUEI and the resident population; the further the indicator is from 1, the greater the impact of the non-resident population or the presence of economic, tourism, and commuting activities. The territories that report the greatest distances (Figure 1.b) seem to refer to the main tourist areas of our country such as the Ligurian coast, much of the Alpine chain, the Romagna riviera, the Versilia coast, the center of the Adriatic coast, the Calabrian coast and much of the insular territories of Italy. From this perspective, although it seem an obvious result, the proposed analysis thus confirms its robustness and validity.

As shown in the following graphs (Figure 2), the weight of the "population" component is less pronounced in the aforementioned provinces, which fall in the lower quartiles of the distribution, with an incidence between 44% and 71%. Conversely, these areas are shown in darker colors, indicating a higher percentage of the tourism component, which ranges between approximately 27% and 54%.

Figure 2 - *Provincial distribution of the population component (left), tourism component (center) and micro-industry component (right) in percentage values. Colors refer to quartiles of the distributions.*

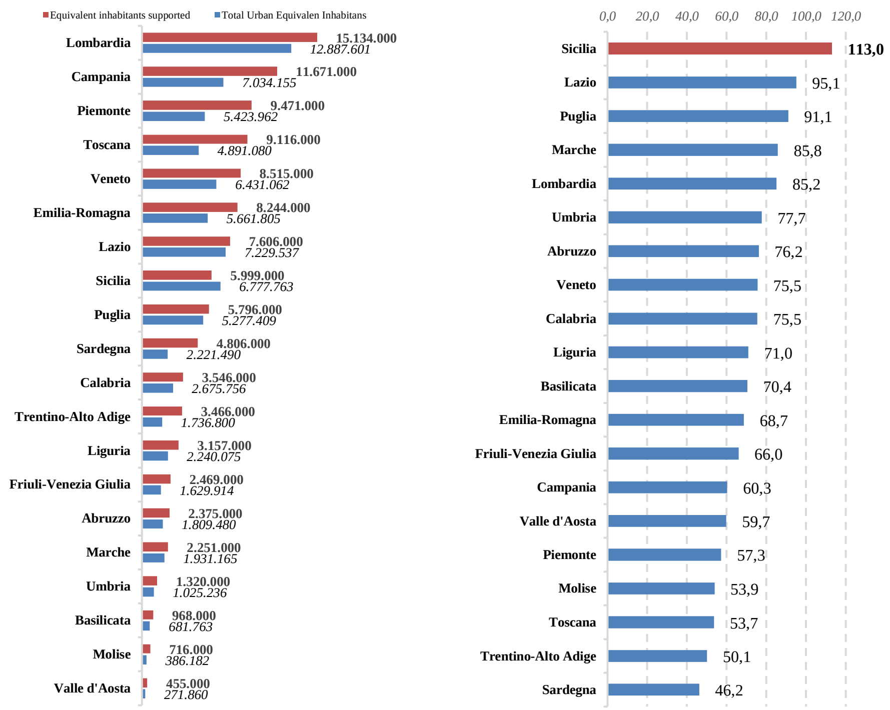
a) b) c)



An interesting aspect that emerged from the analysis is that in many provinces of Southern Italy (particularly in the regions of Puglia, Calabria, and Sicilia), there is a higher percentage incidence of the industrial component compared to the northern regions (Fig. 2.c). This finding may be linked to the fact that industrial activities are present in territories with a smaller population compared to the north, thus increasing the percentage of this component on the total TUEI. However, it should be noted that the percentage values are still marginal, not exceeding 6.4%. Turning finally to the comparison between the actual purification capacities of the plants at the regional scale, (information obtained from the ISTAT survey "Urban Water Census - Year 2020") and the maximum potential pollutant load estimated through the proposed methodology (Fig.3a) the region where the discrepancy (Fig. 3.b) is greatest is Sardegna, with a percentage difference of 46.2%. This means that, overall, Sardinian regional plants are capable of treating wastewater from a number of equivalent inhabitants more than double that potentially present in the territory (TUEI).

Figure 3 - *Regional distribution of maximum loads supported by plants in absolute values (left) and percentage of load generated in TUEI according to the proposed methodology on maximum supported load (right).*

a) b)



In most regions, the total pollutant load that can be purified by municipal wastewater treatment plants is greater than the potential TUEI present in the territory. The most problematic situation is observed in the region of Sicily, where the estimated number of equivalent inhabitants during the period of maximum load exceeds the maximum capacity of the plants present in the region. According to the data from the Urban Water Census, the Sicilian region has a treatment plant capacity of about 6 million equivalent inhabitants, while the estimated total load generated in the territory is over than 6.7 million TUEI, highlighting a significant purification deficit. A condition that deserves more attention and supervision is that of Lazio and Puglia, which show a smaller discrepancy: the TUEI present within their jurisdiction represents over 90% of their plants' capacity.

4. Conclusions: limitations and further development

In line with the initial goals set, the work succeeded in developing a uniform and nationally shared estimation method capable of quantifying the pollutant potential produced by territories in the week of maximum plant load.
This methodology also reported realistic results, with a good degree of reliability and certainly more usable than the variety of calculation methods adopted to date. The analysis also made it possible to highlight regional areas where greater attention is needed regarding plant capacities to prevent potential critical situations.

On the other hand, it is necessary to point out the inherent limitations of established system. A first major point of criticism concerns the use of outdated sources.

The proposed estimates have tried to circumvent this obstacle, however, pointing out this criticality also allows us to remark a greater statistical attention on the issue and to urge a greater collection of quality and up-to-date data, information and analysis from all the stakeholders involved.

The work presented represents a possible starting point for new and more in-depth studies on the topic. Future research paths could aim, for instance, to adapt the methodology to the new, more stringent regulations currently under approval or to refine the calculations for new census polygons in development. Further applications of the TUEI calculation with the new methodology applied in this work could involve comparisons with calculations made by regions at the municipal level. This would allow for an assessment of the actual capacity of the urban wastewater system and existing agglomerations at a level of detail never previously investigated.

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MOBILE PHONE DATA TO SUPPORT AIR POLLUTION EXPOSURE ASSESSMENT

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Abstract. Air pollution is one of the greatest environmental risks to health according to the World Health Organization. Depending on the characteristics of the data sources we can organise the personal exposure assessment methods in two classification criteria: (i) spatial-temporal variations of individuals' activities (point-fixed or trajectory-based) and (ii) characterisation of air quality (variable or uniform).
In line with this approach, the paper presents a study based on Mobile Network Operator (MNO) data to evaluate spatial-temporal variations in human presence along with pollutant measurements to estimate people's exposure to air pollutants. MNO data enable a longitudinal analysis of human presence with high spatial and time resolution. This allows assigning different levels of air pollution exposure to the population at a specific time and in a specific location.
The proposed method can be useful for policymakers to assess the crowdedness of air-polluted areas over time and to find suitable solutions to mitigate the exposure. In addition, our results can be exploited for improved estimation of the risks inherent to the population exposure to air pollution in urban areas and for epidemiological studies.

1. Introduction

Outdoor air pollution is one of the greatest environmental risks to health according to the World Health Organization (WHO), estimated to have caused 4.2 million premature deaths worldwide in 2019[1]. Indeed, exposure to fine particulate matter and nitrogen compounds causes cardiovascular and respiratory diseases both chronic and acute, including asthma (Beelen *et al.* 2014).

Several pollutants are monitored in urban and industrial areas to ensure the air quality is in line with the guidelines provided by the WHO. In order to estimate population exposure levels to different pollutants, data on the air quality measured by the monitoring stations need to be combined with data on population presence in the areas. Usually, Census and administrative data are used for this scope, but of

[1] https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health

course, it is a rough approximation: the presence assessment is static and derived only from the place of usual residence (Gray *et al*., 2013).

The spatial-temporal variations of individuals' activities would be preferred to estimate the exposure of the population to pollution in urban areas. However, this information is usually omitted in exposure studies due to the lack of reliable data sources. Mobile Network Operator (MNO) data give the opportunity to fill the gap by assessing the actual frequented places by the population (Dewulf *et al.*, 2016).

The aim of this work is to develop a method for estimating exposure to air pollutants by associating individuals with locations, and thus the corresponding pollution levels, using MNO and air quality data.

MNO data have received increasing attention in recent years to enrich and complement traditional data sources, surveys and administrative data, in Official Statistics. Nevertheless, many of the experiences in exploiting this new data source are often experimental and still require a well-defined standardized methodological framework, which encompasses the requirements for sound methodologies, transparent procedures, coherence and comparability, and in general the commitment to quality that marks the official statistical products. Recently, the Italian National Institute, Istat, has been involved in several initiatives at the national level and at the European level, co-funded by the European Commission. Indeed, the Multi-MNO[2] project (2023-2025) is a first-of-its-kind project in the European Statistical System: a team of industry specialists and NSI experts for co-developing together an open methodological standard. In addition, the research project MNO-MINDS[3] (Methods for Integrating New Data Sources, 2023-2025) focuses on methods for the integration of MNO and non-MNO data (e.g., survey data, census data, other big data sources etc.) with 10 NSIs involved across Europe. The work presented in this paper benefits from both the two projects and it is an example of the potential exploitation of MNO data for innovative official statistics.

2. Data

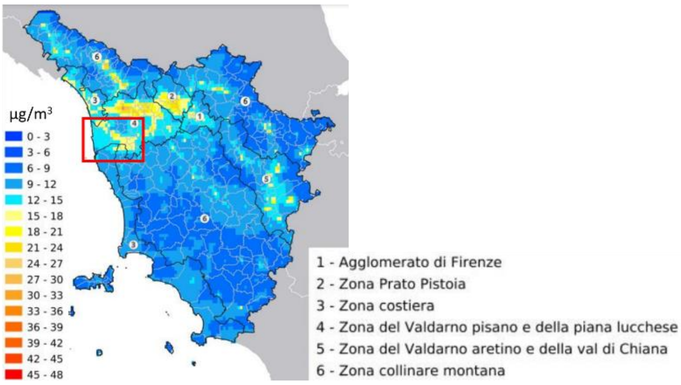
2.1. Study area

The study area is part of "Zona del Valdarno pisano e della piana lucchese" which is the most critical area in terms of air quality in the Tuscany region as it is shown in Figure 1. The map displays the output of the SPARTA modelling system run officially by the LAMMA consortium for ARPAT (Busillo *et al.* 2022) and

[2] https://cros.ec.europa.eu/multi-mno-project
[3] https://cros.ec.europa.eu/mno-minds

represents the average PM10 concentration for the year corresponding to available MNO data, the boundaries are not administrative units but environmental zoning. Valdarno is the focus of this study and is highlighted in the map within the red box.

Figure 1 – *Average PM10 concentration, year 2017.*



2.2. Mobile Network data

The spread of mobile communication technology has provided access to large amounts of data that can be used to analyse human and social behaviour. Usually, Mobile Network Operators (MNOs) store Call Detail Records (CDRs) which contain information about call events, such as time, duration, and location of the used network cell. In addition to CDRs, MNOs also collect additional data for tasks like network management and troubleshooting, e.g. signalling and probe data, which can offer a valuable resource for studying human behaviour and presence. We refer to the totality of these different data as Mobile Network Operator data (MNO data).

Unlike CDRs, signalling data present a higher level of complexity due to the large volume (an event is recorded on average every 2 seconds for each mobile device) and due to the peculiarities of mobile networks for different MNOs. Thanks to the progress in the available computational power and storage capability, many analyses are now focusing on signalling data, rather than CDRs, since in many countries and within some sub-groups phone calls are more and more infrequent due to the spread of online services of instant communication (instant messaging, VoIP calls).

Despite this limitation, in this study we use a sample of pseudo-anonymized CDRs of an Italian province, Pisa, for a study period of 6 weeks starting from January 1 to February 13, 2017. The data are described in detail in De Fausti *et al.*, 2024.

2.3. Air quality data

The air quality data are provided by ARPAT, the regional environmental agency which administers the monitoring network of the Tuscany region. In the study area, we have four monitoring stations. Table 1 specifies the location and type of each station.

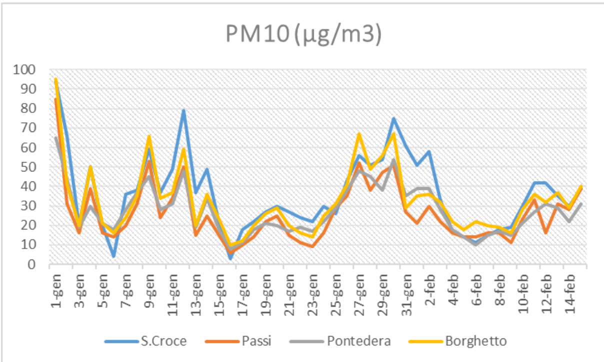
Table 1 – *Monitoring stations in the study zone.*

Station	Municipality	Station type	Zone
Passi	Pisa	Background	Urban
Borghetto	Pisa	Traffic	Urban
Pontedera	Pontedera	Traffic	Urban
Santacroce	Sc Sull'arno	Background	Suburban

Background monitoring stations measure air quality in areas not directly influenced by specific sources of pollution, providing information on regional pollution levels. Traffic monitoring stations, on the other hand, are located near roads and highways to measure pollution from vehicle emissions, reflecting local traffic-related air quality.

The graph in Figure 2 shows the trends in PM10 levels as recorded by the four stations during the study period.

Figure 2 – *PM10 concentration values measured during the study period.*



As mentioned, MNO data available for the current study are CDRs. Since CDR events are rare in a day, they are not appropriate for air pollutants regulated with hourly concentration limit. This is the reason why we use the PM10 pollutant to assess the exposure, for PM10 regulations set daily and yearly average concentration limits. The methodology can be easily extended to other pollutants with hourly concentration limits (O_3, NO_x, CO and SO_2), when other MNO data (e.g. signalling data) become available. The regulation sets for PM10 concentration an annual average limit of 40 μg/m³ and a daily average limit of 50 μg/m³.

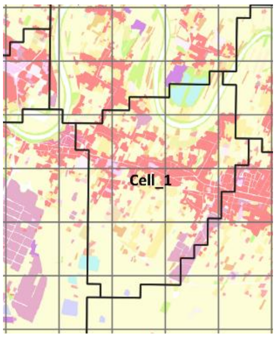
3. Data elaboration and methods

3.1. Positional and temporal features of mobile data and monitoring stations

The geolocation of the SIM associated with each CDR is estimated through the coverage area of the cell to which the device is connected when the call starts and ends. The cell coverage area is defined as the Best Service Area (BSA), which is the area where the connected mobile device has the highest probability of being located and is provided by the MNO under a confidentiality agreement. MNOs estimate the probability by using several parameters, like the quality of the cell signal, the technology of the cell, the coverage orography, the density of potential users, etc. An example of BSA is represented in Figure 3.

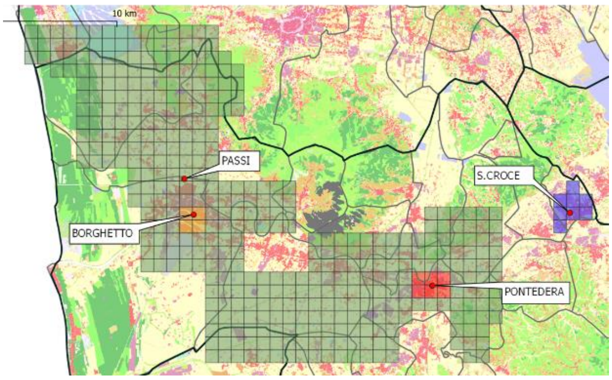
The data provide two events for each call, corresponding to the call start and the call end. Each event is identified by a timestamp and an associated cell ID. In the analysis, the time is discretized into 1-hour slots.

Figure 3– *The Best Service Areas of some cells (black lines) for LTE superimposed to the regular 1x1km grid used in the analysis (grey lines).*



Air monitoring stations' location is fixed in time and space and represents point-based data. Since we are interested in having a measure of the pollution levels for areas around the stations (covering the geographical area of our study), we used two different methods depending on the type of the considered stations. For background stations, we estimated the spatial representativeness of pollution measures by using the output of the SPARTA model system (Busillo *et al.* 2022). For traffic stations, we consider only the urban areas located around the stations. “Passi” station has the largest area of representativeness, extending towards the coast as can be seen in Figure 4.

Figure 4 – *Spatial coverage of the monitoring stations.*



3.2. Spatial and temporal integration: monitoring stations/cells association

CDRs and pollution data from monitoring stations have different spatial and temporal scales, an integration step is then required to get the final indicators. As a reference spatial system we adopted the INSPIRE (Infrastructure for Spatial Information in Europe) grid system provided by the European Commission to improve harmonization[4]. The chosen scale for the reference spatial grid is 1km x 1km.

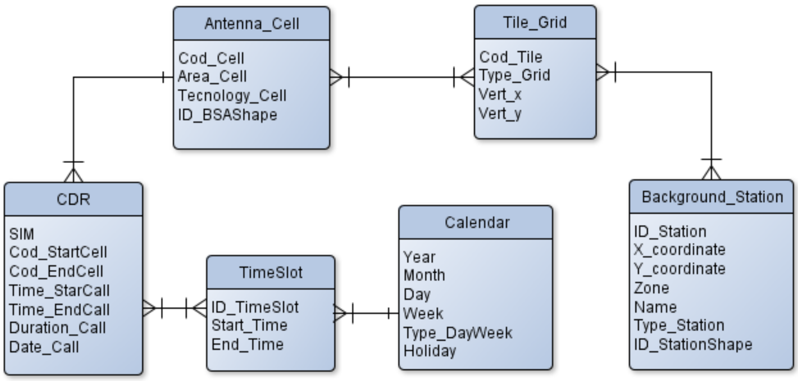
We implemented the following steps:

- the study area was divided into 1km x 1km tiles according to the INSPIRE grid, each tile is uniquely identified by a code;
- the cell coverage areas (BSAs) and the stations' spatial representativeness areas are encoded by shape files mapped to the INSPIRE 1km x 1km through spatial superimposition, as shown in Figure 3 and Figure 4.

After this processing, data were structured according to the entity and relationship scheme shown in Figure 5.

[4] INSPIRE, https://inspire.ec.europa.eu

Figure 5 – *Entity and Relationship Scheme of Data integration: CDR, station and grid*.



As shown in Figure 6, each cell coverage and each station coverage are associated to a set of tiles falling into the relative areas.

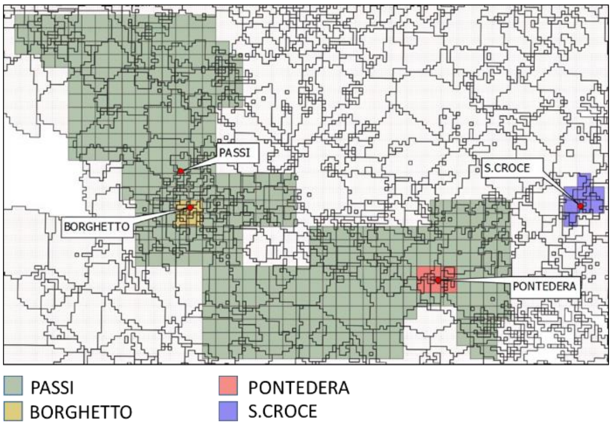
The presence of devices in the study area over the observation period has been estimated via a Permanence Score (PS). As already mentioned, the time dimension was discretized into 1-hour time slots. For each SIM, the PS value is assigned to each time slot of a day. The PS takes value:

- 1 if a call of the SIM occurs at any time in the time slot
- 0 if in the entire 1-hour time slot no calls occur

The permanence score is then a discretized measure of the SIM presence with 1 1-hour time resolution. A set of tiles is also assigned to each time-slot, which is the tiles composing the BSA of the cell to which the device is connected during the call. Note that if during a call the device connects to more than one cell, the time slot will be assigned to PS=1 for all the tiles corresponding to both cells. In this way, for each device and for each tile we calculated the amount of time (measured in number of one-hour time slots) during which a call occurs. Using the permanence score it is possible to carry out different analyses by aggregating the information over the entire period observed. We are able to carry out:

- **longitudinal analyses** for single SIM to obtain a daily exposure time and frequency. This aggregated and discretized information allows us to study the number of SIMs exposed in terms of hours, days or frequency.
- **spatial analyses** to detect, based on the presences and the temporal and spatial trend of pollution, how many SIMs have been affected.

Figure 6– *Overlapping of cells and stations coverage area.*

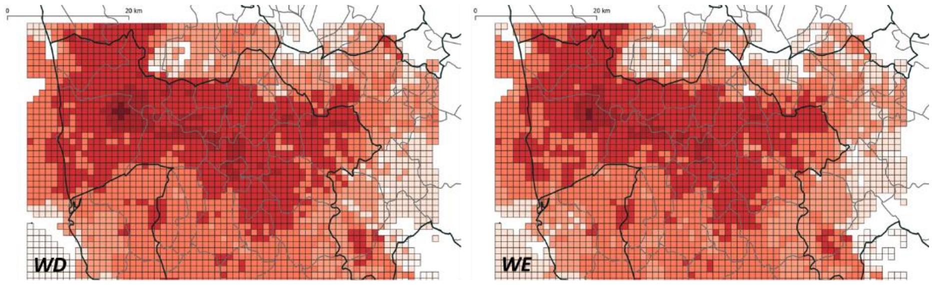


4. Results

4.1. Dynamic human presence

The maps in Figure 7 illustrate the SIMs population estimated using the methodology described in the previous section. It shows the dynamic presence in typical weekday (WD) and weekend (WE) days of January.

Figure 7 – *Dynamic human presence for typical weekday (WD) and weekend (WE) days.*



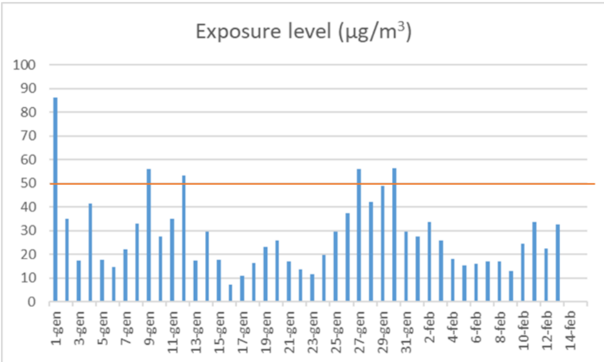
Different presence patterns can be observed with a level of detail that cannot be achieved with any other data sources. It can be observed that during the weekend days there is less dispersion of the population, likely indicating greater mobility for work-related reasons during the weekdays. At the same time Pisa urban centre shows a higher population density during the working day, likely due to the effect of commuting.

Numerical references are intentionally omitted for privacy reasons and because the dataset is not representative of the entire population.

4.2. Longitudinal analysis: daily exposure

Figure 8 shows the average daily exposure of the SIM population, obtained by averaging the values of each SIM separately observed throughout the day and being associated with different pollutant values in function of frequented places and time spent, as described in section 3.2.

Figure 8– *Daily average exposure of the observed SIM population.*



4.3. Longitudinal analysis: long term exposure

Due to the unavailability of a full year's data, we analysed the entire period at our disposal, going from the 1st of January to the 13th of February, as an indicator of long-term exposure.

The average monthly exposure of the observed population is obtained by averaging the values of each SIM. The spatial-temporal variations of each SIM individually contributed to the exposure estimate.

Table 2 shows the PM10 exposure levels of the SIM population. It can be noted that 1% of the SIM population is exposed to a pollution level exceeding the annual limit.

Table 2 – *PM10 exposure levels for the SIM population in the study period.*

Exposure Level (μg/m^3)	Percentage of population (%)
[0,10]	0
(10,20]	1
(20,30]	71
(30,40]	28
(40,50]	1
(50,Inf]	0

5. Concluding remarks

In this paper, we propose a first attempt to improve the estimations of air pollution exposure using MNO data. So far, in fact, the exposure to pollutants levels was calculated considering the usual residence of each inhabitant, disregarding the time spent outside official residence (e.g. at work, school, etc.) that can be significantly large. MNO data give the opportunity to assess the amount of time a user spends in different locations, and, hence, to increase substantially the accuracy of exposure estimations. However, CDRs are quite sparse to exploit the whole potentiality of MNO data. In future, we are going to apply the developed method to signalling data.

In this work, we consider the mobile devices detected in the study area as our target population. Future works will be devoted to the challenge of producing statistics referring to human beings present in the area. This is not a trivial task, since the present population is a composite of different groups: usual residents, commuters, tourists, passing-by, etc. and the mobile devices associated with them may require different estimation factors. Finally, additional data sources like satellites and models can help provide air quality data for areas not covered by monitoring stations.

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THE GEOGRAPHY OF GREEN INNOVATION

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Abstract. In the last decades, the geography of innovation activity became much more concentrated. By focusing on the metropolitan statistical area of residence of the inventors of patents granted by the United States Patents and Trademark Office between 1976 and 2020, we investigate whether this is true also for "green" innovation, *i.e.* patents covering mitigation or adaptation to climate change. We find a sharp increase in concentration across areas after the beginning of the 2000s, with areas that are generally more innovative also producing more green patents. Moreover, for an in-depth analysis of spatial dependence patterns, we firstly survey the literature to find tests suitable for comparing spatial patterns and then apply these tests to the data on green patenting in comparison with non-green patenting. We find significant differences between the two phenomena.

1. Introduction

It is an established result in the literature on innovation and agglomeration that innovation activities are spatially concentrated (e.g., Audretsch & Feldman, 1996; Buzard *et al.*, 2017). Some authors, in particular, view innovation essentially as an urban phenomenon (e.g., Florida, 2009). One of the underlying explanations, dating back to Marshall (1890), is that geographic proximity facilitates the transfer of knowledge. The idea that informal interactions are central to innovation and knowledge spillover has then become a fundamental element of recent theories if economic growth.

A sizeable literature has then provided empirical estimates of the size and the properties of local knowledge and productivity externalities. Jaffe *et al.* (1993) find that patents citations display a significant bias towards patens that were produced in the same state and metropolitan area. Greenstone *et al.* (2010) estimate significant agglomeration spillovers on Total Factor Productivity by comparing winning and losing countries bidding to attract large plants. Kerr and Kominers (2015) propose a theory of cluster formation based on firm’s location and interaction choices and confront its predictions using data on patents citations by technology class, finding out that the geographical properties of innovation clusters are controlled by the spatial range of knowledge transmission which is specific to each technology class.

Several studies focus on the role of specialization and diversity in driving innovation and economic outcomes in cities (Glaeser and Gottlieb, 2009; Delgado *et al.* 2014). Berkes and Gaetani (2021) focus on the geography of unconventional innovation and on how economic geography shapes the creative content of innovation. In particular, they show that high-density areas tend to have an advantage in producing unconventional ideas and that the combination of ideas embedded into inventions is determined by the local technology mix.

In this paper we focus on “green" innovation, loosely speaking patents covering mitigation or adaptation to climate change and see if the way this type of innovation distributes over space shows any significant difference compared to “non-green” innovative activity. More in detail, we firstly create a database of utility patents granted to inventors residing in the conterminous US from 1976 to 2016 at the Metropolitan Statistical Area level. Then, we measure spatial concentration in green and non-green innovative activities, finding a sharp increase in concentration across areas after the beginning of the 2000s, with areas that are generally more innovative also producing more green patents. Then, we examine the evolution of the cross-sectional distribution of green and non-green patents per capita across MSAs. Furthermore, we survey the literature to find tests suitable for comparing spatial patterns and then apply two of these tests to the data on green patenting in comparison to non-green patenting; here, we find significant differences between the two phenomena. Finally, we analyse the intensity of the spatial association of green and non-green patents. Our results document the presence of positive spatial correlation and indicate the existence of a High-High cluster in the North-East of the nation.

2. Data

We measure innovation with the flow number of patents (an exclusionary right conferred for a set period to the patent holder, in exchange for sharing the details of the invention) filed between 1976 and 2016 and eventually granted by the United States Patents and Trademarks Office (USPTO). We associate a patent to a year using the application date, which is the year when the provisional application is considered complete by the USPTO.[1]

[1] We follow the patent literature in focusing on application year rather than on the award year. As noted by Lerner and Seru (2022), the motivation is that, whereas firms will generally tend to file for patents as soon as the discoveries are made in order to protect their intellectual property, the time at which the patent is granted depends on many external factors, like the technological area or the state of the patent office.

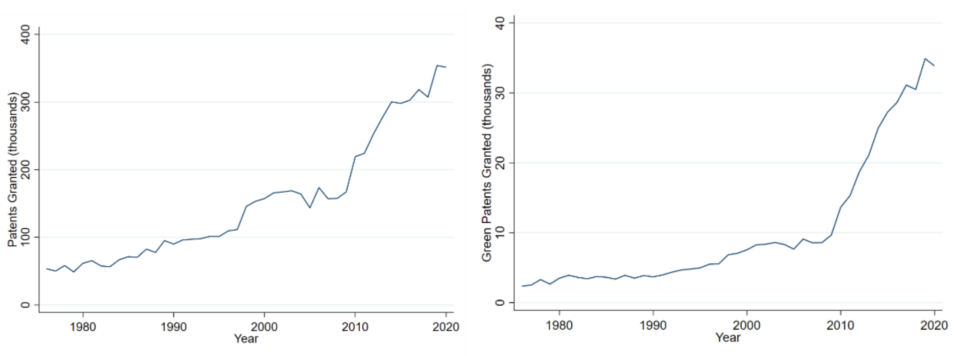
Withdrawn applications are excluded from the analysis. As common in the literature, we restrict our attention to utility patents (thus excluding design patents and plant patents), which cover the creation of a new or improved product, process or machine; these represent approximately 90% of all patents granted by USPTO.

We assign patents to areas according to the location in which the inventor resides as in, e.g., Castaldi and Lobs (2017), Aghion *et al.* (2019), Berkes and Gaetani (2021), Moretti (2021), which is extracted from patent text and used to determine latitude and longitude. We use the residential addresses of the inventors and not the one of the assignee (usually, the company that first owned the patent), because we are mainly interested in the location of processes that lead to inventions, whereas the assignee address often reflects the address of the corporate headquarters and not the R&D facility (Moretti, 2021). When a patent is coauthored by more than one inventor, we split it equally among them, as in Aghion *et al.* (2019), Berkes and Gaetani (2021) and Moretti (2021). Henceforth, we attribute a fraction m/n of a patent to an area a, where n is the total number of inventors reported in that patent and m is the number of inventors in that patent who reside in area a.

In 2013, the USPTO and the European Patent Office introduced a new system of Cooperative Patent Classifications (CPC) that, unlike existing patent classifications such as the International Patent Classifications, can also be indexed with a focus on emerging technologies (Veefkind *et al.*, 2012). These new classifications have been backtracked into the existing databases. We exploit this system by classifying a patent as “green” if it belongs to at least one subclass in the Y02/Y04S scheme, like e.g. Corrocher *et al.* (2021). Within the CPC, the Y02 class covers technologies which control, reduce, or prevent anthropogenic emissions of greenhouse gases (GHG), in the framework of the Kyoto Protocol and the Paris Agreement, and technologies which allow the adaptation to the adverse effects of climate change, whereas the Y04S covers systems integrating technologies related to power network operation, communication, or information technologies for improving the electrical power generation, transmission, distribution, management, or usage.

We focus on inventors residing in the conterminous United States (i.e., the 48 adjoining states and the District of Columbia). In our database, there are 3,836,007 utility patents granted to inventors residing in the conterminous US, of which 249,501 belong to at least one green subclass. It is well known that the number of patents issued by the USPTO annually has steadily increased since the 1990s, as shown in the left panel of Figure 1. The right panel of Figure 1 shows that the number of green patents granted has been growing slowly up until 2006, when an impressive acceleration can be observed, in line with the findings by Corrocher *et al.* (2021).

Figure 1 – *Evolution over time of the patents granted by USPTO.*



(a) All patents *(b) Green patents*

The first (second) panel shows the number of utility (green) patents granted by USPTO in any given year between 1976 and 2020. (Own elaborations using data from USPTO).

In terms of areas, we focus on Metropolitan Statistical Areas (MSAs), i.e. regions consisting of a large urban core together with surrounding communities that have a high degree of economic and social integration with the urban core. We consider MSAs for various reasons. First, MSAs represent economic spatial units and so are considered more appropriate to study economic dynamics than states, regions, or even counties Drennan (2005). Second, innovation is mainly an urban phenomenon; for example, the vast majority of patents in our dataset come from inventors residing in a metropolitan area (approximately 85% for utility patents and 83% for green patents). Third, there is large heterogeneity across MSAs in terms of capacity to innovate.

We assign an inventor location to a MSA using the 2010 Cartographic Boundary Files provided by the United States Census Bureau.[2]

3. Concentration

There is ample evidence that research and development activities tend to be more concentrated than manufacturing activities (Buzard *et al.*, 2017). Moreover, US patenting activities have become more geographically concentrated since the end of the last century (Castaldi and Lobs, 2017; Andrews and Whalley, 2021; Forman and

[2] Source: https://www.census.gov/geographies/mapping-files/time-series/geo/cartographic-boundary.html. The definition used for the identification of MSAs has evolved over time, with significant changes made especially around census years: results are qualitatively identical independently of the boundary files used.

Goldfarb, 2021; Magrini and Spiganti, 2024). For example, Andrews and Whalley (2021) and Forman and Goldfarb (2021) report a particularly pronounced increase in the geographic concentration of patenting at the US county level starting from the 1990s, while Castaldi and Lobs (2017) highlight that concentration is even more pronounced for highly-cited patents at the state level.

Here, we first measure the spatial concentration in green innovative activities and then examine the evolution of the cross-sectional distribution of green patents per capita across MSAs, comparing these to those for non-green patents. We do so using the Herfindahl–Hirschman Index and the Dartboard Index.

The Herfindahl–Hirschman Index (HHI) provides a measure of the size of innovation in an area in relation to the overall amount of innovation in the nation. For each year t and each area a, where $a = 1,\dots, A$, the Herfindahl–Hirschman Index concentration index is:

$$HHI_t = \sum_{a=1}^{A} (SharePat_{at})^2 \tag{1}$$

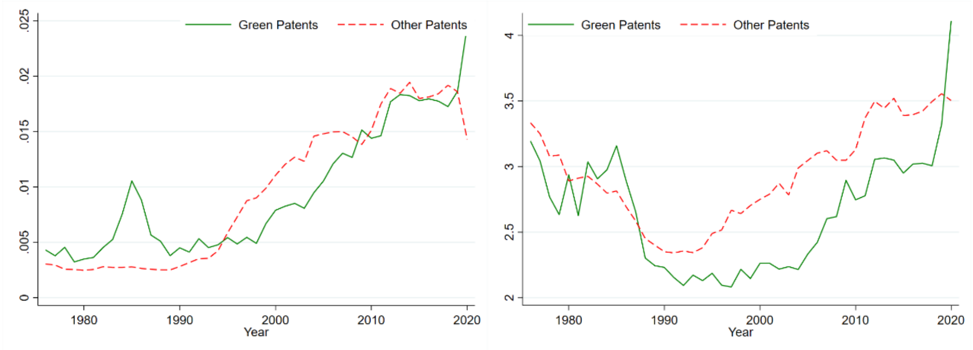
where $SharePat_{at}$ is the patent share of area a. The scale of the index is such that a value of zero can be interpreted as indicating a complete lack of concentration, whereas a value of one would indicate that all patenting occurs in one area.

The spatial concentration index by Ellison and Glaeser (1997), also known as Dartboard Index (*EGI*), compares the observed spatial distribution of innovation to what it would have been if it was proportional to population distribution. In particular, for each year t and all areas a, where a = 1,…,A, the Dartboard Index is

$$EGI_t = \frac{\sum_{a=1}^{A} (SharePat_{at} - SharePop_{at})^2}{1 - \sum_{a=1}^{A} SharePop_{at}^2} \tag{2}$$

where $SharePat_{at}$ and $SharePop_{at}$ are, respectively, the share of patents granted and the share of population living in area a and year t. The scale of this index is such that a value of zero can be interpreted as indicating a complete lack of agglomerative forces, whereas a value of one would indicate that all patenting occurs in one area.

Figure 2 – *Evolution over time of the concentration of the patents.*



(a) Dartboard Index *(b) HH Index*

The first (second) panel shows the Dartboard (Herfindahl-Hirschman) innovation intensity concentration index across metropolitan statistical areas in the United States between 1976 and 2020. (Own elaborations using data from USPTO).

Figure 2, which reports the evolution of the indexes, documents a sharp increase in concentration across areas; it starts in the mid-1990s for non-green patents and at the beginning of the 2000s for green ones.[3] Specifically, we observe that the HHI exhibits an initial decline in concentration, which Andrews and Whalley (2021) suggest could be due to improvements in transportation, increasing access to higher education, and the expansion of direct federal funding for research. Conversely, the increase in concentration goes hand-in-hand with increasing assortative sorting of skills across cities and the emergence of superstar cities. Towards the end of the 2020s, concentration shows a tendency to decline, at least for non-green patents.

4. Geographical patterns

4.1. Stochastic spatial processes

Spatial data can be thought as resulting from observations of a stochastic process $\{Z(s): s \in D \subset R^d\}$, where D is a set of R^d, $d = 2$, and Z(s) denotes the attribute we observe at s. In case of patents, spatial referenced data can be of two types, according to the assumptions made on **D**:

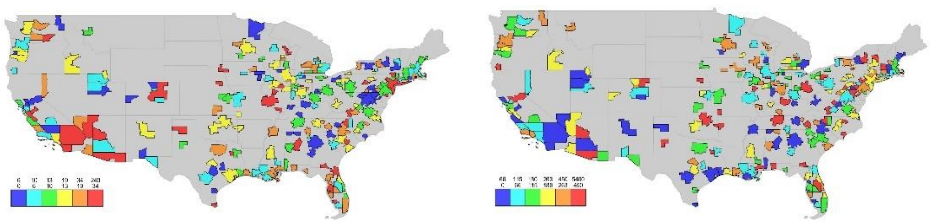
[3] The spike in 1987 in the concentration of green patents is due to an increase of the fraction of green patents coming from innovators residing in Pittsburgh, PA, and in particular in Allegheny County (by 4.2 percentage points) and Westmoreland County (by 1.9 percentage points), which mostly reversed in 1988.

i) areal (or lattice) data: the domain is a fixed countable collection of irregular areal units at which variables are observed. Here patenting of given characteristics is aggregated into areas that form a partition of the study region.

ii) point patterns: the domain is random. The index set gives the location of random events of the spatial point pattern.

Here we will focus on areal-based spatial point patterns. In the graphs below we present the geographical distribution of the patents data analysed in this paper.

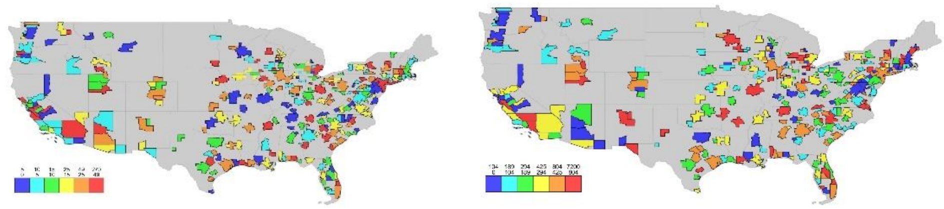
Figure 3 – *Spatial point pattern of patents in 1980.*



(a) Green patents *(b) Other patents*

Notes: patent activity is divided into sextiles going from blue (low activity) to red (high).

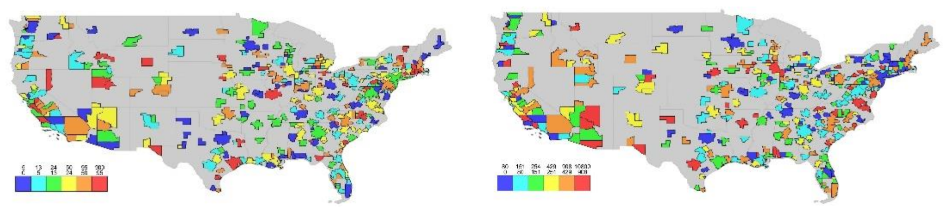
Figure 4 – *Spatial point pattern of patents in 2000.*



(a) Green patents *(b) Other patents*

Notes: patent activity is divided into sextiles going from blue (low activity) to red (high).

Figure 5 – *Spatial point pattern of patents in 2020.*



(a) Green patents *(b) Other patents*

Notes: patent activity is divided into sextiles going from blue (low activity) to red (high).

At a first glance, in 1980 and 2000 green patenting tends to concentrate in area where non-green patenting is not particularly concentrated. A clear example of this is the South-West of the nation. Conversely, in 2020 the spatial patters appear to be more alike.

4.2. Testing for similarity of point patterns

The method that is mostly adopted in the literature to test for similarity of spatial point patterns is Andresen's (2009) test; this test however is not applicable in the present case, due to some peculiarities of the data: the USPTO usually attributed the location of the inventor to the central point of the county of residence, thus leading to more than one observation per a specific spatial point in each area. Therefore, we adopt a sort of combined approach. In a first step, we will resort to the so-called modified T test for assessing the correlation between two spatial processes proposed by Clifford *et al.* (1989) and further modified by Dutilleul *et al.* (1993). The null hypothesis is the absence of correlation between two spatial point patterns; the original test statistics has been modified to improve the approximation of the variance of the sample correlation coefficient.

Then, in a second step, we adopt two similarity tests by Alba-Fernandez *et al.* (2016). The null hypothesis here is the similarity of two spatial point patterns. Both tests move from a preliminary phase of counting the number of occurrences per each areal units and the idea is to find out whether it is obtained a sample of a multinomial distribution. To do this, in one case (the so-called T_1 test) it is adopted a Chi-square test for homogeneity, while the second test (the so-called T_2 test) is based on the negative of Matusita's affinity. For both tests the reference distribution is χ^2. For space reasons, we refer to the papers by Dutilleul *et al.* (1993) and Alba-Fernandez *et al.* (2016) for the formal details of the tests and here we focus instead on the results on our data, summed in the following tables:

Table 1 – *Spatial point pattern correlation test: null hypothesis is absence of correlation.*

Year	T-value	P-values
1980	0.0003	0.938
2000	0.0060	0.750
2020	0.0100	0.704

Notes. The test is performed using the SpatialPack package in R. (Vallejos et al., 2020).

Table 1 reveals that we cannot reject the null hypothesis of absence of correlation between the patterns; this can be considered as signal of lack of similarity between the point patterns. Given this result, we move to the second set of tests to confirm or disconfirm this evidence.

Table 2 – *Similarity tests: null hypothesis is the similarity of two spatial point patterns.*

Year	T_1	T_2	$\chi^2(0.90)$	$\chi^2(0.95)$	$\chi^2(0.99)$
1980	580.330	3540.883	262.117	270.684	287.247
2000	505.392	2944.563	308.614	317.888	335.776
2020	195.379	8102.683	371.719	381.872	401.408

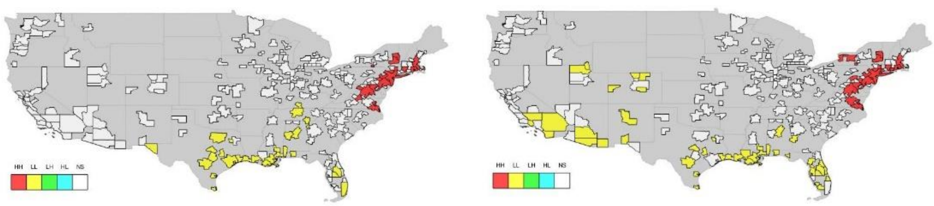
Notes. H0 is rejected for large values of the statistic. The test is run in R following Alba-Fernandez et al. (2016).

Table 2 shows that we can reject the null hypothesis that the patterns are similar for 1980, 2000 for both tests. As for 2020, we cannot reject the null hypothesis for T_1. Looking at these results, it seems that the geographical distribution of patenting activities, somewhat different at the beginning, has become more similar towards the end of the period.

5. Spatial correlation analysis

Local Moran's I is a local spatial autocorrelation statistic developed by Anselin (1995) and based on the Moran's I statistic. It is a Local Indicator of Spatial Association (LISA) and, consequently, it has the following two properties: i) for each observation, it gives an indication of the extent of significant spatial clustering of similar values around that observation ii) the sum of LISAs for all observations is proportional to a global indicator of spatial association. For space reasons, we refer to the papers by Anselin (1995) for the formal details and here we focus instead on the results on our data. Below there is a list of graphs presenting the local Moran significance maps for our data, obtained with a Matlab code. In particular, we show local associations which are significant at the 15% level, using a spatial weight matrix based on 15% nearest-neighbours.

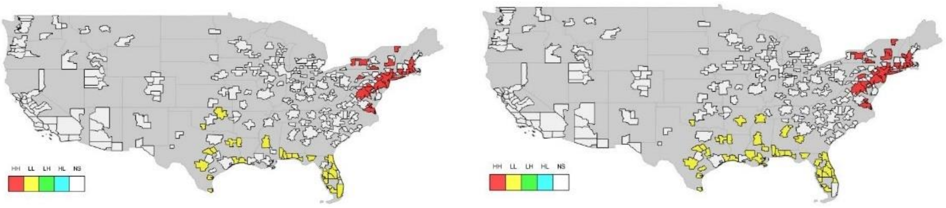
Figure 6 – *Local Moran map 1980.*



(a) Green patents *(b) Other patents*

Notes: red indicates High-High significant local spatial correlations; yellow indicates Low-Low significant local spatial correlations.

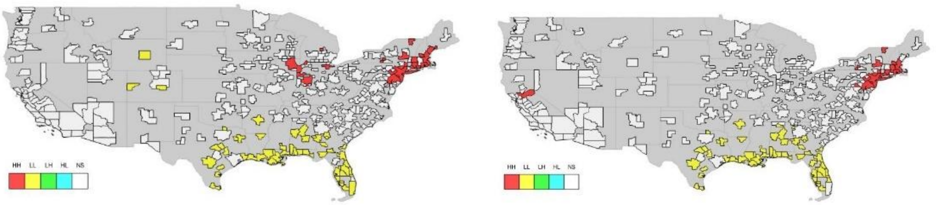
Figure 7 – *Local Moran 2000.*



(a) Green patents *(b) Other patents*

Notes: red indicates High-High significant local spatial correlations; yellow indicates Low-Low significant local spatial correlations.

Figure 8 – *Local Moran 2020.*



(a) Green patents ***(b)*** *Other patents*

Notes: red indicates High-High significant local spatial correlations; yellow indicates Low-Low significant local spatial correlations.

We observe that Moran's *I* test shows the presence of positive spatial correlation and indicates the existence of a High-High cluster in the North-East of the nation. However, the spatial extent of this cluster seems to have reduced by 2020.

6. Conclusions

Patenting activity has increased in general, more so in the case of green patenting after 2010. Concentration shows similar trends overall, but with a visible difference in the last years where concentration of green patents strongly increases while concentration of other patents has remained constant or decreased. The geographical distribution of patenting activities, somewhat different at the beginning, has become more similar towards the end of the period. The Moran's *I* test show the presence of positive spatial correlation and indicates the existence of a High-High cluster in the North-East of the nation.

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SOCIAL CAPITAL: A NEW COMPOSITE INDEX

Angela Pepe

Abstract. The paper aims to propose a new measure of social capital by means of the construction of a composite index based on Adjusted Mazziotta-Pareto Index (AMPI) methodology, in order to study its dynamic during the period 2018-2022 at the level of Italian municipalities, giving its contribution to the limited literature on the effects of the CoViD-19 pandemic on social capital at local level. The results suggest that pandemic shock have had its impact not only on the level of social capital but also on its territorial distribution, causing, on the one hand, a reduction in municipalities with high endowments and, on the other hand, an increase in those with lower endowments.

1. Introduction

Social capital has always attracted the attention of economists and other social scientists. Such an interest is essentially motivated by the relationship between the stock of social capital and various other phenomena such as economic growth, development traps, political participation, health and so on. However, despite the immense amount of studies on it, its definition has remained complex and elusive. The reason for this is due to the multidimensional nature of the phenomenon that requires the overcoming of conceptual and definitional issues in order to measure it. A direct consequence of the multiplicity of dimensions is the diversity of variables and indicators used to analyse social capital in the empirical works such as counts of associations or associational memberships, levels of trust and civic engagement, volunteering, crime rates, voter turnout, charitable-giving, blood donors and car-pooling. In some cases, these are used individually; however, a single measure may not capture completely a concept with complex and multiple dimensions like social capital. In other cases, several individual indicators are aggregated in order to create a synthetic index of social capital. In the latter case, the generally adopted approach is that of principal component analysis (PCA) as in the works of Portela *et al.* (2013) and Gannon and Roberts (2020). However, the PCA is not suitable for analysis over time (historical series) as it cannot be applied to matrices containing the values of a set of individual indicators (columns) for different periods (rows), since the correlations between the indicators must be calculated on the basis of independent observations (Mazziotta and Pareto, 2020). The lack of both a universal measurement method and a single indicator commonly accepted by the literature is also complicated by the chronic lack of suitable data, especially when it comes to analyse the phenomenon for more detailed territorial areas. Often it is precisely this lack of data that forces the choice of variables to be used as an expression of the social capital.

The aim of this paper is to propose a new framework for the measurement of social capital through the construction of a composite index, as well as to test it, taking into account the changes in social capital in the period 2018-2022 in the Italian municipalities.

The composite index proposed in this work presents three innovative aspects. The first of these consists in its construction methodology, that is the Adjusted Mazziotta-Pareto Index Approach (AMPI). It is a method for the construction of composite indices and the extension of Mazziotta-Pareto Index (MPI), whose peculiarity is that it allows the measurement of changes over time. This is an aspect of vital importance when it comes to analyse the evolution over time of a multidimensional phenomenon such as social capital.

The second aspect concerns the definition of a set of several indicators of social capital at the level of Italian municipalities, used for the construction of the composite index. For a phenomenon such as social capital, whose definition is linked to the relationships between individuals within a given community, the focus on detailed space level should be ideal, as it allows to grasp its local nature. In the literature on social capital, Italy has always been considered an ideal case study due to its profoundly uneven distribution between the North and the South of the country. However, few studies are based on data at municipal level (Albanese and De Blasio, 2014; Batinti *et al.*, 2019) and they take into consideration a single measure of social capital which may not be suitable for a multidimensional phenomenon such as social capital.

The last aspect concerns the possibility of studying the effects of the CoViD-19 pandemic on social capital at a local level. Since social capital is normally associated with a wide variety of positive outcomes, scholars have focused on the role it might have had in containing the spread of the virus. However, there are few studies on the impact of the pandemic crisis on social capital itself, and in particular on local communities.

The rest of the paper is organized as follows: in the next section the indicators used in the construction of the composite index are presented. In the third and fourth sections, the definition and the construction methodology of the composite index are discussed, respectively. In the fifth section, main results are presented. Finally, the paper ends with the conclusions arising from this study.

2. The indicators selection

The criteria leading to the individual indicators selection derive from the need to address two issues. The first one has a conceptual nature, as it picks individual indicators theoretically representative of phenomenon of interest. The second one has empirical nature and it is due to the availability of data on Italian municipality over those years subject of study. The indicators chosen are described below.

- *(A)* *Volunteering*. It is the number of the voluntary association per capita built on the data taken from the list published annually by the Italian Revenue Agency on voluntary associations registered in the “elenco permanente degli Enti del Terzo Settore” and recipients of the “5 per 1000” contribution.
- *(B)* *Electoral participation*. It is given by the percentage of registered voters (voter turnout) in the national (2018) and referendum (2020 and 2022) elections. Voter turnout is calculated on the basis of data collected by the Italian Ministry of the Interior.
- *(C)* *Virtuousness*. It is obtained from the Revenue Agency annual lists on the contribution to be given to each municipality for participation in both the tax and the contribution assessment.
- *(D)* *Willingness to organ donation*. The indicator is given by the ratio of the number of consents to the donation of organs and tissues expressed on the occasion of the issuance of the electronic identity card (CIE) compared to the total of declarations of intent. It is based on the data published annually by the “Sistema Informativo Trapianti” of Ministry of Health.
- *(E)* *Educational level of political representation*. It has been constructed as the share of component of the city council that have at least a college degree. This information is available from the Registry of Local Administrators, assembled by the Italian Ministry of Interior.
- *(F)* *Waste sorting*. It is measured by the percentage of municipal waste subject to separate collection based on data available from Waste Catalogue assembled by the Italian Institute for Environmental Protection and Research (ISPRA).
- *(G)* *Broadband diffusion*. It is the percentage of schools in which the "Connected School" plan has been implemented out of the total number of participating schools. It is based on the data published by the Ministry for Business and Made in Italy.
- *(H)* *Women’s political representation*. It is obtained from the Registry of Local Administrators, assembled by the Italian Ministry of Interior as the ratio between the number of female members of the municipal council and the total number of members.

3. Definition of composite index

Social capital, as many social economic phenomena has a multidimensional nature. This involves that one individual indicator is not suitable to measure it accurately; therefore, a composite index is required. Composite index is based on aggregation of several indicators that represent the different components of the multidimensional phenomenon to be measured by means of an analytical method in order to obtain an overall score for each statistical unit (such as country, regions or other geographical areas). It is thus possible to use the results either to summarize the data or create a statistic unit ranking (OECD, 2008). Despite the composite index facilitates the representation of a multidimensional phenomenon, many pitfalls lie behind each stage of its construction once defined what to analyse. In fact, several methodological decisions and subjective choices need to be taken: each of them could affect the ability of the composite index to represent the phenomenon for which it was built. It should be taken into account that the composite index is not the phenomenon but the expression of a synthesis of several variables (or indicators) that contribute to define a complex phenomenon. As well explained by Mazziotta and Pareto (2020), the switch from a multidimensional phenomenon to its synthesis in a single index inevitably determines an approximation error, therefore the perfect composite index does not exist. However, several criteria can be used as a guide in the research of the best "method", such as the type of a) model (reflective/formative), b) indicators (compensatory/non-compensatory); c) aggregation (simple or complex); d) comparisons (absolute/relative); e) weights (objective or subjective). According to these criteria, given the non-compensatory (or partially compensatory) nature of indicators, the need to carry out temporal comparisons in order to capture the variations that occurred in the period taken into consideration, as well as the need to obtain an easy to read synthetic index in order to guarantee a simpler interpretation of the final results, the Adjusted Mazziotta-Pareto Index (AMPI) is the method chosen for the construction of the composite index in order to analyse the social capital dynamic in the Italian municipalities.

4. Adjusted Mazziotta - Pareto Index (AMPI): construction methodology

AMPI’s composite index is based on aggregation of non-compensatory (or partially compensatory) indicators and it is an extension of the Mazziotta-Pareto Index (MPI). The difference between them is that AMPI re-scales the individual indicators by a Min-Max transformation, allowing to measure absolute comparisons over time; whereas MPI normalizes the indicators by a linear combination of z-scores, allowing only relative comparisons over time. Therefore, the AMPI is more suitable in the dynamic analysis such as time series (Mazziotta and Pareto, 2016). More specifically, given the matrix $X = \{x_{ij}\}$ where $i = 1, \ldots., n$ are the statistical units (for instance geographical areas), and $j = 1, \ldots., m$ are the indicators, the normalized matrix $R = \{r_{ij}\}$ is calculated, whose generic element r_{ij} is defined as follows:

$$r_{ij} = \begin{cases} \dfrac{\left(x_{ij} - Min_{x_j}\right)}{\left(Max_{x_j} - Min_{x_j}\right)} * 60 + 70 \;\; iff\ indicator\ j\ has\ positive\ polarity \\ \dfrac{\left(Max_{x_j} - x_{ij}\right)}{\left(Max_{x_j} - Min_{x_j}\right)} * 60 + 70 \;\; iff\ indicator\ j\ has\ negative\ polarity \end{cases}$$

Min_{x_j} e Max_{x_j} are the goalposts of the indicator j, i. e. the values that define the variation range of the indicator j. Generally, in case of time series, the goalposts are the minimum and maximum of the indicator j in all the time periods considered. In order to facilitate the interpretation of the results, the goalposts are chosen so that 100 represents a reference value or 'benchmark' (for example, the average value of a given year). As shown, the normalization is based on a correct Min-Max transformation. This correction involves multiplying the resultant of the Min-Max method by 60 and subsequently adding the value 70, which guarantees a better reading of the composite index and therefore a simpler interpretation of the final results. To the normalized matrix $R = \{r_{ij}\}$ the aggregation function is applied, by means of which AMPI (Adjusted MPI) is obtained. Its generalized form is the following:

$$AMPI_i^{+/-} = M_i \pm S_i * cv_i$$

where and M_i, S_i and cv_i respectively, stand for the mean, the standard deviation and the coefficient of variation of normalized values of indicators for unit i. The $\pm$ sign depends on the type of phenomenon to be measured[1]. As shown, in the aggregation phase, the AMPI is characterized by the combination of an "average" effect and a "penalty" effect, the latter based on the coefficient of variation and it is equal to zero if all values are equal. The aim is to penalize statistical units such as geographical areas with unbalanced value of the individual indicators used. The

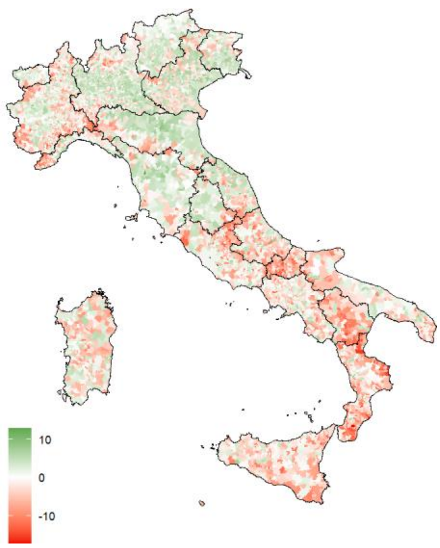
[1] If the index is positive, that is its increase corresponds to a positive variation in the phenomenon, a downward penalty is applied. On the contrary, if the index is negative, that is its increase corresponds to a negative variation in the phenomenon, an upward penalty is applied.

AMPI values vary between 70 and 130, where 100 is the reference value to which the entire measurement system is anchored.

5. The main results

This paragraph presents the results deriving from the application of the social capital index constructed by means of the AMPI method on the panel data based on the Italian municipality in the years 2018, 2020, 2022 in order to measure the endowments and the variations of social capital during the aforementioned years. Figure 1 shows the level of social capital of each municipality compared to the national one.

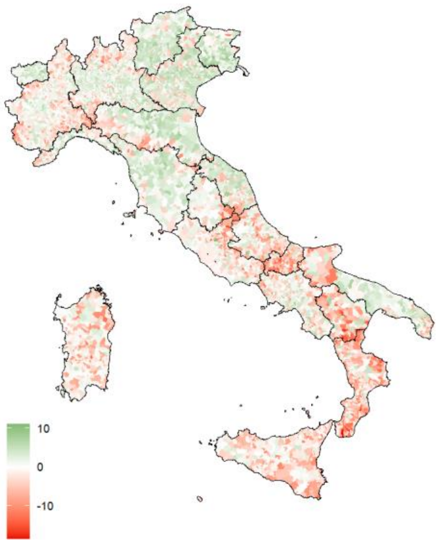
Figure 1 – *Geography of social capital at municipal level measured with AMPI - Year 2018*



In particular, the white colour centred on zero indicates that the municipality has the same level of social capital as the national one; while the red and green colours indicate, respectively, a lower and higher level than the national one. In addition to this, the intensity of the gradation of the two colours provides a measure of the distance between the social capital of the municipality and the national level: the more intense the red, the more the municipality has a lower level of social capital than the national one; at the same time, the more intense the green, the more the municipality has a higher level of social capital than the national one. The geographical distribution of the index highlights the existence of two macro-areas:

the first represented by Northern and Northern-Central Italy, where there is a prevalence of municipalities with levels of social capital higher than the national one; the second represented by Southern and Southern-Central Italy, where there is a prevalence of municipalities with lower levels of social capital compared to the rest of the country. This result is in line with the literature on social capital which, in the case of Italy, highlights this heterogeneity in the distribution of social capital such as in Putnam (1993), Guiso et al. (2004) and Durante et al. (2023). In 2018, the municipality with the highest level of social capital was Santa Maria a Monte (AMPI=112.84) in Tuscany, while the one with the lowest was Platì (AMPI=82.67) in Calabria. As regards the year 2020, there is a slight reduction (-0.67) in the level of social capital at a national level which goes from the reference value of 100 in the base year 2018 to 99.33; this evidence has been found in other economies too, such as Germany (Burrmann *et al.*, 2022), England (Borkowska and Laurence, 2021) and China (Luo *et al.*, 2022). In 2020, the municipality with the highest level of social capital was Fara in Sabina (AMPI=110.34) in Lazio, while the one with the lowest level of social capital was San Lorenzo (AMPI=80.66) in Calabria. Although the national level of social capital decreased, in 2020 the situation at the municipal level was very heterogeneous (Figure 2).

Figure 2 – *Geography of social capital at municipal level measured with AMPI - Year 2020.*



In fact, comparing the municipal geography of social capital between 2018 (Figure 1). and 2020 (Figure 2), the first evidence is that the second graph has fainter colours than the first one. In fact, a less intense shade of green can be seen in those municipalities that in 2018 had much higher levels of social capital than the national one; on the contrary, lighter shades of red can be seen in those municipalities that had much lower levels than the national one. This means that, in 2020, on the one hand, there was a reduction in social capital in well-endowed municipalities, whereas on the other hand there was an approach to the national level in those with lower endowments. The year 2020 went down in history as that of the CoViD-19 pandemic and this shock event might have had an impact not only on the level of social capital but also on its distribution at a territorial level. The literature on the effects of CoViD-19 on social capital is not extensive and has mainly focused on the national territorial level, while no study has gone to such a detailed territorial level as the municipal one.

Before delving into the search for a possible explanation for this empirical evidence, a first consideration to make is that in Italy the areas most affected by CoViD-19 were those of Northern Italy[2], that is the area of the country most endowed in terms of social capital. The degree of spread of the virus could help explain the reduction in social capital levels of those areas that, in 2018, had high endowments, however it is not sufficient to explain the increase in social capital levels in low endowment areas. Generally speaking, the literature on social capital has highlighted how, in normal situations, the low levels of social capital of a community are attributable to the lack of civic commitment of individuals and their inclination to invest their time in individualistic activities. This tendency towards social segregation is what Putnam (2000) refers to as "bowling alone". In this sense, the pandemic has forced each of us to limit social relationships, appealing to everyone's civic responsibility.

The conditions posed by an emergency situation such as the pandemic have placed all Italian municipalities on the same level, regardless of the starting level of social capital, determining a condition of generalized bowling alone. In this circumstance, municipalities with lower endowments of social capital might have shown better abilities to withstand and react to the pandemic shock, thanks to their familiarity with the so-called bowling alone condition, maintaining or improving their levels of social capital. On the contrary, municipalities with higher endowments might have suffered a greater impact as they are more oriented towards a so-called "bowling together". This could be an explanation of the diversified effect that the pandemic might have had at the local level.

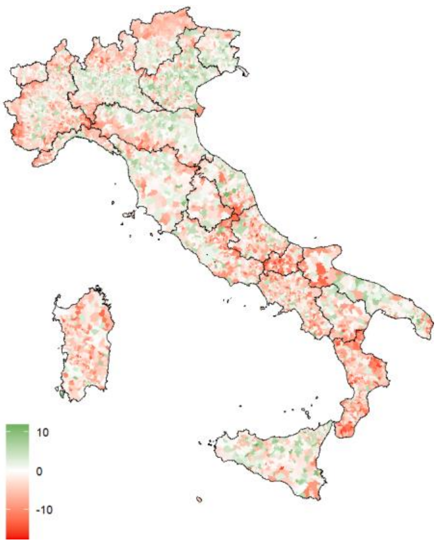
Another possible explanation could be linked to the role played by local administrations in managing the pandemic. Several studies (Lee, 2021; Carlin *et al.*,

[2] According to Istat (2020) data, the increase in deaths in March 2020, compared to the average in the same period 2015-2019, was 188% in Lombardy; it is followed by Emilia-Romagna, with an increase in March of 71%, Trentino South-Tyrol (69.5%), Aosta Valley (60.9%), Liguria (54.3%), Piedmont (51.6%) and Marche (48.9%).

2014) have highlighted that in the presence of an exceptional event such as the pandemic, if the members of a community perceive weakness or poor capacity in the political class to face the emergency, a downward spiral gets started, in which distrust towards institutions pushes the level of social capital further and further downwards.

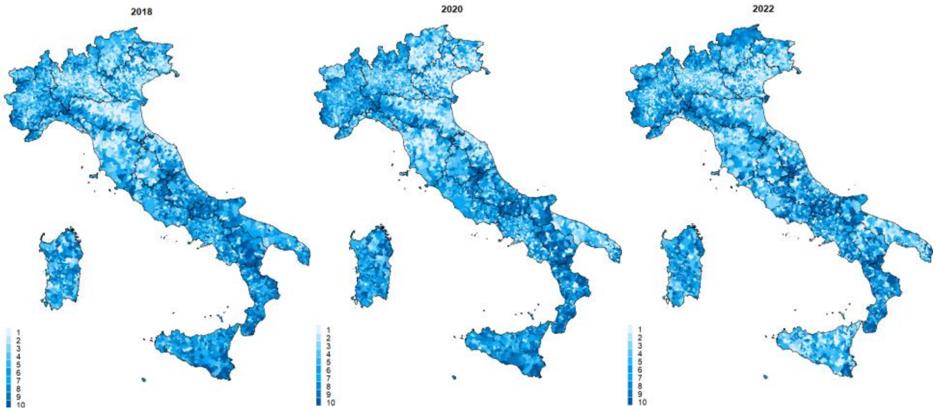
In the year 2022 (Figure 3) there is a further reduction (-0.4) in the social capital (AMPI=98.93) at national level, though slighter.

Figure 3 – *Geography of social capital at municipal level measured with AMPI - Year 2022.*



At that time, the municipality with the highest level of social capital was Sinagra (AMPI=110.80) in Sicily, while the one with the lowest level of social capital was Sant'Alessio in Aspromonte (AMPI=81.25) in Calabria. As regards the municipal geography of social capital in 2022, the reduction observed at national level results in a generalized reduction at municipal level, although it is more marked along national borders. Thus, this reduction, unlike the one already observed between the years 2018 and 2020, is not centred on high endowments municipalities, but it is more widespread among all the municipalities and therefore not linked to initial endowments. This means that the differentiated effect, based on the initial endowments of social capital, is greatly weakened, as well as a sign that the pandemic shock was being reabsorbed. In Figures 4, the ranking deciles at municipal level are graphically represented, respectively, for the years 2018, 2020 and 2022.

Figure 4 – *Ranking deciles at municipal level - Years 2018, 2020, 2022.*



A darker colour indicates a worse position in the municipal ranking and, therefore, a lower value of the composite index; on the contrary, a lighter colour is associated with those municipalities that take better positions. From these figures, comparing 2018 to 2020 and 2022, CoViD-19 has partially modified the geography of the ranking between the municipalities. In fact, several Southern municipalities have gained positions, moving from the lowest to medium-high deciles, especially in Sicily [3], Basilicata and the lower part of Apulia. On the contrary, several municipalities in the North have lost positions in the ranking, especially in South-Tyrol and those located in the Lunigiana area, that is the border territory among the regions of Liguria, Tuscany and Emilia-Romagna.

6. Conclusions

In this paper local economies have been viewed through the lens of social capital by using an innovative composite index based on the Adjusted Mazziotta-Pareto Index (AMPI), which allows to value the subtle web of connections among mutual trust, respect for rules and interpersonal relationships that regulate common life and define civic commitment. The findings confirm the existence of a clear geographical gap in the distribution of social capital in Italy: municipalities in the North Central areas generally show higher levels of social capital than those in the South. This

[3] This region, as part of the post-CoViD-19 recovery programme, launched intense regional cohesion activities aimed at relaunching the growth potential of the regional economy, boosting productivity and employment.

result leads to think that both the set of indicators and the AMPI construction methodology are suitable for measuring social capital. In addition, the results reveal important insights into the dynamics of social capital at the local level following the CoViD-19 pandemic: high-endowment municipalities in Northern Italy experienced a reduction in social capital while municipalities in the South showed signs of improvement. This phenomenon could be attributed to low endowed municipalities better ability to react to the pandemic shock, which may have made them more resilient and adaptable to the changes induced by the pandemic ("bowling alone"). Conversely, municipalities with higher initial levels of social capital, more familiar with collaborative social dynamics ("bowling together"), may have found it more challenging to adapt themselves to the limitations imposed by the pandemic. Moreover, the role of local administrations cannot be underestimated. Their effective leadership during the pandemic appears to have played a critical role in maintaining or even enhancing social capital in some municipalities. This highlights the importance of local governance in fostering social cohesion during exceptional events such as the pandemic.

As much as other capital types, such as human and physical capital, social capital is capable of influencing the well-being of citizens, the quality of their associated life, the efficiency of the economy; therefore, they would improve along with any policy aimed at strengthening social capital.

Future research could be built upon these findings by examining the long-term effects of the pandemic on social capital, exploring the role of different policy interventions, and further investigating the interplay between local governance and social capital in times of crisis, also in other countries

Acknowledgements

I would express my sincere thanks to independent referees appointed by the editor for all the helpful comments and contributions that improved this study.

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DOES EDUCATIONAL MISMATCH HAVE AN IMPACT ON THE HEALTH OF INDIVIDUALS IN ITALY?

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Abstract: Our study investigates the health consequences of educational mismatch by considering both over-education and under-education within the working population of Italy. The educational mismatch is the difference between the individual's attained qualifications and those required to perform their current job. According to the OECD (2019) Skills and Work report, approximately 38% of workers in Italy are classified as educationally mismatched. To date, very few studies have examined the relationship between educational mismatch and health. Our study aims at bridging this gap.

Our study is based on data from the 'Aspects of Life Survey' by ISTAT (2021). The dependent variable is self-reported health, measured on an ordinal and categorical scale. We measure educational mismatch (over- and under-education) following the methodology of Verdugo and Verdugo (1989). An individual is classified as over-educated (under-educated) if their attained level of education exceeds one standard deviation above (below) the average years of education in their professional sphere. We focus exclusively on individuals in the labour force, resulting in a final sample of about 15800 individuals.

Our study includes a gender-specific analysis and estimates ordered probit models for our categorical dependent variable. Our econometric specification incorporates sociodemographic controls such as age, marital status, education and economic conditions, as well as work-related controls such as employment industry, self-employment status and level of physical activity involved in the job. We also control for geographical location and health behaviours (obesity and smoking). The results of our gender-specific analysis reveal that while educational mismatch (over-education and under-education) does not significantly impact the health of women, undereducation has a detrimental effect on the health of males in Italy.

1. Introduction

Our study investigates the health consequences of educational mismatch by considering over-education within the working population of Italy and exploiting data from the "Aspects of Life Survey” by ISTAT (2021). Economic efficiency, a global concern, requires aligning individuals to the jobs that suit their abilities and training. Addressing these inefficiencies through policy has been a pivotal focus for international organisations such as the OECD and the International Labour Organization (Cervantes and Cooper, 2022). The disparity between the actual knowledge and skills individuals have and the labour market's requirements shows the existence of structural inefficiencies, commonly known as educational mismatch. These structural inefficiencies might be due to imbalances in the labour market or institutional factors, among other factors, such as technological change or economic recession.

Educational mismatch refers to the difference between an individual's attained level of education and the level required for his/her current job. This educational mismatch is further classified into vertical mismatch and horizontal mismatch. About vertical mismatch, if an individual's attained level of education surpasses (falls short of) their job's educational requirement, they are categorised as over-educated (under-educated). Differently, a horizontal mismatch occurs when the individuals' field of study differs from the field of their occupation.

The presence of educational mismatch has already been observed in developed economies (Ghaffarzadegan, Xue, and Larson 2017). In the last few years, there has been a significant increase in the share of educational and skill mismatches (Esposito and Scicchitano, 2019). According to the OECD Skills for Jobs database (2019), 32% of the average workers across the European Union are educationally mismatched, around 16% are undereducated, and 15% are over-educated. Similarly, around 32% of the average workers faced horizontal mismatch across European economies in 2019. However, the number of educationally mismatched individuals is expected to increase across Europe (Cedefo, 2018). This phenomenon can negatively impact an economic system's competitiveness, with negative implications at both macroeconomic and microeconomic levels. At the macroeconomic level, underutilising workers' potential due to overeducation across the economy wastes human capital resources and adversely affects productivity growth and innovation activities (Mcgowan and Andrews, 2015). At the microeconomic level, overeducation impacts workers' job satisfaction (Boll *et al*., 2016), leading to higher workforce turnover (Sloane *et al.*, 1999). Furthermore, overeducation is also associated with a loss in earnings; as an example, over-educated workers have been shown to earn more than their job colleagues but less than the educationally matched workers with similar education (Boll and Leppin, 2014).

Since the 1970s, when the study by Freeman (1975) started to raise a concern about the phenomena of overeducation, much work has been done to explore its relationship with macroeconomic and social factors. Numerous studies have attempted to explain the impact of educational mismatch on labour market outcomes such as wages and return to education (Cervantes and Cooper, 2022; Caroleo and Pastore, 2018 and Cattani *et al.*, 2014), job satisfaction (Shi *et al.*, 2023), earnings and job search (Quintano *et al.*, 2008). These studies mostly show that over-educated workers suffer a wage loss and are less satisfied with their jobs. Other studies in the domain of educational mismatch explore the relationship of overeducation with spatial mobility of individuals (Croce and Ghignoni, 2015) and interregional migration (Iammarino and Marinelli, 2015; Van Wolleghem *et al.*, 2023).

The relationship between educational mismatch and health has also been explored in the last decade. Recent studies suggest that there is an association of overeducation with poor health (Dunlavy *et al.*, 2016; Vasiakina and Robone, 2018), suffering from diabetes (Padkapayeva *et al.*, 2022), higher mortality (Garcy 2015), higher risk of hospitalisation for psychiatric and somatic diseases (Brendler-Lindqvist *et al.*, 2022), long-term sickness (Madsen and Kittelsen Røberg, 2021), higher level of depressive symptoms and less satisfaction with lives across individuals (Bracke *et al.*, 2013; Wassermann and Hoppe, 2019; Espinoza-Castro *et al.*, 2019). The studies presented so far provide evidence that, in general, over-educated individuals suffer from poorer health, have higher depressive symptoms and are less satisfied with their lives compared to their matched counterparts.

The studies in this literature which exploits data from Italy consider several research questions, such as the impact of overeducation on wages (Ordine and Rose, 2015), the effect of time and effort spent studying at university on labour market outcomes (Boccuzzo *et al.* 2016), the role of interregional migration and spatial mobility in deriving the education-job match (Iammarino and Marinelli, 2015; Croce and Ghignoni, 2015), the relationship between educational mismatch and unemployment risk in Italy (Esposito and Scicchitano, 2022) and to what extent over-education might affect migrants (Van Wolleghem *et al.*, 2023).

Despite the evidence of the influence of vertical education mismatch on health reported in the literature, no study has considered this relationship with regard to the Italian context so far. Our study fills this gap in the literature by exploiting data from the "Aspects of Life Survey" by ISTAT, wave 2021. The dependent variable in our study is self-reported health by individuals, measured on an ordinal and categorical scale. In our study we measure educational mismatch (over- and under-education) by following the approach of Verdugo and Verdugo (1989). We only consider individuals in the labour force, and our final sample comprises about 15800 individuals. We conduct a gender-specific analysis and estimate ordered probit models for our categorical dependent variable. The results indicate that educational mismatch (over-education and under-education) does not have any considerable impact on the health of women. However, undereducation negatively influences the health of males in Italy.

2. Data

We conducted our analysis by exploiting the survey data from the "Aspects of Life Survey" ("Aspetti della Vita Quotidiana") by ISTAT in 2021 (AVQ onwards). AVQ is an annual survey carried out by interviewing a sample of 20,000 households, including about 50,000 individuals.[1] For our analysis, we consider only those working and who have reported their professions and educational status.[2] The dependent variable in our analysis is a self-reported categorical health variable measured on the ordinal scale from 1 to 5. The AVQ survey asked respondents about their health in general and provided them with five options on an ordinal scale, that is "very good", "well", "neither good nor bad", "bad", and "very bad".In our analysis, we combine the two responses "bad" and "very bad" together and rename them "poor health".

Educational mismatch is one of the main variables in our analysis. Broadly, three approaches are documented in the literature to measure educational mismatch: subjective, empirical, and job evaluation. The subjective approach is based on the workers' self-assessment of their qualifications and profession (Bracke *et al.*, 2013; Madsen and Kittelsen Røberg, 2021). The principal disadvantage of this approach is that the respondents might exaggerate their occupational or qualification status, leading to a downward bias (McGuinness, 2006). Secondly, the empirical approach, known in the literature as the "realised method approach", was first introduced by Verdugo and Verdugo in 1989. This compares, for each respondent, the respondent' attained level of education with the average level of education for individuals in his/her occupational class (Garcy, 2015; Dunlavy *et al.*, 2016b; Vasiakina and Robone, 2018; Pholphirul, 2017; and Padkapayeva *et al.*, 2022). If the respondent's attained level of education is above (below) the mean years of schooling in his/her occupation, he/she is classified as over-educated (under-educated). The major drawback of this empirical approach is that it does not account for the actual skill requirements of the job because it is based on the average credentials of workers in the context of years of education in their occupation (McGuinness, Pouliakas, and Redmond 2018).

The third approach reported in the literature to calculate the educational mismatch is the Job-evaluation approach. It is based on the assessment of professional job analysts who measure the academic requirements of occupations by constructing some dictionaries and comparing individuals' attained levels of education with those

[1] The AVQ is part of the integrated social survey system of Italian households collecting information on individuals' daily lives. This survey aims to understand the lives of Italian families and individuals and the problems they face in their everyday lives. Thematic areas covered in the survey on the social aspects of life allow us to understand how individuals are living their lives and how satisfied they are with their living conditions, including the economic situation, the social aspects of the life of individuals, i.e., the functioning and availability of public services that contribute to improving quality of life. This also includes data on work conditions, family and relationship life, free time, political and social participation, health, lifestyles and access to services are investigated.

[2] Our analysis is based on a rigorous selection process. We only consider those available respondents who responded to the questions related to their professional and qualification level. This meticulous approach ensures the accuracy and reliability of our findings.

dictionaries. Examples of such dictionaries are O*Net in the United States and Standard Occupational Classification (SOC) in the United Kingdom (McGuinness *et al*., 2018).[3]

This study uses the “empirical approach” of Verdugo and Verdugo (1989) to measure educational mismatch because our analysis is based on survey data collected by ISTAT (2021), which does not include information on the workers' self-assessments of their qualifications and current job match. The AVQ does not provide information on the exact number of years of education of the respondent but instead classifies the respondents based on their attained level of education into four categories (undergraduate/postgraduate, diploma, middle school diploma, elementary school/no qualifications). We create a variable “years of education” by assigning to each individual the number of years that he/she had to be in education to obtain his/her educational qualification. The AVQ survey classifies all working individuals into four categories. The first category includes managers, self-employed an entrepreneur and freelancers; the second category comprises executives; the third category includes worker leaders, subordinate workers and apprentices working from home on behalf of a company; and lastly, self-employed workers, cooperative members to produce goods/services and occasional workers.

Due to data limitations, this study is only considering vertical educational mismatch because the information on the individuals' qualifications (like having a degree in accounting or engineering) along with that professional occupational title (like accountant or engineer) is not reported in the AVQ survey, and this kind of information is required to measure horizontal mismatch. To calculate the vertical educational mismatch, firstly, we estimate the average years of education in each of the four occupations classified by the "AVQ”, and then we compare it with the individuals' attained years of education in the occupation from which they belong. If the “attained year of education” is one standard deviation above (below) the average year of education in his/her occupation, the individual is classified as overeducated (undereducated).

In our regression model, we include socio-demographic characteristics such as age, marital status, and economic condition.[4] We also include work-related controls such as employment industry, self-employment status, and level of physical activity involved in the job. Furthermore, we control for the geographical location and health behaviours such as obesity and smoking. Table 1 describes the variables used in the regression model, and Table 2 reports the summary statistics of these variables.

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[3] Madsen and Kittelsen Røberg (2021) and Frank and Hou (2018) have used the job evaluation method to measure educational mismatch. Cattani *et al.* (2014) used the job-analyst approach and allocated each of the official 800 Italian occupational categories into four groups. They distinguish them into graduate and non-graduate groups based on their relative level of knowledge and skills requirements following the British SOC (2010) classification.

[4] We are using satisfaction with the economic condition in last 12 months as a proxy because the data on the income of the individuals are not reported in the ISTAT dataset.

Table 1 – *Description of the variables used in the regression analysis.*

Variable Name	Description
Under Education	If individuals' attained level of education is one standard deviation below the average years of education in their professional sphere.
Over Education	If individuals' attained level of education is one standard deviation above the average years of education in their professional sphere.
Health	Self-reported health on a scale of 1 to 5. The last two categories, bad and very bad, are merged into one category: poor health.
Age	Age of Individuals (Number of years)
Gender	Dummy variable for gender (Male = 1, Female= 2)
Years of Education	Total years of education decoded from the attained level of degrees of the individuals
Northwest	Dummy variable, 1 if the individual isbased in the Northwest of Italy, 0 otherwise
Centre	Dummy variable, 1 if the individual is based in the Centre of Italy, 0 otherwise
South	Dummy variable, 1 if the individual is based in the South of Italy, 0 otherwise
Islands	Dummy variable, 1 if the individual is based in the Islands of Italy, 0 otherwise
Freelancer	Dummy variable for the individuals working as freelancers
Executives	Dummy variable for the individuals holding the position of Executive
Work Leader	Dummy variable for the individuals working as Work leaders
Self Employed	Dummy variable for the self-employed individuals
Working (Agri-Sector)	Dummy variable of the individuals working in the agriculture sector
Working (Construction)	Dummy variable for the individuals working in the construction industry
Working (Services-Sector)	Dummy variable for the individuals working in the services sector
Working (Rest of the Sectors)	Dummy variable for the individuals who are working in the rest of the sectors
Poor Physical activity at work	Dummy for the individuals who reported that there is poor physical activity involved in their jobs
Overweight	Dummy variable is for individuals classified as overweight based on their Body Mass Index (BMI).
Smoking	Dummy variable for the individuals who report to be smoking currently
Satisfied with economic Condition	Dummy variable for the individuals who are satisfied with their economic conditions

Table 2 –*Summary Statistics of the variables used in the regression analysis.*

Variable	Male (n=9,011)				Female (n=6,789)			
	M	SD	Min	Max	M	SD	Min	Max
Under Education	0.13	0.34	0.00	1.00	0.09	0.29	0.00	1.00
Over Education	0.14	0.35	0.00	1.00	0.28	0.45	0.00	1.00
Age	45.69	12.32	18.00	92.00	45.37	12.36	18.00	96.00
Health	2.02	0.67	1.00	4.00	2.14	0.70	1.00	4.00
Years of Education	12.10	3.05	5.00	16.00	13.01	2.95	5.00	16.00
Northwest	0.24	0.43	0.00	1.00	0.27	0.44	0.00	1.00
Centre	0.20	0.40	0.00	1.00	0.21	0.41	0.00	1.00
South	0.25	0.43	0.00	1.00	0.21	0.40	0.00	1.00
Islands	0.09	0.29	0.00	1.00	0.08	0.27	0.00	1.00
Freelancer	0.17	0.37	0.00	1.00	0.10	0.31	0.00	1.00
Executives	0.33	0.47	0.00	1.00	0.55	0.50	0.00	1.00
Work Leader	0.36	0.48	0.00	1.00	0.25	0.43	0.00	1.00
Self Employed	0.14	0.35	0.00	1.00	0.10	0.30	0.00	1.00
Working (Agri-Sector)	0.06	0.23	0.00	1.00	0.02	0.15	0.00	1.00
Working (Construction)	0.13	0.34	0.00	1.00	0.14	0.35	0.00	1.00
Working (Services-Sector)	0.48	0.50	0.00	1.00	0.70	0.46	0.00	1.00
Working (Rest of the Sectors)	0.30	0.46	0.00	1.00	0.09	0.28	0.00	1.00
Poor Physical activity at work	0.25	0.43	0.00	1.00	0.24	0.43	0.00	1.00
Overweight	0.42	0.49	0.00	1.00	0.22	0.41	0.00	1.00
Smoking	0.27	0.44	0.00	1.00	0.19	0.39	0.00	1.00
Satisfied with economic Condition	0.06	0.24	0.00	1.00	0.06	0.24	0.00	1.00

Notes: M shows the mean value, SD is the standard deviation.

3. Estimation Methods

In our study we conducted a gender-specific analysis and estimated ordered probit models for our categorical dependent variable. Let h_i^s be a self-reported health response from the individual i and assumed to be generated by the true latent health

$$h_i^{s*} = x_i\beta + \varepsilon_i^s \sim N(0,1) \tag{1}$$

here in equation (1) x_i is a vector of observed respondent characteristics and ε_i^s is a random error term that is independent of x_i. The latent variable is unobserved, and its observed counterpart is categorical; neither the scale nor the location is identified; for this reason, the variance of the error term is normalised to 1 and the constant term to 0 (Jones *et al.*, 2013). The observed categorical response $\mathrm{h}_{\mathrm{i}}^{\mathrm{s}}$ relates to $\mathrm{h}_{\mathrm{i}}^{\mathrm{s}*}$ in the following way:

$$h_i^s = k \leftrightarrow \mu^{k-1} \leq h_i^{s*} < \mu^k, k = 1, \ldots, 4 \tag{2}$$

Where $\mu^0 < \mu^1 < \cdots < \mu^3 < \mu^4,$ and $\mu^0 = -\infty$ and $\mu^4 = \infty$

The assumption of homogenous reporting inherent to the ordered probit model arises from the assumption that cut point μ^{k} are constant (Jones *et al.*, 2013).

4. Results and Discussion

Table 3 reports the results obtained from the ordered probit model described in Section 3 by considering self-reported health as our dependent variable. Age appears to affect individuals' health significantly and negatively, showing that individuals with higher age report not having good health despite their gender and educational mismatch status. The results of the economic condition coefficient show that individuals who reported being satisfied with their economic conditions are more likely to have a positive and significant effect on their health. The coefficient of marital status shows that unmarried individuals, particularly women, are more likely to have negative health consequences. The individuals who suffer from health conditions like obesity, irrespective of their gender and educational mismatch status, reported negative consequences on their general health. All these results are consistent with previous literature.

Table 3 – *Probit model, estimated coefficients and standard errors for the Self-Assessed Health Variable (SAH).*

Dependent Variable (Health)	**Full Sample**	**Men**	**Women**
		Coef/Se	
Over-Education	-0.015	-0.089	0.048
	0.054	0.08	0.075
Under-Education	-0.073**	-0.119***	-0.01
	0.031	0.039	0.05
Age	-0.023***	-0.025***	-0.021***
	0.001	0.001	0.001

*p<0.10, **p<0.05, ***p<0.01

Table 3 (cont.) – *Probit model, estimated coefficients and standard errors for the Self-Assessed Health Variable (SAH).*

Dependent Variable (Health)	Full Sample	Men	Women
		Coef/Se	
Economic Condition	0.440***	0.507***	0.361***
	0.039	0.051	0.059
Not Married	-0.046**	-0.035	-0.055*
	0.019	0.026	0.028
Working (Agr-Sector)	0.05	0.09	-0.071
	0.048	0.055	0.099
Working (Construction-Sector)	0.041	0.076**	-0.029
	0.031	0.039	0.041
Working (Services-Sector)	0.016	0.034	-0.034
	0.022	0.027	0.041
Self Employed	-0.009	0.004	-0.012
	0.03	0.038	0.049
Female	-0.225***		
	0.019		
Smoking	-0.011	-0.032	0.017
	0.021	0.027	0.035
Obesity	-0.070***	-0.056**	-0.095***
	0.02	0.024	0.033
No Physical Activity at Work	-0.117***	-0.105***	-0.134***
	0.022	0.029	0.033
Northwest	-0.058**	-0.060*	-0.061
	0.026	0.035	0.038
Centre	0.007	0.018	-0.008
	0.027	0.037	0.041
South	0.026	0.028	0.024
	0.027	0.036	0.042
Island	0.047	0.086*	-0.012
	0.036	0.047	0.057

As far as the results of the vertical educational mismatch are concerned, the negative and significant coefficient of under-education for men indicates that those who are vertically mismatched (under-educated) are more at risk of having adverse health consequences as compared to their counterparts who are matched; however, no statistically significant effect is reported for women. These findings contradict the findings of Vasiakina and Robone (2018), who find that the impact of educational mismatch is significantly prevalent among Russian female workers.

Despite the original contribution that our study provides to the literature, our study has some limitations, mostly due to data availability. For instance, regarding the calculation of horizontal educational mismatch, the match between the information on the individual's qualification (like having a degree in accounting or engineering) and their professional occupational title (like accountant or engineer) is not reported in the ISTAT dataset. Moreover, the information on the individual's profession is classified into four categories, which are too broad for our aim. More disaggregated information would help investigate the phenomenon of educational mismatch in Italy. This paper considers only one wave of AVQ (2021); however, as a future line of research, we intend to extend the analysis by considering a longer time span.

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THE ONLINE SERVICES OF MUNICIPALITIES IN ITALY: THE DIGITAL DIVIDE [1]

Chiara Orsini, Fabrizio De Fausti, Sergio Leonardi

Abstract. In Italy, the enhancement of online public services is one of the main goals of the National Recovery and Resilience Plan (NRRP), including relevant investment on digital identity. To this respect, traditional methods for data collection in official statistics may lack the capability to grasp relevant information to assess the digital transition of public institutions, especially in a timely fashion.
The main objective of the paper is to measure in a systematic manner the capacity of local institutions in offering online public services, by collecting relevant information directly through municipal websites using Machine Learning (ML) techniques, while highlighting territorial digital gaps in providing online services. Particularly, the study aims to develop an automatic classification framework to investigate whether and to what extent Italian municipalities implement the digital identity system. This is achieved by comparing the effectiveness of random forest and naive Bayes supervised ML algorithms commonly used for text classification. The classification procedure is based on two different approaches: 1) the integration and use of auxiliary online sources with official statistics sources, such as the Permanent Census of Public Institutions conducted by the Italian National Institute of Statistics (ISTAT) in 2023, and 2) gathering information on relevant features of municipalities' websites by means of web scraping techniques.
By combining official statistics information with big data, the analysis draws the attention on municipalities' digital divide, by comparing online access to public services of citizens living in different areas of the Country, e.g. regions and provinces.

1. The digitalization of public services

Digitalization is a cornerstone of the EU's strategy for future growth and development. It enhances economic competitiveness, improves public services, fosters social inclusion, and supports sustainable development. Particularly, the

[1] This Working Paper is the result of the joint work of Chiara Orsini, Fabrizio De Fausti, Sergio Leonardi. However, each chapter was drafted by a lead author. The lead author of the paragraphs 1, 4, 5 is Chiara Orsini, the paragraphs 2 is drafted by Sergio Leonardi and the paragraphs 3 and 5 by Fabrizio De Fausti.
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"Digital Decade"[2], the initiative by the European Union aimed at empowering Europe's digital transformation by 2030, focuses on enhancing the EU's digital capabilities and infrastructure, by ensuring that Europe remains competitive and sovereign in the digital age. The comprehensive strategy is intended to harness the potential of digital technologies, making Europe a leader in the digital world while ensuring that this transformation benefits all citizens and businesses in a sustainable, secure, and inclusive manner.

The digitalization of public services[3] is one of the main priorities in the EU, consisting of a multifaceted effort involving significant investments, policy initiatives, and technological advancements. While substantial progress has been made, ongoing efforts are needed to address infrastructure gaps, improve digital literacy, and ensure the security and efficiency of digital public services. By continuing to focus on these areas, the EU creates a structured, transparent and shared monitoring system based on the Digital Economy and Society Index (DESI) to measure progress towards human capital, connectivity, integration of digital technology and digital public services. In Italy the digitalization of public services is a significant aspect of Italian NRRP[4], which has invested 255 million euro in the use of digital identity. This process aims to improve the efficiency, accessibility, and transparency of Public Administration (PA) and services, by enhancing digital public services, modernizing infrastructure, and promoting digital literacy, thorough using digital identity systems[5].

In Italy measuring digitalization of municipalities is essential for driving effective digital transformation. It helps in assessing progress, guiding resource allocation, identifying best practices, enhancing public services, ensuring transparency, and fostering economic and social development. Regularly evaluating performance of municipalities progress towards the online access of public services is needed. The main objective of the paper is to provide a new methodological model to support official statistics in measuring, in a systematic manner how and to what extent the public sector is conducting the digitalization transition of local institutions. Particularly, the ML techniques and web scraping methods are studied and tested in this paper to investigate the capacity of local institutions in offering online public services, highlighting territorial digital gaps. Moreover, the study is intended to show the opportunities and challenges when ML methods are combined

[2] European Commission, Communication establishing the Union-level projected trajectories for the digital targets, 2023.

[3] European Commission, Digital Economy and Society Index Report— Digital Public Services, 2022.

[4] Presidenza del Consiglio dei ministri, Piano Nazionale di Ripresa e resilienza, 2021.

[5] Digital identity system consists of the use of SPID (Public Digital Identity System) or CIE (Electronic Identity Card), or the National Service Card (Carta Nazionale dei Servizi - CNS) a unified digital identity that allows citizens and businesses to access online services securely.

with official statistics. The digitalization of local institutions is conducted by identifying inhabitants who have online access through digital identity in the municipalities, measured as the share of municipalities having SPID/CNS/CIE gateway on their websites, as well as inhabitants who have online access (single gateway for construction), measured as the share of municipalities implementing SUE (Sportello Unico per l'Edilizia) on their websites. Furthermore, the methodological approach consists of using official statistics to have the list of municipalities (7,904) and their structural characteristics through the 2022 Permanent Census of the Public Institutions[6]. The list of municipalities has been processed through web scraping technique, applied as data collection in creating the Term Document Matrix (TDM), while creating a labelled dataset, though python routine, to identify a municipality sample which identify the institutions which implemented digital identity and SUE as online services. Moreover, the study tests several supervised ML algorithms to make inference on Italian municipalities, which use digital identity system and make SUE as online service. The replicable model is intended to offer updated data of digital transition of local public institutions. Previous studies have demonstrated the effectiveness of extracting information from websites to enrich and automate processes that support statistical analyses using machine learning (De Fausti *et al.* 2019). This study aims to explore for the first time the potential of machine learning algorithms to automate and enrich information on the digitalization of administrations at the local level.

2. Web scraping technique

Generic web scraping is a technique that aims to extract information from municipalities' websites leading to a TDM, which summarizes in an incidence matrix such information. Considering the number of municipalities, 7,904 at December 31, 2022, and the pages per municipality website, potentially unlimited, two main phases have been processed: information retrieval and storage, matrix construction.

In the first phase, municipalities' Uniform Resource Locator (URL) list has been cleaned from transcription mistakes and web protocol updates. Afterwards, RootJuice application was applied to visit the cleaned list of sites and extract relevant information from it. Table 1 outlines the main results of web scraping conducted by RootJuice.

[6] The Permanent Census of Public Institutions is conducted by the Italian Institute of Statistics every three years, combining administrative sources and information gathered through surveys. Istat, Permanent Census of Public Institutions, 2022.

Table 1 – *RootJuice report for scraping websites.*

MAIN ITEMS	RESULTS
Total visited pages	68,562
Total municipality IDS detected	7,991
Number of municipalities with at least 1 page retrieved	6,239
Number of municipalities with 0 page retrieved	1,662
Number of URLs in seed file	7,903
Number of URLs filtered out	2
Number of URLs after filter	7,991
Reached sites percentage	79,0
Started and ending data time	11/03/2023 time 10:48-22:45

Source: RootJuice output run by the authors

RootJuice makes use of a list of forbidden domains, to avoid visiting non-relevant sites, e.g. government or general-purpose websites. Other configuration parameters allow to increase the visit number of pages that could be visited starting from the root of a municipality site) and the total number of pages per Municipality site. After several RootJuice runs we reach 98% municipalities sites, that is 7,741, missing 162, mainly because of site structural problems such as SSL (Secure Sockets Layer) certificate issues, website unavailable at scraping time, outdated or invalid URL. RootJuice, as per its name, squeezes textual information from each visited page, storing them in a CSV structure, a textual Comma-Separated Values file, in which each column holds text taken from a different page source (e.g. HTML[7] elements, alt properties, title properties and so on) along with their navigation properties (e.g. page URL, referral, URL list element and so on). This huge CSV file is stored in an Apache SolR collection by SolrTsvImporter application, which chunks the file and send it to the Apache SolR collection. To tune this step we configure in SolrTsvImporter the number of threads and the number of CSV rows per chunk. Apache SolR stores all the content, one chunk at a time, indexing all of the words in the collection, thus preparing them for the next phase. At the end of this step it's possible to check the matching between the number of content retrieved from RootJuice and the size of the SolR collection.

In the second phase, we use FirmsDocTermMatrixGenerator to build the TDM from the Apache SolR collection. Application configuration parameters span several aspects of natural language parsing. The first stage is the identification of a primary and a secondary language of the textual content. For the sake of this work, we use just the Italian language. The second stage is the specification of a special set of words to add to the language, to include acronyms, specific language and so on. We call this set go words list and comprehends a few relevant acronyms.

[7] HyperText Markup Language

Another parameter is the set of words to ignore in the analysis because their frequency in the language is too high. We call this set stop words list, which comprehends Italian and English stop words. We use English stop words in order to reduce web programming language noise, whose terms are mostly English words.

We configure a range of word length, in order to filter unwanted noisy text. In our runs we configure a minimum of 3 and a maximum of 25 letters for a valid word. The application creates the column list from SolR indexed words by removing words whose length is outside of the range and removing words TreeTagger does not recognize to be in the Italian dictionary or by go words list, then removing words from stop words list. For each remaining word, we obtain its stem, with Snowball Stemmer, and put this stem in the column index of the TDM.

The application counts the number of occurrences of each stem in each content, aggregating them on a per-municipality basis, leading to an incidence matrix with one row per municipality and one column per stem. Table 2 outlines the main configurations of the TDM.

Table 2 – *Parameters in creating the TDM.*

MAIN ITEMS	RESULTS
Number of rows (Municipalities)	6,239
Number of columns (words)	12,807
Starting data time	19/03/2023 07:20
Ending data time	19/03/2023 07:50

Source: TDM processing run by the author

3. ML models

The textual data collected from Italian municipal websites using web scraping techniques described in section 2 aims at extracting information and keywords from the websites, focusing on the digital services offered by each municipality. Also, in the first phase of data collection and pre-processing, the cleaned textual data is tokenized and processed through stemming. Then, the data are gathered into a TDM, which is a fundamental data structure for the analysis, and the ML algorithms are used to classify and identify the presence or absence of online services for the citizens living in a certain municipality. TDM represents a sparse matrix with the frequency of terms from a dictionary existing in the documents (municipal websites). This matrix facilitates the application of ML algorithms by quantifying the textual data in a form that the algorithms can process.

In the test, two separate classifiers are trained: one is trained in order to identify the presence or absence of the SPID identification service, and the other in order to identify the SUE online service. The target variable is therefore dichotomous and indicates (1 = presence of the service, 0 = absence of the service).

The SPID target variable is automatically labelled using the technique described in section 3. Whereas the SUE target variable requires manual labelling processing conducted on 500 municipalities, which were randomly sampled from the total of 7,904 municipalities gathered by the TDM.

In preparing the model training, the TDM is re-designed by excluding documents that contain insufficient information. Particularly, municipalities with only three or fewer terms were omitted, reducing the dataset to 448 municipalities.

For feature selection, the chi-squared (χ^2) statistic was used to identify terms that are statistically significant with respect to the class labels. Various models are trained, by using terms that exceed the 70th, 80th, 90th, 93rd, 95th, and 99th percentiles in chi-squared values. The performance is evaluated using accuracy metrics and the average F1-macro score, calculated on the test dataset derived from a 70%-30% train-test split of the dataset. This division is commonly adopted for dataset splitting (Kohavi 1995). To enhance the robustness of the model validation in terms of mean and variance, a bootstrap approach (Efron, and Tibshirani 1994) is implemented, conducting 10 different runs.

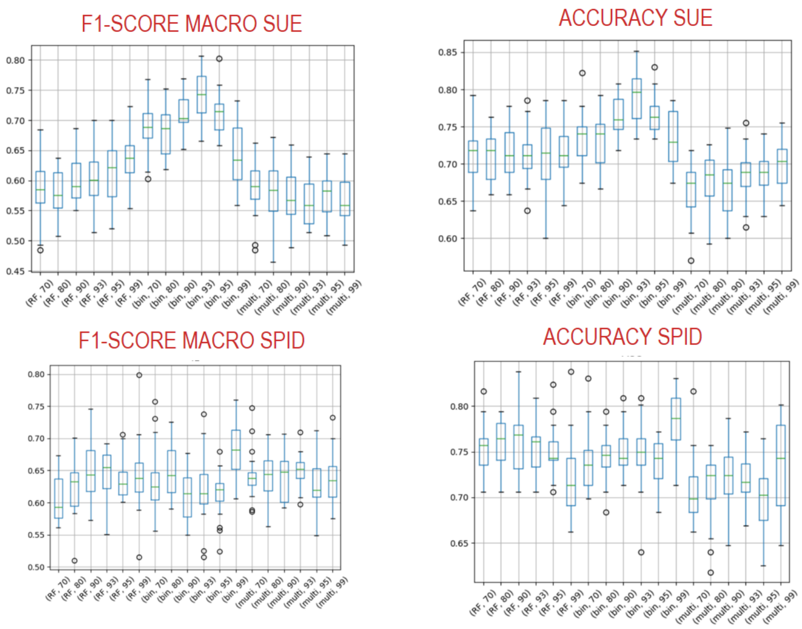
The study focuses on training and comparing three different ML models widely recognized for their effectiveness in text classification. This methodological choice aims to assess which model best suits the characteristics of the dataset and it provides the most reliable performance in recognizing and in classifying the digital services offered by Italian municipalities. The models selected for this comparison include multinomial naive Bayes, Bernoulli naive Bayes, and random forest, each of which has distinctive features that could influence the accuracy and effectiveness of classification in different contexts.

Multinomial naive Bayes classifier (Mccallum and Nigam 1998) is particularly suited for classification with discrete features (e.g., word counts for text classification). It calculates the probability of each category based on the frequency of words and the Bayes theorem, with the assumption that features are conditionally independent given the class label. It is known for its simplicity and effectiveness in handling large datasets.

Bernoulli naive Bayes represents a variant of the multinomial naive Bayes approach. Distinctly, this model utilizes binary feature representation to denote the presence or absence of terms, rather than their frequency counts, it is particularly adept at handling datasets where the mere occurrence of specific terms is more telling than their frequency.

Random forest (Breiman 2001) is an ensemble learning method used for classification, regression, and other tasks that operates by constructing a multitude of decision trees during the training phase. Each tree is trained on a random subset of the training data, obtained through bootstrap sampling. Through the bootstrap mechanism and the aggregation of each tree's decision—known as bagging—this approach allows each tree to learn from a slightly different version of the dataset, thereby reducing the overall model variance without increasing bias. This makes the model less sensitive to outliers and erroneous data, enhancing its robustness against noise and its ability to manage overfitting.

Figure 1 - *Boxplot of F1- macro score and accuracy over 10 runs for each ML model (random-forest:RF, multinomial-naive-bayes:multi and Bernoulli-naive bayes:bin) and chi-square cut-off for SUE and SPID classifier*.



Source: ML processing run by the author

For each model and for each feature selection made by cutting off at percentiles relative to the chi-squared statistic, we perform 10 runs to account for variability. Figure 1 displays the boxplots pertaining to the performance of the SUE classifier and the SPID classifier.

With regards to the SUE classifier, the choice of the best model is easy; indeed, a peak in performance for the Bernoulli naive Bayes model with a cut-off at the 93rd percentile is observed, the measure of macro F1-score is 74.1% and the accuracy is 79.1%.

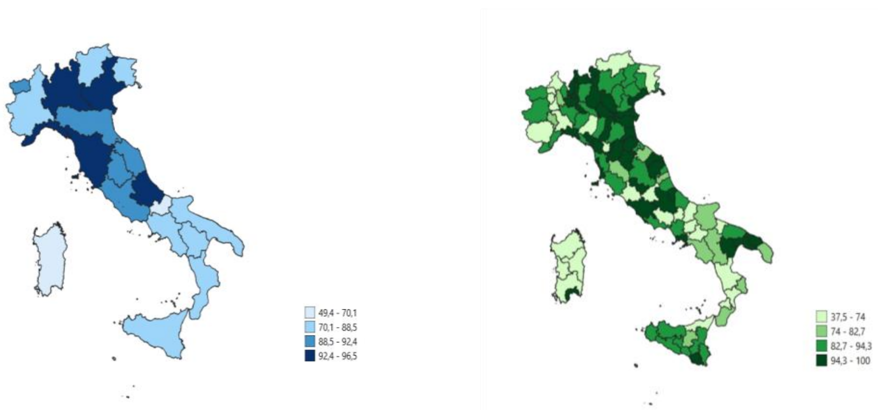
Concerning the SPID classifier, the selection of the best model is not as clear-cut. We ultimately chose the random forest model with a chi-squared cut-off at the 90th percentile, which achieves a macro F1-score of 64.8% and an accuracy of 76.3%. Although this is not the model with the highest scores, it has the lowest cut-off, allowing for a larger number of features on which the model can perform classification. This choice enhances the classifier generalization capabilities.

The models selected and trained on the sample of 448 municipalities are then applied to make inferences and automatically classify all Italian municipal websites collected during the web scraping process.

4. Main results: Services provided by Municipalities

According to the data processed by ML model, in Italy 87.7% of the population has access to public services through the identity systems, particularly 9 inhabitants over 10 have access in Liguria, Lombardia and Veneto, as well as by province Forlì-Cesena, Prato, Trieste have registered the same level.

Figure 2 - *Population with access to public services through digital identity by region and province.*

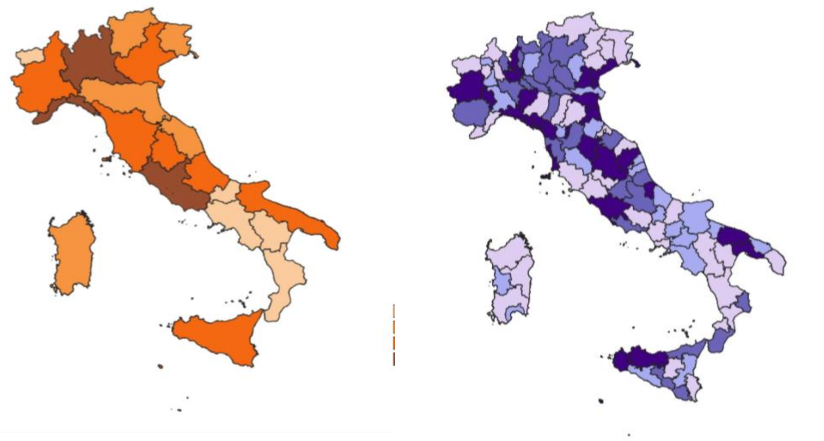


Source: QGIS[8] output run by the author

While in Calabria, Molise and Sardinia less than 7 inhabitants over 10 manage to have access to the identity system and by local areas the municipalities located in Vibo Valentia, Isernia, Oristano show a percentage below 50 per cent. (Figure 2)

[8] QGIS is a geographical information system software

Figure 3 - *Population with access to SUE as online services, by region and province*.



Source: QGIS output run by the author

In Italy 44.4% of the population have online access to SUE, particularly 6 inhabitants over 10 have online access through the municipalities located in Lazio, Lombardia, Liguria and 8 inhabitants over 10 benefit from SUE services provided by the local institutions in Trieste, Genova, Como. Whereas, less than 2 inhabitants over 10 have online access to SUE in Val d'Aosta, Basilicata, Molise and by province in Enna, Matera, Imperia.

The integration of official statistics data lead to profile the municipalities which implemented the digital identity system and online SUE service, particularly the municipalities with digital identity system are mainly located in urban areas in the northeast, employing more than 250 workers and with 20,000 inhabitants and over, while the municipalities with SUE are mainly located in Urban areas in the northwest, employing more than 250 workers and with 20,000 inhabitants and over. Those profiles are in line with official statistics data disseminated by survey on information and communication technologies in the PA[9].

[9] The survey aims to acquire information on the technological equipment available in the Administrations to support internal administrative activities and relations with citizens, businesses and other PAs, in compliance with EU Regulation.

5. Conclusions and lessons learned

The paper shows how official statistics and machine learning methods may be combined to investigate digitalization at the local level in Italy. The estimation produced by using ML models are fully in line with the official statistics results on public institutions digitalization disseminated by Istat in 2023. Particularly, the study shows that the citizens living in urban areas and in the most populated municipalities are more likely to have access online to public services than people living in remote areas. On the other hand, the analysis highlights that the small size Municipalities located in the North-east of Italy manages to provide online services through centralising ICT provider, which is their Region website.

From a methodological point of view, the study explores the application of ML techniques to analyze and classify the digital services provided by Italian municipalities, utilizing data extracted via web scraping. By employing a TDM and three distinctive ML models—multinomial naive Bayes, Bernoulli naive Bayes, and random forest—the analysis highlights the performance of each model.

This research introduces a new approach which adds timeliness and detailed territorial insights to the analysis. The integration of chi-squared for feature selection is useful, in order to trim the inputs for ML models while obtaining more accurate classifications.

The findings provide municipalities with insights of digital service provisions. Effective classification and analysis of digital services may support policymakers to identify service gaps and to plan policy adjustment, in order to have efficient resource allocation and fostering digitally inclusive governance.

Further research is needed to explore the integration of advanced natural language processing techniques to handle linguistic issues more effectively. Expanding the dataset to include a broader range of municipal profiles is needed to enhance the robustness and applicability of the models. Moreover, incorporating more sophisticated ML algorithms such as transformers and BERT (Bidirectional Encoder Representations from Transformers) may provide new opportunities to strengthen the classification accuracy and processing efficiency.

Moreover, the creation of a systematic approach in gathering data through web scraping and measuring digitalization can be applied on other statistical units: enterprises and nonprofit institutions, for instance.

To conclude, the study is intended to show the application of ML models in public sector analytics, as well as it creates a basis for the development of innovative research for digital governance and data-driven decision-making processes. The approach and the result of the working paper provides significant insights on how digital services can be measured and analysed to monitor digital policy advancements.

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MONITORING DATA COLLECTION FOR HOUSEHOLD BUDGET SURVEY AND DIGITAL TRANSFORMATION: AN INTEGRATED APPROACH TO IMPROVE SURVEY TECHNIQUES

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Abstract. The Household Budget Survey is a key pillar for understanding consumption dynamics and informing national political and economic decisions. The accuracy and reliability of the data collected depend, to a large extent, on the effectiveness of the survey process. This study aims to explore data monitoring for the Household Budget Survey in detail, analysing current challenges and possible solutions to optimize survey techniques and adapt them to the new needs of the socio-economic context. It seems necessary to exploit the potential offered by technological and methodological innovation and reduce the use of paper-based survey questionnaires in favour of data acquisition systems more suitable for certain respondent profiles, such as web questionnaires and applications for mobile devices. Particular emphasis is placed on training personnel involved in data collection, who are asked to acquire new interdisciplinary skills, and on the need to implement meticulous and continuous quality control strategies and tools.

1. Introduction

The Household Budget Survey is a fundamental source of information for understanding consumer behaviours and socio-economic dynamics (Istat, 2023).

Monitoring data collection plays a crucial role in ensuring the accuracy and efficiency of the process, as well as the quality of the collected data. It enables the identification of critical issues and facilitates timely intervention during the data collection phase, resulting in more reliable outcomes and an in-depth understanding of household spending behaviours (Barcherini *et al.*, 2002).

At the European level, ensuring high data quality, interoperability, and integrity has become a strategic priority, driven by the growing demand for publicly available data that can be easily reused for various purposes (Publications Office of the European Union, 2021).

Over the past years, as part of the European Strategy for Data, the European Commission has promoted the adoption of harmonized standards, protocols, and reference frameworks for data gathering and processing, to improve data consistency and accessibility across sectors and member states (European Commission, 2020).

Key initiatives have been launched, including the Rolling Plan for ICT Standardisation, the European Interoperability Framework, and the ISA² Programme[1], to promote semantic operability. These initiatives encourage the adoption of semantic assets, such as shared data models and Core Vocabularies, and machine-readable formats, to facilitate data exchange and reuse across different applications and systems (European Commission, 2019, 2021).

In the age of technological innovations, digital transformation enables the automation of data collection through online tools and mobile applications. Additionally, it offers significant opportunities to enhance the efficiency of data collection, conduct advanced analyses, and improve overall information management. The transition toward digital and automated data collection methods aligns with European guidelines to modernize statistical processes and leverage technology for better data governance. These efforts are particularly relevant for large-scale surveys like the Household Budget Survey, as they foster comparability, accuracy, and consistency in socio-economic data collection.

Following an outline of the current monitoring activities for the survey, this paper presents the results of an analysis conducted on the notes recorded by the interviewers in the initial and final questionnaires of the 2023 survey edition. The study specifically focused on the challenges encountered, along with improvement suggestions provided by both respondents and interviewers. Based on these insights, and with the perspective of introducing a mobile application for expenditure recording, new monitoring reports are proposed.

Lastly, the document highlights the benefits of advanced survey tools on interviewers' fieldwork, as well as their role in the modernization of the data collection process.

2. Monitoring the quality of the survey: methods and tools

The current monitoring activities of the survey's quality make use of traditional processing techniques based on SAS datasets of microdata relating to contacts and outcomes recorded by the interviewers during the survey period. Since the Household Budget Survey provides for at least three occasions of contact between

[1] Among the initiatives funded by the ISA² programme are the "SEMIC Study on Data Quality Management", which explores how semantic methodologies—such as controlled vocabularies, shared data models, and standard metadata schemas—can enhance data quality by linking data governance principles with interoperability frameworks, and the "Data Quality Guidelines for the Publication of Datasets in the EU Open Data Portal" project, which provides EU data providers with recommendations to prepare and publish high-quality data sets, in alignment with the FAIR (Findable, Accessible, Interoperable, Reusable) principles.

the sample family and the interviewer to whom it is assigned (initial interview, intermediate visit, and final interview), the indicators that are developed also refer to all three occasions in which the interaction between respondents and interviewers could generate critical issues, interruptions, and abandonments.

The focus of the analysis is placed on the completion of the interviews, both within the sextuplets of families extracted to be part of the sample and on the individual families, but also the performance of the interviewers, in a specific reference period (quarter/month/fortnightly).

As regards the analysis of the performance of the interviewers, tables are drawn up which, starting from the contact attempts recorded for each reference month, highlight the most important characteristic elements of the work carried out. For example: attempts made (at home or by telephone), families contacted, families interviewed, minimum, median, average and maximum duration of contacts made and of the final interview, average number of members within the families interviewed. Below is an exemplary extract (Table 1), relating to the reference month "December" of the 2023 survey year.

Table 1 – *Performance indicators of the interviewers - reference month 12, year 2023.*

Interviewer code	Attempts	By phone	At home	Completed interviews	Duration of final interview (hh:mm)				Ncomp
					average	median	Min	max	
R_1	99	31	66	13	0:40	0:38	0:28	1:04	2.2
R_2	29	0	29	8	0:28	0:29	0:14	0:35	1.8
R_3	28	7	21	6	1:31	1:29	1:11	1:52	3.0
R_4	70	0	70	15	0:25	0:24	0:15	0:33	1.7
R_5	67	7	60	12	0:34	0:34	0:31	0:41	2.8
R_6	52	1	51	10	0:19	0:20	0:13	0:25	1.8
…	…	…	…	…					
TOTAL	12,202	1,748	10,347	2,339	0:36	0:31	0:09	7:08	2.1

Source: calculations based on Istat data.

The monitoring of performance indicators allows for observing the presence of any critical issues that deserve additional training intervention within the survey network, for example in correspondence with a too high number of families contacted compared to families with complete interviews - symptomatic of excessive use frequent replacement procedures that allow moving on to a substitute family if the first one does not intend to collaborate - or the duration of the final interview is too short, on average, compared to the overall performance of the entire network - a phenomenon that could hide a hasty behaviour on the part of the interviewer and therefore less accurate in gathering information.

Furthermore, such a widespread survey across the territory cannot lack the support of synthetic indicators that allow the monitoring of the survey by territorial aggregations. At a regional level, summary tables are drawn up which represent the main interest rates: loyalty rate, drop rate, rejection rate, and interruption rate.

Tables 2 and 3 show the regional indicators referring to month 12, year 2023, both taking the sextuplets as a reference base, i.e. the aggregates of 6 families extracted to form a homogeneous group – the first family and five potential substitutes – and all families contacted, regardless of their position in the sextuplet.

Through these monitoring tables, it is possible to analyse the different performances of the survey network across the territory and to identify in which phase of the complex process of completing a family interview the greatest critical issues occur (initial interview, intermediate visit, and final interview).

In fact, between the initial and final interviews, the survey provides that time is left for families to fill out a paper diary of the expenses incurred and it is precisely this commitment that can lead to a lack of willingness on the part of families to continue with the interview. This can occur especially if the network is unable to support the respondents in their daily recording of the information requested by the diary.

Table 2 – *Sextuplets indicators and completeness rate by Region, month 12, year 2023*.

Region	Assigned	Completed initial interview	Completed intermediate visit	Completed final interview	Completeness rates		
					Initial	Intermediate	Total
Piemonte	162	151	151	145	93.21	100.00	89.51
Valle d'Aosta	44	42	42	42	95.45	100.00	95.45
Lombardia	378	327	325	321	86.51	99.39	84.92
Trentino-Alto Adige	122	103	101	99	84.43	98.06	81.15
Veneto	178	168	167	161	94.38	99.40	90.45
Friuli-Venezia Giulia	62	62	62	61	100.00	100.00	98.39
Liguria	76	72	72	69	94.74	100.00	90.79
Emilia-Romagna	198	141	141	131	71.21	100.00	66.16
Toscana	204	193	193	190	94.61	100.00	93.14
Umbria	78	75	75	73	96.15	100.00	93.59
Marche	88	73	73	73	82.95	100.00	82.95
Lazio	250	213	212	200	85.20	99.53	80.00
Abruzzo	84	77	76	73	91.67	98.70	86.90
Molise	62	59	59	58	95.16	100.00	93.55
Campania	198	182	181	171	91.92	99.45	86.36
Puglia	130	119	119	117	91.54	100.00	90.00
Basilicata	56	54	54	52	96.43	100.00	92.86
Calabria	92	81	81	75	88.04	100.00	81.52
Sicilia	186	176	176	172	94.62	100.00	92.47
Sardegna	62	57	57	56	91.94	100.00	90.32
TOTAL	2,710	2,425	2,417	2,339	89.48	99.67	86.31

Source: calculations based on Istat data.

Finally, Table 3 reports the main indicators per family, therefore considering all the families contacted as a whole, regardless of their position in the sextuplet.

This data allows us to plan targeted interventions on the interviewers' network, intervening in those areas where the dropout rate is too high and where there is a tendency to replace the family by hastening the process that leads to substitutions, to allow for the higher rate of possible fidelity to the extracted base sample.

There are then other indicators to complete the general picture represented so far. The main ones monitor the number of interviews carried out for each day of the week, making it possible to observe, in a survey in which the time factor is so relevant, whether there is a concentration of interviews on the survey calendar on specific days of the week. Overall, the entire survey process is monitored at its nodal points, to be able to ascertain its fluidity and continuity over time and intervene where critical issues arise at a local or even individual level.

Table 3 – *Indicators on assigned families, loyalty rates, and drop by Region, month 12, year 2023.*

Region	Assigned	Contacts	Completed	Rates[2]		
				Fidelity	Dropout	Refusal
Piemonte	972	381	145	40.69	61.68	13.19
Valle d'Aosta	264	85	42	38,10	50,59	0.00
Lombardia	2.268	990	321	36,76	67,37	14,84
Trentino-Alto Adige	732	232	99	45,45	56,90	10,61
Veneto	1.068	432	161	32,92	62,50	42,22
Friuli-Venezia Giulia	372	158	61	29,51	61,39	9,28
Liguria	456	189	69	26,09	63,49	12,50
Emilia-Romagna	1.188	515	131	31,30	72,23	29,84
Toscana	1.224	490	190	44,21	58,98	33,22
Umbria	468	176	73	36,99	56,82	22,00
Marche	528	266	73	23,29	72,56	5,70
Lazio	1.500	734	200	33,50	70,44	11,03
Abruzzo	504	179	73	43,84	59,22	30,19
Molise	372	143	58	44,83	59,44	20,00
Campania	1.188	442	171	49,71	61,09	17,78
Puglia	780	368	117	37,61	67,93	55,60
Basilicata	336	123	52	42,31	57,72	22,54
Calabria	552	299	75	24,00	73,91	43,44
Sicilia	1.116	421	172	52,91	57,96	41,39
Sardegna	372	155	56	51,79	63,87	18,18
TOTAL	16,260	6,778	2,339	38,91	64,64	23,88

Source: calculations based on Istat data.

[2] The loyalty, dropout, and refusal rates are calculated as follows. The fidelity rate is given by the ratio of interviews completed on the base family compared to the total number of interviews completed. The dropout rate is given by the ratio between the total of definitive negative outcomes (i.e. refusal, prolonged absence of the family, etc.) and the total of families with at least one contact attempt. Finally, the refusal rate is calculated as the ratio between the number of refusals (recorded before the start of the initial interview) and the total of definitive negative outcomes.

3. Monitoring the survey: analysis of the interview notes field

In the perspective of introducing a digital tool for expense annotation, an analysis was conducted on the notes recorded in the initial interview and final interview questionnaires of the 2023 survey edition. The feedbacks from both interviewers and respondents provide a comprehensive view of the challenges encountered during the data collection phase. Therefore, this analysis can inform adjustments to certain aspects of data collection aimed at reducing the statistical burden on respondents, adopting a bottom-up approach (see Table 4).

During the reference year, a total of 2,808 comments were recorded. From these, notes deemed most pertinent to the intended purposes were selected and analysed using an interpretative approach (Guidicini and Castrignano, 1997). As a result, four distinct macro-topics were identified:

- **difficulties in making contact**: this group includes cases where the interviewers are unable to reach the family or the family is absent during the data collection period.
- **Difficulties in completing the questionnaire**: this category encompasses notes about the complexity and specificity of the questions, language comprehension issues, and instances where injury or illness hindered the ability to make expenditures. In many cases, to overcome these challenges, respondents opted to provide receipts for their expenses, which were then transcribed by the interviewer or a trusted person.
- **Willingness to participate**: this group includes issues such as distrust towards the interviewers or scepticism about the survey's purpose, the perception of the commitment as burdensome and time-consuming, concerns about privacy, and apprehensions regarding the collection, use, and protection of the provided data.
- **Optimization of response methods**: this category encompasses requests for modernizing the survey technique and for advance notification regarding the data collection period and the types of expenses to be recorded.

Each identified issue contributes to a significant statistical disturbance, often resulting in interruptions or refusals to participate in the survey. The results of the analysis suggest that implementing a mobile application for expense recording could effectively mitigate these problems and offer valuable insights for enhancing the data collection process. For instance, incorporating a predefined list of products to be recorded, sending in-app notifications to increase engagement, adding smart features such as receipt scanning, including a FAQ section and tooltips for better question comprehension, providing multilingual support, integrating internal consistency checks would likely reduce the response burden and improve the accuracy and completeness of the collected data (De Vitiis *et al.*, 2023). An additional feature that could be implemented in the App is the integration of summary reports. This functionality would enable families to have a comprehensive overview of their expenses categorized by type, potentially promoting expenditure recording.

Table 4 – *Issues identified from the analysis of interview notes and proposed features for the mobile application.*

Critical issues encountered	Possible solutions to implement in the App
• Difficulty in contact • Family absent during the survey period • Complexity and high specificity of the questions • Language difficulties • Health problems • Lack of trust or interest • Survey too long and burdensome • Privacy concerns • Questions perceived as excessively intrusive • Mode of completion considered outdated • Short notice on the period and mode of completion	• Pre-loaded product list • In-app notifications • Receipt scanner • FAQ and tooltips • Multilingual support • Summary reports • Respondents' engagement programs

Source: authors' elaborations on Istat data.

4. Proposals for new monitoring reports

Introducing a mobile application for recording household expenses necessitates focused attention on implementing advanced new reporting. The newly proposed summary reports are intended to fulfil a dual purpose: first, to act as a survey supervision tool for the Statistical Institute, and second, to serve as a means of monitoring personal expenses for families, as proposed in the preceding paragraph. A primary objective is to supervise the use of the mobile application and the input data, providing the Statistical Institute with a system to enhance the realization of the intended sample and ensure consistency in expenditures recording. In this context, it is crucial to also monitor the performance of interviewers, whose roles require redefinition with the introduction of the App.

Table 5 presents some proposals for monitoring reports to be integrated into the infrastructure supporting the new application. Each category of the report –

household spending trends, data quality, interviewers' fieldwork efficiency, and application usage – is accompanied by a set of indicators to be produced (Istat, 2022).

Table 5 – *Proposed reports and related monitoring indicators.*

Type of report	Indicators
Report on household spending trends	• Analysis of weekly expenses (line graph processing, identification of sudden peaks or dips in expenses, and analysis of their causes). • Detailed monthly analysis of major spending categories such as groceries, transportation, housing, healthcare, entertainment, etc. (processing pie and/or bar charts to visualize the percentage of spending allocated to each category, identifying categories with the highest expenses, and comparing the results with the established budget).
Report on data quality	• Verification of correct categorization of expenses, completeness of input data, and adherence to defined procedures. • Identification of missing or incorrect data. • Identification of deviations from guidelines and necessary corrective actions, such as additional training or clarifications on procedures.
Report on interviewers' fieldwork efficiency* ****(initial interviews, final interviews, and diary completion via the App)***	• Evaluation of the average time taken by interviewers to complete household expense registrations. • Analysis of response times to assigned tasks and any discrepancies compared to expected timelines. • Detailed quality control of interviewers' expense recording (accurate categorization of expense items, consistency with actual family consumption expenditure through cross-checking with receipts) and identification of causes for discrepancies (such as typing errors or missing data). • Analysis of mutual feedback and interactions among interviewers during the survey period. Identification of collaboration issues and promotion of initiatives to improve knowledge sharing among interviewers. • Continuous monitoring of how frequently interviewers update family expense data in the mobile application (identifying delays in data recording and underlying causes such as technical issues or difficulties in obtaining information, implementing measures to ensure timely data updates and improved responsiveness to monitoring needs). • In-depth examination of interviewers' utilization of specific features of the mobile application.
Report on application usage	• Monitoring of respondents' interactions with the application, including access times, frequency of data updates, and usage of specific features, such as receipt scanning. • Analysis of usage trends, including peaks or lows in the utilization of specific functionalities.

This initial set of indicators will be subject to continuous assessments by the competent Istat Directorates, data collectors, and the respondents themselves, to ensure they remain relevant and effectively meet the evolving needs of their users.

5. The role of the interviewer in the digital transition

The digital transition aims to simplify the data collection process, reducing the burden on respondents and the survey network, while enhancing the accuracy and timeliness of data collection.

In addition to the potential benefits mentioned in paragraph 3, this section addresses aspects related to the role of interviewers. Firstly, digitally collected data are immediately available and do not require manual transcription, thereby relieving interviewers of this task and significantly reducing the likelihood of human error. Moreover, the entire survey network can benefit from automatic reporting provided by the mobile application. The collected data can be promptly analysed and converted into preliminary reports, facilitating the identification of common spending patterns among users and enabling early detection of anomalies. Additionally, advanced reporting features offer enhanced customization and flexibility, according to the users' specific needs.

Nevertheless, alongside the opportunities, this transformation is not without its challenges. In this regard, it is important to emphasize that interviewers will continue to play a key role in ensuring the accuracy and completeness of survey data. The adoption of a mobile application entails a redefinition of their role and skill set, potentially including the capability to receive periodic updates on diary compilation status and provide support to respondents. An important consideration is the security of the collected personal data, which must be managed appropriately to preserve users' privacy (De Vitiis *et al.*, 2023). Interviewers will need comprehensive training on the use of digital tools, data interpretation in a digital context, and associated risks.

6. Conclusions

Optimizing data collection is essential for improving the accuracy and efficiency of the Household Budget Survey and addressing identified issues through monitoring activities. Digital tools, particularly mobile applications, offer significant advantages in this regard.

For respondents, an application would simplify the data collection process, allowing them to enter information quickly and accurately from their mobile devices.

This reduces the risk of human errors and enhances the reliability of the data collected. Furthermore, respondents gain quick and intuitive access to their personal expenditure data, enhancing transparency and the effectiveness of communication with interviewers. This capability proves particularly valuable in situations where the timeliness of information is crucial (i.e., managing survey completion difficulties).

For interviewers, the adoption of mobile applications for expenditure recording relieves them of the burden of manual data entry and enables them to focus on more significant monitoring activities. Moreover, these tools provide detailed real-time reporting of collected data, allowing the detect of trends, anomalies, and areas of interest promptly. This capability facilitates prompt responses to critical situations and supports informed adjustments to the fieldwork plan.

Implementation of a mobile application also entails addressing new and specific requirements. Interviewers play a pivotal role in ensuring the success and sustainability of this change. Comprehensive training and ongoing support are essential to facilitate the transition from paper-based methods to the adoption of new technologies. Active involvement of interviewers in the testing phases is required to identify potential issues early on and pinpoint opportunities for improvement.

With appropriate measures to address weaknesses and threats related to the project, the modernization of the Household Budget Survey has the potential to pave the way for further innovations in other socioeconomic surveys.

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WORKING THROUGH DIGITAL PLATFORM EMPLOYMENT. THE ORGANISATIONAL MODEL AND THE CHARACTERISTICS OF THE PHENOMENON

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Abstract. Globalisation and digitalisation have profoundly transformed the configuration of the labour market, enabling the emergence of new organisational models. Digital platforms are the emblem of this change and challenge official statistics. Available statistics on workers involved in digital platform employment yield results that are not easily comparable due to methodological issues and the phenomenon's heterogeneous and relatively rare nature. Reflection on the measurement of digital platforms in terms of definitions and methodologies is the basis of the Handbook on Measuring Digital Platform Employment and Work published in 2023 in collaboration between OECD, ILO and the European Commission. In 2022, Eurostat promoted an experimental module on Digital Platform Employment and attached it to the Labour Force Survey. The module was voluntarily submitted in 2022 by 17 European countries, including Italy. The study aimed to test the methodology, definitions and questionnaire model to produce the first data on employment mediated by digital platforms, in view of an ad hoc module planned for 2026. The module collected data on the phenomenon's prevalence over the previous 12 months and the four weeks before the interview. The present paper introduces the specificity of the phenomenon, discusses methodological aspects related to its measurement, and presents the results of the DPE module concerning Italy, investigating the main profiles that emerge from the associations between the key variables associated with digital platform employment and other characteristics of individuals.

1. Labour Market Transformation

Advancements in information and communication technology (ICT), along with the emergence of cloud computing, artificial intelligence, and other innovations, have spurred the expansion of the digital economy. This transformation sees a growing reliance on digital channels for economic transactions and social interactions, affecting individuals and businesses.

Digitalisation has taken precedence in the 21st century labour market, driven by various forms of connectivity, interoperability, and georeferencing (Semenza, 2020). In recent years, digital platforms have epitomised this shift, serving as conduits for new services, business opportunities, and emerging economic and organisational models (Srnicek, 2016; Bonacini et al. 2020; Perani, 2022).

Online platform-mediated work stands out as a significant and innovative aspect of the contemporary labour market, representing one of the most discussed non-standard forms of employment. Our focus is on digital platform employment, which has emerged as a distinctive digital economy component, facilitating connections between businesses, clients, and workers through technological advancements. These platforms bridge workers and clients/consumers, offering transportation, delivery, cleaning, consulting, scheduling, and design services. This phenomenon led to the adoption of new work organisation models, radically changing work processes and patterns.

To some extent, digital platforms seem to benefit both workers and clients/customers, including enhanced flexibility, accessibility, and diversification of services. While they offer several advantages, such as improved labour market matching efficiency for workers, they also pose significant policy challenges.

In digital platforms, algorithmic management plays a pivotal role in workforce coordination. This involves using sophisticated algorithms to control work activities, make decisions, and evaluate performance (Beverungen et al., 2019; Flyverbom, 2019).

The policy challenges focus on managing precarious work, inadequate social protection, unfair competition, discrimination, and safeguarding fundamental rights in the digital labour market.

2. European Regulation

Algorithmic discrimination and contractual issues related to platform workers' rights have fuelled the debate, both at the national and European level, on the need for adequate regulation to protect this specific category of workers and make transparent the anomalies found in labour management.

In the European scenario, an attempt to meet the need for regulation in this area is the proposal for a Directive presented by the Commission in December 2021[1]. The Commission's proposal reached an agreement on the Council's general orientation during the session of June 2023. Negotiations with the European Parliament began in July 2023, culminating in an agreement reached on February 2024[2]. The regulation’s general objective is to increase platform workers' working conditions

[1]European Commission, Brussels, 9 December 2021, Proposal for a Directive of the European Parliament and of the Council on improving working conditions in platform work¸ COM(2021) 762 final 2021/0414 (COD)

[2]Council of the European Union, Brussels, 8 March 2024, Proposal for the Directive of the European Parliament and of the Council on improving working conditions in platform work - Analysis of the final compromise text with a view to agreement, 7212/24 ADD 1

and protect the platform workers' personal data. Key elements include a legal presumption to accurately determine the employment status of individuals working through digital platforms. The agreement with the Parliament also ensures that workers are adequately informed about "automated decision-making and monitoring systems" regarding their hiring, working conditions, and earnings. It also prohibits algorithmic decision-making or monitoring systems for processing certain types of personal data, such as biometric data or data relating to their emotional or psychological state.

The agreement text will now be finalised in all official languages and formally adopted by both institutions. After the formal adoption stages, Member States will have two years to transpose the directive's provisions into national legislation.

3. Statistical measurement and methodological issues

Traditional labour market statistics and economic indicators have yet to be fully developed. In recent years, several attempts have been made to measure digital platform employment; however, available statistics on the number of workers involved, their characteristics, and the tasks performed yield results that are difficult to compare due to methodological issues. The phenomenon itself is still relatively unknown, highly heterogeneous, and relatively rare.

Among the primary difficulties highlighted by studies based on population surveys are the challenges in conveying to respondents what digital platform employment means, with the need to stress the difference with the mere use of company software or applications facilitating remote work or meetings. The difficulty in accurately identifying this type of work in statistical terms requires careful data cleaning and validation.

Another critical aspect is related to the definitions adopted and the boundaries of the analysis domain. This involves identifying the key characteristics of platform employment, adopting a sectoral taxonomy of digital platforms, and establishing criteria for inclusion and exclusion. Again, data collection exercises conducted thus far have varied.

A further problematic issue is the choice of the reference period. Official employment statistics and general sample surveys tend to underestimate rare jobs performed for a few hours and short periods. Even surveys with robust samples, such as Istat's Labour Force Survey, inevitably need help accurately capture such phenomena. Specifically, in the Labour Force Survey, which provides official employment estimates and is harmonised at the European level, the condition of being employed is defined as having worked at least one hour during the reference week.

According to some scholars (De Groen and Maselli, 2016; Beck, 2017), platform-mediated work is inevitably underestimated in household and individual statistics. Respondents' perception of their occupational status is one of the main reasons for this underrepresentation. Despite engaging in internet-mediated work activities, they tend not to consider it actual employment and thus do not report it during interviews. Instead, they identify themselves as students, homemakers, or unemployed[3].

3.1. Digital Platform Employment: definition and sources

Different purposes have led to varying definitions of digital platforms. Most of these definitions conceptualise a digital platform as a "digital interface" or an "online service provider." In these definitions, the digital platform stands between service or goods providers and their clients or customers.

From a methodological point of view, there is a need to harmonise the defining approaches, and ILO, OECD, and Eurostat's efforts are moving in this direction. The Handbook published in 2023 (OECD et al.) helps identify the essential aspects of digital platform employment and work that statisticians should consider when designing their research objectives and operational metadata. The work identifies a conceptual framework and specifies terminology and internationally agreed statistical standards for measuring digital platforms in OECD countries.

The handbook indicates that *Digital platform employment includes all activities carried out by a person through or on a digital platform to generate pay or profit"*[4] (OECD et al., 2023, p. 47). Moreover, the OECD and ILO definition underlines that a digital platform or a phone app controls and organises essential aspects of the activities, such as access to clients, evaluation of the activities carried out, tools needed for conducting the work, facilitation of payments, distribution and prioritisation of the work to do.

Finally, from a labour statistics point of view, digital platform employment is carried out by persons and not by economic units, which is an important distinction.

Also, the Handbook specifies that *"Labour force surveys are best placed to give accurate and robust estimates on the overall prevalence of digital platform employment, although problems of sample size reduce their suitability for gaining insights on the characteristics of digital platform workers"* (OECD et al., 2023, p. 8). Other sources that can provide a helpful complement are: ad-hoc surveys,

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[3] This is evidenced, for example, by the 9% of platform workers estimated in the COLLEEM survey. Another risk of underrepresentation occurs in interviews conducted through proxies, which are common in household surveys.

[4] As such, the definition recognises that digital platform employment is only one out of many forms of work that can take place on or through a digital platform, following the definition of work provided by Resolution I of the 19th International Conference of Labour Statisticians (ICLS).

household surveys covering different issues, administrative datasets or big data. Evidently and as usual, the choice of the method depends on the research objectives, the available resources and the trade-offs faced by statistical agencies or researchers.

Tax registers, or in general other administrative registers, can provide information from both the platforms (when it is possible to identify them as taxpayers) and from the workers (when it is possible to identify them as DPE workers). An example of acquiring administrative data on the phenomenon is offered by France, which, as of 2019, has stated that online platforms are required to report the annual gross income of all those who receive remuneration to the tax authorities[5]. Likewise, in Belgium, as of 2016, a favourable tax regime is envisaged for income derived from a platform (reduced tax rate and tax exemption up to a certain amount), which should encourage the emergence of job positions.

Web scraping can also help assess trends in parts of the digital platform labour market. In this respect, the Online Labour Index (OLI) is an experimental economic indicator that tracks the use of online labour. It measures the utilisation of digital platforms mediating online labour over time across countries and occupations based on monitoring all projects and tasks posted on a sample of platforms using an application programming interface and web scraping.

4. Eurostat and DPE Module

In the growing debate on the methodology and statistical measurement of digital platform employment comes the pilot survey on the Digital Employment Platform (DPE) within the Labour Force Survey (LFS) in 2022, implemented voluntarily by 17 European countries, including Italy. The pilot aimed to test the methodology, definitions, and questionnaire and produce the first data on employment mediated by digital platforms in the EU, in view of an ad hoc module planned for 2026.

In the pilot survey, for estimating platform workers the testing module focuses on individuals aged 16 to 64 who have worked at least one hour of paid work by performing tasks or activities organised through a digital platform or a telephone app during the 12 months preceding the interview[6]. Some insights were made concerning

[5] The tax obligation occurs when the platform's workers, or collaborators, exceed a certain amount of income or a certain number of transactions per year through the platform.

[6] The activities considered are: 1) taxi or passenger transport services; 2) transport services (delivery of food or other goods); 3) accommodation services (only where time is spent in the management of the ad on the platform, cleaning, catering for guests, carrying the keys (and not just making the house/room available); 4) sale of goods (only if produced or acquired to be sold); 5) handiwork and cleaning (including plumbing, electrician works or similar services); 6) child and elderly care; 7) medical and health care services; 8) teaching and tutoring services; 9) translations services; 10) IT services

the previous four weeks: measuring the hours spent on activities, the share of income resulting from them, how tasks are assigned and working hours are defined, the consequences of rejecting work assigned by the platform, and how prices are determined.

5. European and Italian results

In Italy, the number of people in the age group 15-64 who, in 2022, declared to have done at least one hour of work through a digital platform in the 12 months preceding the interview is 565,000, 1.5% of the total population (3.0% on average of the 17 European countries participating in the survey[7]). In line with the European results, Italy reported a higher incidence of the phenomenon among men than women (1.8% compared to 1.3%; 3.2% and 2.8%, respectively, in the 17 EU countries) and among people with a high educational level (2.6% among people with tertiary level of education in Italy; for the European countries the share for females and males is 3.9 % and 4.7 % respectively[8]). Looking at the age groups, in Italy people aged 30-44 recorded a higher share of digital platform workers (in Europe, the work through a platform is more diffused among the people under 30, 3.6 %). Approximately two-thirds of workers used a single platform, 22.3% used at least two platforms to perform the same activity, and 10.1% used multiple platforms to perform different activities.

In Italy, about 16% (89,000 individuals) who worked on tasks or activities organised through a digital platform (or a phone app) during the last year also reported such activity in the previous month (1 in 5 people in the 17 European countries, 21.5 %). The characteristics of this subgroup are similar to those observed among those who carried out the activity in the previous 12 months: more men than women, greater representation of the age groups 30-44 and 45-54, and of tertiary education.

The activities most frequently mediated via the platform are the sale of goods, delivery of goods (including food), content creation (YouTube, Instagram, etc.), rental of houses or rooms, IT services (programming, coding, web design, support and control of online content; Figure 1). The most frequent activities remain the same concerning the four weeks preceding the interview: sale of goods, rental of

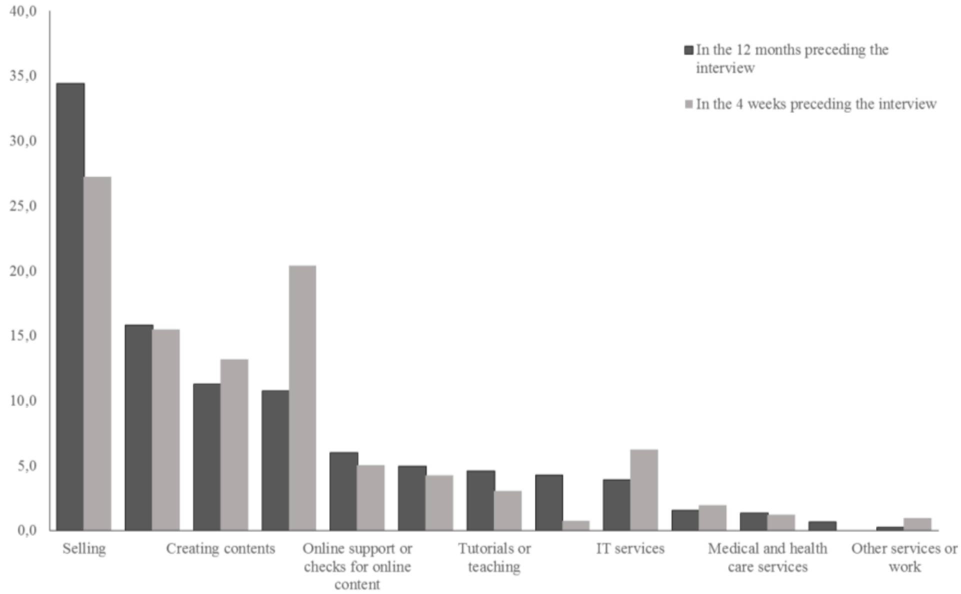
(programming, coding, web or graphic design, data or text entry or editing); 11) online support or checks for online content; 12) creation of content such as videos or texts; 13) other services.

[7] The data were only released on an aggregated level https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Employment_statistics_-_digital_platform_workers .

[8] Data is not available in total.

houses/rooms, delivery of food or other goods, and creation of content represent more than two-thirds of the total.

Figure 1 − *Type of activities carried out via digital platform in the 12 months and 4 weeks preceding the interview. Year 2022 (age group 15-64, percentage values).*

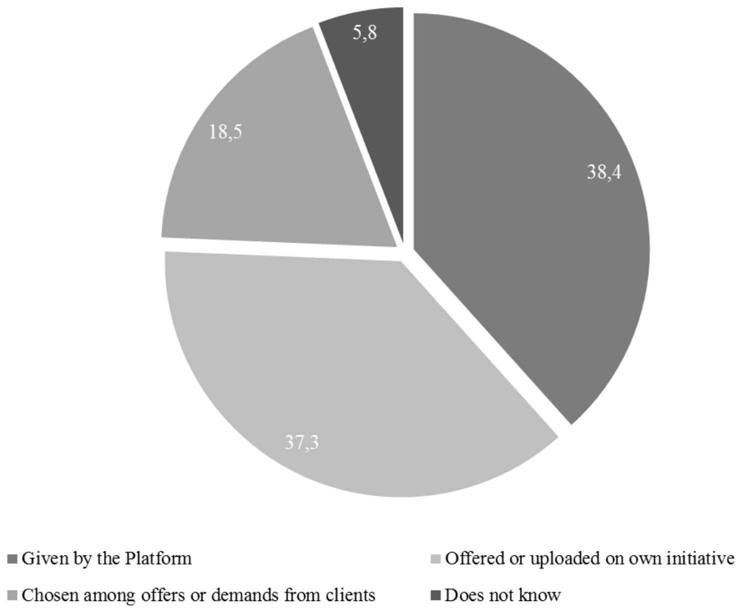


Source: Labour Force Survey, 2022.

In the area of activities related to the sale of goods, 37 per cent of employed people using a platform are self-employed, both with and without employees; almost half of these have a primary job that involves selling products (shopkeepers or sellers, commercial distribution operators, or operators in food service or entertainment activities). In this case, the platform is probably used as an additional channel for marketing. The situation is similar for delivering food or other goods and the activities related to house rental.

The number of hours worked on digital platforms is low on average: one in three worked for the platform less than one hour; slightly more than one in three less than 10 hours; in total, eight out of 10 individuals worked for the platform less than 20 hours in the four weeks preceding the interview. This is consistent with the share of income derived from platform work, which for more than two out of three individuals represents at most half of the total revenue earned in the four weeks (for nearly half, it is less than a quarter). In almost four out of 10 cases, the platform directly assigns the activity (38.4% of respondents); a similar proportion applies to those who do it on their own initiative (about 37%); only 18% state that they can choose between different options or customer requests (Figure 2).

Figure 2 – *Assignment of work carried out through digital platform in the last 4 weeks before the interview. Year 2022 (percentage values).*



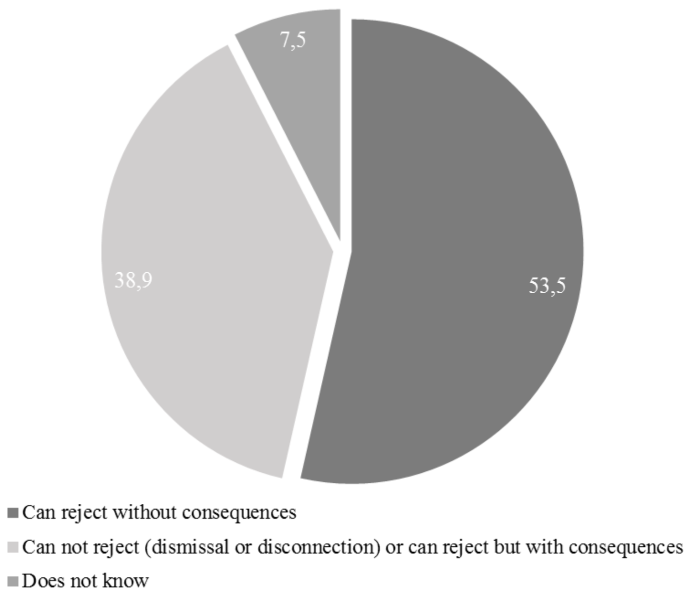
Source: Labour Force Survey, 2022.

Rejecting the assignment given by the platform does not lead to any consequences for 53.5% of the respondents. In comparison, 38.9% state rejection could lead to consequences (such as loss of job, disconnection from the platform, loss of relevant assignments or worsening of ratings; Figure 3). In over eight out of 10 cases, working time is self-determined, confirming the high degree of flexibility characterising this work organisation.

In just over 20% of cases, the platform determines the remuneration for the work; in 13.5% of cases, the platform negotiates with the worker; and finally, in more than six out of 10 cases, the compensation is set by the worker (or by another party in cases where there are regulated prices).

The degree of freedom and autonomy in the organisation and management of work through digital platforms is generally high, consistently with the European data. This is due to the nature of the prevailing activities - selling property, renting housing, delivering food and creating content - and to the type of workers who, for the four reference weeks are mainly self-employed, often with employees. In many cases, those profiles suggest that the platform is used as a marketing channel for goods that are produced or sold as part of their primary activity.

Figure 3 − *Consequences of rejecting a work assigned through the digital platform in the 4 weeks preceding the interview. Year 2022 (percentage values).*



Source: Labour Force Survey, 2022.

To deepen the descriptive analysis, we apply multiple correspondence analysis to the data to observe the relationships between the modes of the main variables. Looking at the most widespread activities, it emerges that self-defined working hours are associated with renting houses (generating between a quarter and a half of the total income). Similarly, the ability to set the price independently and the possibility to reject the assignment without consequences are associated with sales and content creation activities. More constricting conditions, on the other hand, concern the delivery of goods, including food, where there are consequences in case of refusal, and freedom on schedules and prices is lost; in these cases, the share of income derived from the platform, and thus the economic dependence on these jobs, it is also more substantial.

6. Conclusions

The phenomenon of digital platform-mediated work is evolving rapidly, in line with the spread of the technologies that make it possible. Even ten years ago, digital platforms handled a limited number of relatively skilled jobs usually performed remotely, often related to computer programming. With the spread of digital devices and different forms of connectivity, platform work has also included low-skilled types of work, usually associated with services that require the work provider's on-site presence. The data show that platform work generally provides excellent flexibility and autonomy, but much depends on the activity.

Moreover, these are often non-prevalent work activities carried out to supplement income. In several cases, however, platform work constitutes the main occupation and thus the sole source of income for workers who also have to cope with the lack of adequate legal and social security protection.

There is a growing body of experience in measuring and describing the phenomenon of digital platform work from which to learn. In the future, it will be essential to monitor the evolution of this phenomenon, not only for the workers whose activities are governed by these platforms (a probably growing share of the world of work) but more generally for the knowledge of the future labour market, in which specific characteristics of platform work may spread to other areas of employment. In addition, more in-depth knowledge of the phenomenon can help to improve the working conditions of platform workers by establishing more appropriate regulation.

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TECHNOLOGY TRANSFER IN ITALY: A QUANTITATIVE ANALYSIS

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Abstract. Literature review discusses the evolution of economic growth theories, particularly the transition from the neoclassical model to endogenous growth theories that emphasize the role of knowledge, ideas, and human capital in increasing productivity and output. Empirical research supports the positive relationship between R&D and productivity growth, with university R&D showing long-term benefits and corporate R&D yielding quicker returns.
Moreover, innovation is historically considered the main driver of economic and social development and, above all, investments in R&D are considered essential for enhancing national competitiveness and productivity.
This study investigates the impact of patent and research and development (R&D) expenditures by universities and firms on economic growth in Italy, highlighting the mechanisms of innovation propagation and diffusion and contributing to the debate on the differential role of universities versus firms in growth processes.
Utilizing a panel data technique, the analysis demonstrates a positive correlation between value added per worker and R&D expenditures per capita. The empirical findings indicate that university R&D expenditures have a higher impact on value added per worker compared to firm R&D expenditures. Gross fixed investments show an immediate but lower impact, while patents significantly influence economic growth after a five-year lag. Notably, the results reveal a time lag in the impact: university R&D investments generally exhibit an immediate effect on economic growth, whereas firms experience positive spillovers on regional growth after some years.
The findings suggest that policies supporting technology transfer should strengthen the role of universities in areas with low industrial intensity by enhancing intermediation tools (such as Technology Transfer Offices, incubators, and contamination labs).

1. Introduction

In recent years, particular attention has been given to the role of universities in the process of technology transfer to enterprises. Indeed, academic institutions are not only centres of knowledge production, but also crucial intermediaries in the transfer of scientific knowledge to the businesses.

Technology transfer in universities refers to the process through which academic research and innovations are transferred from academic institutions to the market.

This activity, which is one of the most formal activities within the so-called Third Mission of Universities[1], can assume different forms: academic entrepreneurship (spin-offs, start-ups, contamination labs, etc.); valorisation of intellectual or industrial property (e.g. patents); intermediation and technology transfer structures (e.g. technology transfer offices, incubators); cross-innovation and cross-fertilisation initiatives, enterprise-university collaborations.

The importance of technology transfer lies in its ability to bridge the gap between research and practical application, thereby accelerating innovation. By transferring cutting-edge research and technologies to businesses, universities enable companies to access novel advancements without bearing the full cost and risk of internal Research and Development (R&D). This symbiotic relationship boosts the innovative capacity of firms, leading to the development of new products, services, and processes that enhance their competitiveness in the global market (Rambe and Khaola, 2023; Padilla Bejarano *et al.*, 2023).

Through collaborations, patents and spin-offs, and all the other highlighted activities, Universities help to transform scientific discoveries into practical applications, thus generating innovation and consequently economic and social value for companies and the territories to which they propagate (Secundo *et al.,* 2017).

After all, innovation has always been the main driver of economic growth and social development (Ciccarelli, 2008). In recent decades, it has been verified that innovation is less and less the result of ‘accidental’ behaviours and more and more the result of structured activities – such as investments in research and development (R&D) – which become a crucial element in stimulating the competitiveness and productivity of territory.

In this context, it becomes crucial to know in detail how innovation spreads across the territory, and how structured research activities contribute to the growth of business productivity and output. Indeed, although the effects of investments and research and development on output have been widely discussed in the literature, this study aims to contribute to the scientific debate by providing a systematic comparison of different sources of innovation and their varying capacity for diffusion. These findings have significant policy implications, particularly concerning the design of effective technology transfer instruments aimed at maximizing the socioeconomic impact of public research in the less industrialized areas of the country.

For these reasons, this article aims to explore the impact of investments, R&D expenditure and patents on the Gross Domestic Product (GDP), highlighting how

[1] In the latest documents of ANVUR (National Agency of Evaluation), the so-called Third Mission of Universities has been given a partially different name, taking on the name of Knowledge Enhancement (Third Mission/Social Impact); see ANVUR Decree no. 8/2023 Research Quality Assessment 2020-2024.

innovation can transfer into a significant increase in production at the national level. The aim is to examine the mechanisms of propagation and diffusion of innovative activity, in order to be able to prepare adequate technology transfer policies from universities to enterprises. A comprehensive understanding of these mechanisms is essential to facilitate a two-way flow of knowledge. This process can represent a pillar fostering sustainable growth and long-term competitiveness while promoting an environment conducive to adopting technological innovations throughout the production system.

This work aims to explore how R&D expenditure not only stimulates output but also facilitates knowledge transfer within business networks or through partnerships between the public and private sectors. We believe that this contribution would be relevant especially for policymakers seeking to encourage sustainable economic growth.

The paper is organized as follow: section 2 we highlight the literature review; section 3 we show data and methodology description; section 4 we discuss the empirical results; section 5 conclusion.

2. Literature review

Economic growth theories have evolved significantly over time, reflecting changing understandings of what drives increases in a nation's output and living standards.

The concept of endogenous growth emerged as a response to the limitations of the neoclassical growth model, particularly the Solow-Swan model, which treated technological progress as an exogenous factor. In the 1980s a group of growth economists led by Paul Romer started a paradigm shift in the economic growth theory. By now the key determinant of growth were endogenous.

Romer (1986) introduced the idea that knowledges, ideas and human capital are not rival-goods, meaning that their use by one individual does not affect the possibility of another to use it too. This characteristic can lead the economic system to a sustainable economic growth, due to the increasing return to scale.

The importance of the human capital is an extension of the endogenous economic growth argued by Lucas (1988), who highlighted the positive contribution of education and training in order to enhance the productivity.

Jones, in his paper "R&D-Based Models of Economic Growth" (1995), provided a critical assessment of R&D-based endogenous growth models. He pointed out that these models often predicted scale effects—that larger economies should grow faster—which were not always supported by empirical evidence. Studying the total factor productivity growth and the number of engineers and scientists in developed countries as United States, Germany, France and Japan he finds no proof that there is a relationship between these two variables.

However, Aghion and Howitt (1998) tried to explain Jones' results i) distinguishing scale effects and growth drivers; ii) introducing more realistic assumptions about market structures and knowledge spillovers; iii) demonstrating that endogenous technological change could lead to balanced growth paths, iv) providing a framework where growth is driven by the quality of inputs rather than their quantity; v) introducing some variables about the real world, showing that these elements could explain differences in growth rates across countries without relying on scale effects.

Empirical research has played a crucial role in validating and refining endogenous growth models.

In this field we can include Mankiw, Romer and Weil (1992) with their empirical analysis which demonstrated that the differences in human capital accumulation could explain a significant part of the growth rates variations across countries, confirming the previous endogenous growth models.

Important contributors are also Coe and Helpman (1995), who found that R&D not only enhances domestic productivity but also has significant spillover effects for other countries.

In the main literature we can find different studies which argue that there is a positive relationship between countries' R&D and productivity growth using international panel data: it is the case of Frantzen (2000) and Griffith, Redding and Reenen (2004).

Despite their contribution, endogenous growth models have faced several criticism and challenges: for instance, the empirical validity which not always is supported by data; their complexity; about the policy, implementing effective policy in the real world can be harder than in the model.

Overall, endogenous growth theory offers valuable insights into the mechanisms that sustain economic growth and provides a foundation for designing policies that foster innovation, education, and long-term prosperity.

For this reason, we chose to investigate the impact of innovation using the R&D expenditure as a proxy in an endogenous growth model.

Notably, many researchers provide insights into the temporal impact of R&D activities conducted by universities and firms on economic growth, highlighting how the benefits derived from university R&D tend to manifest in the long term, while those from corporate R&D emerge more quickly (e.g. Hall *et al.*, 1986; Jaffe, 1986; Boskin and Lau, 1992; Henderson and Cockburn, 1996; Griliches, 1998; Jaffe and Trajtenberg, 2002; Aghion *et al.*, 2009). Otherwise, Siegel *et al.* (2003) demonstrate that linkages between universities and firms conducted by the technology transfer offices can accelerate the impact of the university R&D expenditures.

Abramovsky and Simpson (2011) studied the impact of geographic proximity between firms and universities, focusing specifically on pharmaceutical companies. The results of their research show that spatial closeness promotes collaboration, thereby facilitating knowledge transfer.

A very interesting study on the impact of research and development on economic growth was conducted by Minviel and Bouheni (2022), who employed the kernel-based regularized least squares (KRLS) to analyze this aspect. This advanced machine learning method allows researchers to move beyond single-point estimates. This technique could represent a further step forward in our research by calculating pointwise marginal effects at the regional level, offering a more detailed analysis than linear methods. In fact, this paper could serve as the starting point for more advanced research that will certainly be implemented in the future. The paper is organized as follows: section 2 we show the model; section 3 data and methodology description; section 4 statistical analysis; section 5 Results and conclusion.

3. Data Description and Methodology

This work stems from the Vitality project, an Innovation Ecosystem funded by the Ministry of University and Research as part of the National Recovery and Resilience Plan (PNRR, Mission 4, Component 2, Investment 1.5). The goal is to facilitate technology transfer and accelerate the digital transformation of business production processes with a focus on economic and environmental sustainability and social impact. Consequently, this article aims to investigate how the growth of the Italian economy is influenced by R&D investments made by both universities and businesses.

The chosen data to investigate the impact of innovation on economic growth consists of universities and firms’ research and development expenditures, as well as the number of patents. The dataset includes annual data for Italian regions and was constructed using information available on the Istat platform and from the Ministry of Enterprise and Made in Italy. This dataset covers the period from 1995 to 2021.

The analysis aims to understand the impact of innovation (here measured by R&D expenditure and patents) on value added per worker.

We built our empirical model starting from Romer’s work (1990), which considers three assumptions: i) technological changes drive growth; ii) technological changes are the result of people’s intentional actions; iii) designs used in the production are not rival goods.

Emphasizing the role of knowledge and technological progress, and starting from the Romer’s model we have

$$Y_t = A_t K_t^{\alpha} L_t^{1-\alpha} \tag{1}$$

where A_t is the technological efficiency of the economic system, K_t and L_t are respectively the capital and the labour at time t, Y_t is the production, α the production elasticity parameter.

The following equation:

$$y_t = \alpha h_t + \gamma i_t + (1 - \alpha - \gamma)\chi_t + \varepsilon_t \tag{2}$$

represents a simplified formulation of how various factors (h_t is the human capital computed as number of employed in the tech sector, i_t the gross fixed investment normalized to the population and γ its elasticity parameter, χ_t is compounded by the firms and universities R&D expenditures and the patent stock) contribute to the value added per worker y_t, with ε_t as the stochastic error.

Table 1 – *Descriptive Statistics***,**

Variables	Obs	Mean	Std. dev.	Min	Max.
Real value added per worker	540	60649.55	8495.186	42500.85	80136.78
Employees in tech sector (%)	418	.4537105	.5463865	.016	2.763
Gross fixed investment per capita	500	5680.484	1869.193	2417.651	11538.46
Universities R&D expenditure	500	88.27814	38.293	0	184.185
Firms R&D expenditure	500	137.9373	124.5743	.2490398	564.2839
Patents stock per capita	497	389.3996	435.3726	2.422626	1730.341

Employing a fixed effects panel regression (confirmed by the Hausman test; Greene, 2011), we used proxy variables for innovation including research and development expenditure by universities and firms, and patent stock. Additionally, following Ulku (2004)'s suggestion, we included the number of employees in the tech sector and gross fixed capital investments per capita in the model. In order to understand the impact over time of the dependent variables that characterize innovation, we apply the same panel regression but with time lags of 1, 3, and 5 years.

The results are reported in the following table:

Table 2 – *Panel regression analysis of value added (per worker) – Italy.*

Variable	Coefficient	Standard error	P>|t|
Constant	54824.18	1057.449	0.000
Employees in tech sector (%)	633.0554	851.4921	0.458
Gross fixed investment per capita	.5219398	.1238106	0.000
Universities R&D expenditure	20.70495	5.35528	0.000
Firms R&D expenditure	6.009479	1.888272	0.002
Patents stock per capita	-.8330457	.803345	0.300

Table 3 – *Panel regression analysis of value added (per worker) after 1 year – Italy.*

Variable	Coefficient	Standard error	P>|t|
Constant	54008.14	1050.229	0.000
Employees in tech sector (%)	1134.209	842.9605	0.179
Gross fixed investment per capita	.4650178	.1225857	0.000
Universities R&D expenditure	27.27929	5.373695	0.000
Firms R&D expenditure	6.45043	1.869041	0.001
Patents stock per capita	-.568667	.7956456	0.475

Table 4 – *Panel regression analysis of value added (per worker) after 3 years – Italy.*

Variable	Coefficient	Standard error	P>|t|
Constant	54092.58	1149.271	0.000
Employees in tech sector (%)	132.1862	920.8986	0.886
Gross fixed investment per capita	.2987241	.1339868	0.026
Universities R&D expenditure	28.19763	5.903485	0.000
Firms R&D expenditure	8.235437	2.041895	0.000
Patents stock per capita	1.109338	.8696172	0.203

Table 5 – *Panel regression analysis of value added (per worker) after 5 years – Italy.*

Variable	Coefficient	Standard error	P>|t|
Constant	56547.26	1264.341	0.000
Employees in tech sector (%)	387.2865	976.066	0.692
Gross fixed investment per capita	-.0017003	.1417273	0.990
Universities R&D expenditure	10.22335	6.427954	0.113
Firms R&D expenditure	7.732536	2.269384	0.001
Patents stock per capita	2.819818	.9158537	0.002

4. Assessing Empirical Results

The empirical analysis shows that structured activities preparatory to innovation (investments, R&D and patents) generally have a positive impact on value added per worker. However, large differences can be found in both the impact itself and the propagation pattern. Research and development expenditure by Universities generally has a higher impact, while R&D expenditure by companies tends to have a more modest impact. In essence, it would appear that university expenditure by its nature has a greater capacity to propagate to a large number of enterprises and throughout the territory, improving the capabilities of a large part of the economic system; business expenditure, on the other hand, would have a more circumscribed impact, since it tends to remain within the enterprise itself and the diffusion effect appears much more limited[2].

Gross fixed investments also seem to show their strength from the earliest years, but the impact they generate on GDP appears lower, perhaps because these investments are more generalist[3] and do not always succeed in influencing the production model.

Patents, on the other hand, do not seem to have a significant impact if we look at the model with time lags of 1 and 3 years, while the impact becomes significant only after 5 years; this element does not seem anomalous, since clearly a patent implemented by a company needs time to penetrate the market and consequently

[2] It should not be forgotten, then, that by their very nature these expenditures tend to be made mainly by medium and large-sized companies, which make up only a fraction of the total, accentuating this lesser capacity for disseminating innovations throughout the entrepreneurial system.

[3] Gross fixed capital formation is defined as the purchase of tangible durable goods by an enterprise, and includes (non-exhaustively) the purchase of machinery, plant, equipment, furniture, means of transport, construction and buildings, land, etc. These investments are, as can be seen, extremely heterogeneous and may not always have a direct impact on increasing the productivity of enterprises.

generate a positive impact at a macro-economic level (Garcia Vega and Vicente-Chirivella, 2020a e 2024; Hu and Zhang, 2021).

The positive and broader impact of university R&D could suggest an optimization of public policies, advising policymakers to promote increased investments in university research and development, while fostering partnerships between businesses and universities. This is particularly important in those areas characterised by small companies that, on their own, would not be able to affordably access R&D and innovation (Apa *et al.*, 2021; Colombelli *et al.*, 2021; Di Marco and Cavaggioli, 2024).

5. Some concluding remarks

Although our research activity is still in its early stages, we can already draw some preliminary indications on the way innovation and research and development activities can activate and increase the productivity of the economic system.

First of all, one of the elements that appears to emerge concerns the dichotomy between the public and private sectors, and the way in which investments in the public sector (universities) have the capacity to influence the results in productive terms by producing a greater impact than private ones, and thus showing a far greater capacity for dissemination than the latter; the reason probably lies in the fact that the public sector's objectives are evidently to carry out research for the benefit of the community, and in any case for a more or less broader set of entrepreneurial realities, thus being more incisive in determining the results in terms of the product obtained; private research activity, carried out within the individual company, evidently has the objective of creating a competitive advantage within the company itself and thus has a lesser capacity to spread across the territory.

Of course, the model tested at the national level could conceal differences in behaviour – even very large ones – between the different regions; from some initial estimates, in fact, it would seem that in regions with a greater presence of large-scale industry, the impact of research at company level is higher than at the average; on the contrary, in smaller regions, the diffusion effect of public research seems to be able to guarantee better impacts on the aggregate product.

Returning to the main objectives of our work, this aspect assumes contours of considerable relevance: it becomes essential to provide universities with effective and efficient intermediation and technology transfer structures, especially in those areas with low industrial intensity, where the entrepreneurial fabric is often fragmented and less structured, which find it very difficult to carry out structured research activities and which, therefore, need to be monitored and directed in order to improve their levels of competitiveness in the markets.

In such contexts, universities can act as catalysts for widespread innovation due to their capacity to generate knowledge and connect diverse actors. It is therefore essential to enhance intermediation tools—such as Technology Transfer Offices (TTOs), university incubators, and cross-contamination initiatives between academia and industry—to facilitate the circulation of skills and the adoption of innovation.

For the future, in order to investigate in even greater detail the impact that innovative activities can have on production at the micro and macro-economic level, it will be necessary to proceed with further verification in the specification of the model, testing possible different production functions or including some confounders in the analysis (although, as we have seen, we have tested variables such as the presence of employees in technology-intensive sectors and this does not seem to have a significant impact on the product obtained); in addition, it will be necessary to investigate databases at the firm level (such as those derived from enterprises micro-data such as the Community Innovation Survey) in order to conveniently test the micro economic issues.

Acknowledgements

This research was funded by the European Union – Next Generation EU. Project Code: ECS00000041; Project CUP: C43C22000380007; Project Title: Innovation, digitalization and sustainability for the diffused economy in Central Italy – VITALITY.

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PIECEWISE LINEAR SURVIVAL FUNCTION: A CONTINUOUS CONTEXT STUDY

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Abstract. We present here some preliminary results of an ongoing study. The subject of this work is a continuous survival function composed of two distinct, linear segments.

1. Introduction

Typically, the survival function, that we will note $S(x)$[1], when plotted on the y-axis depicts the gradual extinction of a generation. Individuals will gradually die off until ω, the age reached by the longest-lived one. $S(x)$ is always non-negative and never increases: at best, no one dies—at least for some time, because at age ω the last survivor passes away.

Specifically, we will examine the case where the function consists of two identifiable, but joined, linear segments, along with some characteristics of the associated stationary population; hereafter, we will not repeat the distinction between the function itself and the associated stationary population.

Let us start with the simplest of these functions, the linear one (or De Moivre):

$$S^{DM}(x) := S(0)\left(1-\frac{x}{\omega}\right) = S(0)\,\frac{\omega-x}{\omega} \tag{1}$$

We split it at an age K not exceeding the maximum longevity ω: in this way S becomes a piecewise continuous linear function. Here we distinguish two parts:

- The first segment S_1, from birth to K, will have a negative slope.
- The second segment S_2, from K to ω, will be similar but with a different inclination; this time it is constrained, since the function must reach zero at the final age ω. Therefore, it will correspond to a linear function starting not from age zero, but from age K. As will be shown, despite a more complex premise, the outcomes are here simpler than those of the first segment.

[1] $l(x)$ is also used in the literature.

The respective formulations are characterized by their linearity (technically, a constant first derivative), differing in points of origin and slopes respectively characterized by the non-negative parameters λ and ν:

$$S(x) = \begin{cases} S_1(x) = S(0)\left(1 - \frac{\lambda}{\omega}x\right) & x \in [0, K) \\ S_2(x) = S(K)\left[1 - \frac{\nu}{\omega}(x - K)\right] & x \in [K, \omega) \end{cases} \tag{2}$$

Since S is positive and $0 \le K \le \omega$, we have the constraint:

$$\lambda \in \left[0, \frac{\omega}{K}\right] \tag{3}$$

From $\lambda \le \frac{\omega}{K}$ follows:

$$\begin{cases} K < \omega & \lambda \le 1 \\ K \le \frac{\omega}{\lambda} & \lambda > 1 \end{cases} \tag{4}$$

Since the S is continuous, we need to set:[2]

$$S_1(K) = S_2(K) = S(0)\frac{(\omega - \lambda K)}{\omega} \tag{5}$$

Moreover, the function S must be vanished when $x = \omega$. This implies that:

$$S_2(\omega) = 0 \iff \nu = \frac{\omega}{\omega - K} \tag{6}$$

Equations (5) and (6) allows us to rewrite the function S without explicating parameter ν:

$$S(x) = \begin{cases} S(0)\left(1 - \frac{\lambda}{\omega}x\right) & x \in [0, K) \\ S(0)\left(\frac{\omega - \lambda K}{\omega}\right)\left(\frac{\omega - x}{\omega - K}\right) & x \in [K, \omega) \end{cases} \tag{7}$$

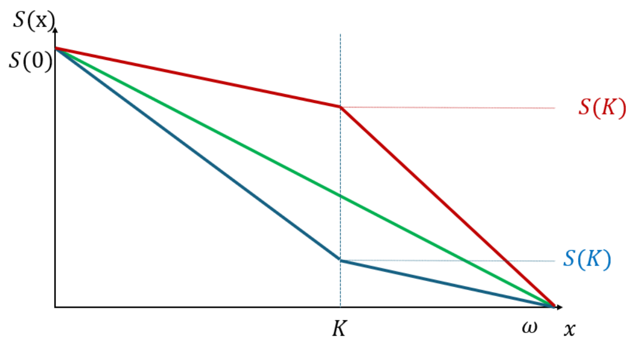
[2] Equation (5) will also have to hold for other biometric variables; incidentally, it is also a method of verifying the correctness of calculations.

We have avoided a more in-depth discussion of the derivation of the model due to space constraints.

The slopes of the two segments are closely related: a relationship conditioned by the point at which the function bends. The earlier the value of K, the less abrupt the correction needed to bring the curve to the bottom right corner: $S(\omega)$ must, in fact, have coordinates (0, ω).

Below is shown how our survival function might appear in the three main cases, which we are overlaying here—red for low mortality ($K < 1$), green for the linear case $K = 1$), and blue for high mortality ($K > 1$):

Figure 1 – *The three cases of the piecewise continuous linear survivor function S(x).*



2. Biometric functions

2.1 Deaths

In the continuous analysis, density of deaths is by definition equivalent to the absolute value of the slope of the survivors; in our case:

$$d(x) = \begin{cases} \lambda \frac{S(0)}{\omega} & x \in [0, K) \\ \frac{\omega - \lambda K}{\omega - K} \frac{S(0)}{\omega} & x \in [K, \omega) \end{cases} \tag{8}$$

Deaths are therefore constant with respect to age, as long as one remains within the same segment of the function: this is why we might omit x.

Constant yearly deceases imply that the initial cohort $S(0)$ is equal to the simple product of this annual deaths and the maximum age reached by the generation: such principle, valid immediately for De Moivre, must in our case be adapted to the existence of two segments with annual deaths respectively d_1 and d_2:

$$S(0) = Kd_1 + (\omega - K)d_2 = \frac{S(0)}{\omega}[\lambda K + (\omega - \lambda K)] \tag{9}$$

We immediately notice from (8) that the slope of the first segment is directly proportional to λ, while that of the second segment to $\frac{\omega-\lambda K}{\omega-K}$ moves in the opposite direction with respect to λ. If the first segment is steeper than the linear case (where λ = 1), then the slope of the second segment will have to compensate with a softer decline in order to reach the bottom right vertex, corresponding to extinction at age ω; and vice versa (see Figure 1).

Now we may introduce the instantaneous mortality rate:

$$\mu(x) = \begin{cases} \frac{\lambda}{\omega-\lambda x} & x \in [0, K) \\ \frac{1}{\omega-x} & x \in [K, \omega) \end{cases} \tag{10}$$

Observe that in the right-piece of the function μ, the parameter λ does not influence the mortality, which is the same as the De Moivre.

2.2 Resistance

Petrioli (1982, pp.177-178) introduces some physical analogies in the field of demography, comparing the number of deaths in an age interval to the "work" of mortality; he then continues with its "average power" π, which is nothing more than the average of deaths per unit of time: [3]

$$\pi(x + \Delta x) := \frac{M(x+\Delta x)}{\Delta x} = \frac{S(x)-S(x+\Delta x)}{\Delta x} \tag{11}$$

Finally, he introduces the "resistance function" *r*, which "depends on the law of elimination and is particularly sensitive to its variations" (p.178):

$$r(x) := \frac{\pi(x,\omega)}{\pi(0,x)} = \frac{xS(x)}{(\omega-x)[S(0)-S(x)]} \tag{12}$$

By applying the general formula (12) to our case, we get:

[3] $M(x, x + \Delta x) = S(x) - S(x + \Delta x)$ holds true in every survival function.

$$r(x) = \begin{cases} \frac{\omega-\lambda x}{\lambda(\omega-x)} & x \in [0,K) \\ \frac{x(\omega-\lambda K)}{\lambda K(\omega-x)+\omega(x-K)} & x \in [K,\omega) \end{cases} \quad (13)$$

Notice that at $x = K$ it holds in both cases:

$$r(K) = \frac{\omega-\lambda K}{\lambda(\omega-K)} \quad (14)$$

At this point, we just need to examine the behavior of $r(x)$, also to check if in our case the "bell-shaped trend" emerges as described in Petrioli and Berti 1979 p. 20: this aspect is currently under investigation.

2.3 Life expectancy

The first step is to retrocumulate the years lived. We start with T_2, because in the logic of retrocumulation T_1 presupposes it:

$$T_2(x) = \int_{x\geq K}^{\omega} S_2(\xi)d\xi = \frac{S(K)}{\omega-K}\int_{x\geq K}^{\omega}(\omega-\xi)\,d\xi = \frac{S(0)}{\omega}\frac{\omega-\lambda K}{\omega-K}\frac{(\omega-x)^2}{2} \quad (15)$$

where ξ is the mute variable of integration. The subscript notation related to the segment is omitted in $S(K)$ because the value coincides in both segments; we will continue to do so where possible. We naturally have also: $T_1(K) = T_2(K) = T(K)$.

Hence:

$$T_1(x) = \int_x^K S_1(\xi)d\xi + T(K) = \frac{S(0)}{2\omega}\left[(\omega^2 - 2\omega x + \lambda x^2) + (1-\lambda)K\omega\right] \quad (16)$$

In particular, it holds:

$$T_1(0) \coloneqq T(0) = S(0)\frac{\omega+(1-\lambda)K}{2} \quad (17)$$

From T, we finally obtain the life expectancy; by applying the general formula $e(x) \coloneqq T(x)/S(x)$, we have:

$$e(x) = \begin{cases} e_1(x) = \frac{(\omega^2-2\omega x+\lambda x^2)+(1-\lambda)K\omega}{2(\omega-\lambda x)} & x < K \\ e_2(x) = \frac{\omega-x}{2} & x \geq K \end{cases} \quad (18)$$

e_1 and e_2 being the left and right sides of the function e respectively, we could alternatively write the former by separating the elements involving λ:

$$e_1(x) = \frac{(\omega^2-2\omega x+K\omega)-\lambda(K\omega-x^2)}{2(\omega-\lambda x)} \tag{19}$$

The value of the second segment e_2 is no longer influenced by λ and K, and it is equivalent to that of De Moivre. In the first segment, however, both ones appear. In particular, the parameters in the second segment affect the number of survivors, but not their life expectancy because they cancel out with $T_2(x)$.

It is unnecessary to add that $e_1(K) = e_2(K)$,.

At birth, we have:

$$e_1(0) := e(0) = \frac{\omega+(1-\lambda)K}{2} = e^{DM}(0) + \frac{(1-\lambda)K}{2} \tag{20}$$

We derive $e_1(x)$ to systematically discover the effect that age, the slope of the first segment, and the bending point have on this:

$$\frac{\partial e_1(x)}{\partial x} = -\frac{\lambda^2x^2-2\lambda\omega x+[(2-\lambda)\omega-\lambda(1-\lambda)K]\omega}{2(\omega-\lambda x)^2} \tag{21}$$

$$\frac{\partial e_1(x)}{\partial \lambda} = -\frac{\omega(K-x)(\omega-x)}{2(\omega-\lambda x)^2} \tag{22}$$

$$\frac{\partial e_1(x)}{\partial K} = \frac{(1-\lambda)\omega}{2(\omega-\lambda x)} \tag{23}$$

Note that everything depends on the numerator—naturally considering any preceding "-" —as the denominator is never negative.

Certainly negative is (22), and it is intuitive why: as λ increases, the area under the survival curve in the ages under K decreases (the critical value ω/K coincides with the slope that zeroes out survivors at the breaking point.); once lost some of such initial life-space because of a steeper λ, the tied behaviour of S_2 does not allow for a full catching-up.

The sign of (23) clearly depends on λ: above the value of 1 it is positive, negative for values below; indeed, increasing K extends the action of λ for a longer period before the final compensatory decline.

The first derivative is the most difficult to evaluate and keeps holds a surprise: it is not always negative, as one might expect: Section 3 delves into this further.

3. Does aging harm health?

Here we study the trend of life expectancy by age in the first segment of the function: after *K*, we are indeed in a straightforward variation (albeit delayed) of De Moivre's law. In this paragraph, for the sake of clarity and ease of treatment, we also exclude the degenerate case $K = 0$, which corresponds to the simple .

As a general principle, $e(x)$ typically declines because, as intuition suggests, over time individuals consume their available life. The inevitability of death implies life expectancy generally decreases over the course of existence.

However, can this function also rise at certain somewhere? The answer, well-known to demographers, is: yes. This typically occurred at the beginning of life, when high mortality rates now were countered by a perspective of lower risks in the future. This is a characteristic of survival curves in populations characterized by very high infant mortality, typically those in pre-transitional stages: hence the use of the imperfect tense. Almost certainly, even today we would observe reversals in life expectancy trends if we could measure it from the moment of conception.

There exists a general formulation for the derivative of life expectancy with respect to age, following directly from the application of Leibniz Rule and making it more intuitive how life expectancy can rise in certain phases; specifically, those characterized by strong immediate mortality followed by high survival for the remainder of life:

$$\frac{de(x)}{dx} = \mu(x)e(x) - 1 \tag{24}$$

A stark example: if one person with a life expectancy of 60 years were forced to play the unhealthy game of Russian roulette, his life expectancy would drop to 50 years, returning then immediately to 60 after (potentially) surviving the ordeal; in this calculation, we neglect the time taken for the unpleasant test (de minimis non curat prætor) and use a six-chamber revolver. We apply here the general formula $e(x) = e_\alpha p_\alpha + e_{\tilde{\alpha}}(1 - p_\alpha)$, more statistical than demographic, where p is the survival probability and $\tilde{\alpha}$ denotes cases other than α.

Now we may focus on equation (21) considering its numerator as a quadratic in the variable x:

$$\frac{\partial e_1(x)}{\partial x} = -\frac{\lambda^2x^2 - 2\lambda\omega x + [(2-\lambda)\omega - \lambda(1-\lambda)K]\omega}{2(\omega-\lambda x)^2} =: -\frac{\Xi(x)}{2(\omega-\lambda x)^2} \tag{25}$$

A positive numerator implies the reassuring downward derivative with respect to age. It should be noted that Ξ is preceded by a minus sign—which we leave in place without including it in our variable—and that the denominator cannot be negative.

However, we will try to establish when the normal trend of life expectancy reverses, increasing with age. To this end we set up the inequality:

$$\Xi(x) < 0 \iff x \in \left[\frac{\omega-\sqrt{\omega(\lambda-1)(\omega-\lambda K)}}{\lambda}, \frac{\omega+\sqrt{\omega(\lambda-1)(\omega-\lambda K)}}{\lambda}\right] \quad (26)$$

The right-hand value of the interval for x would be greater than K^{Max} (formally, we could write $x^R > K^{Max}$, where x^R stands for "right", just as x^L stands for "left") and thus becomes irrelevant; let's rewrite then, also using survival probabilities

$$x > x^L = \frac{\omega-\sqrt{\omega(\lambda-1)(\omega-\lambda K)}}{\lambda} = \left[1-\sqrt{(\lambda-1)p(0,K)}\right]K^{Max} \to \frac{\partial e_1(x)}{\partial x} > 0 \quad (27)$$

Now we evaluate Ξ in the various possible cases, divided into three parts ordered by the values of λ, within which we will distinguish a few subcases.

3.1 La dolce vita: $\lambda \in [0,1)$

From equation (25) it is clear that

$$\begin{aligned} \Xi &\coloneqq \lambda^2 x^2 - 2\lambda\omega x + [(2-\lambda)\omega - \lambda(1-\lambda)K]\omega \\ &= (\omega-\lambda x)^2 + (1-\lambda)(\omega-\lambda K)\omega \end{aligned} \quad (28)$$

This reformulation makes it clear that Ξ will always be positive here; consequently, the derivative (25) will be trivially negative, as expected when the instantaneous mortality is modest. Nevertheless, we will provide a few brief considerations for the notable sub-case $\lambda = 0$, $\Xi = 2\omega^2$; the (25), in its entirety, is instead −1: here, the life expectancy decreases by an amount equivalent to the time elapsed, without partial recoveries for the avoided mortality, which is zero.

3.2. The right path: $\lambda = 1$

We have here a classical Moivre, where the radical contained in (26) becomes zero: the solution would then be $x^{R/L} = K^{Max}$; however, it is better to directly calculate it: by substituting λ with 1 in (25), we simply obtain -1/2.

3.3. Life is hard (and short): $\lambda > 1$

Here things get more complicated (and interesting), because Ξ can be negative; since the term x^L in (27) now becomes decisive, it is important to study its main features. Since the maximum value of *x* here is *K* (recall that we are in the first segment of the function), we can try to see if x^L can be lower[4] thus allowing for our eagerly sought inversion:

$$x^L_{\lambda>1} < K \;\rightarrow\; \omega - \lambda K < \sqrt{\omega(\lambda-1)(\omega-\lambda K)} \;\rightarrow\; \omega - \lambda K < \omega(\lambda-1) \quad (29)$$

By solving (29) for *K*, we obtain:

$$x^L_{\lambda>1} < K \;\Leftrightarrow K > (2-\lambda)\frac{\omega}{\lambda} = (2-\lambda)K^{Max} \quad (30)$$

Alternatively, we can also proceed by considering λ:

$$x^L_{\lambda>1} < K \;\Leftrightarrow \lambda > \frac{2\omega}{K+\omega} \in [1,2] \quad (31)$$

In both formulations, it is evident that the inversion can occur when the slope is steeper than that in the linear case; moreover, since $K \leq \omega$ it appears with certainty for $\lambda > 2$.

Once it is established when the inversion can (or must) occur, it remains to see if we start from birth in negative territory; this is also a matter of great interest because—keeping in mind that, as noted when discussing (26), x^R cannot interfere —in this case, the inversion would occur throughout the entire first segment of the function. Note that this is a sufficient condition, whereas the previous one was necessary.

From (27), we can derive:

$$x^L_{\lambda>1} < 0 \rightarrow \omega < (\lambda-1)(\omega-\lambda K) \rightarrow (\lambda-2)\omega > (\lambda-1)\lambda K \quad (32)$$

Then we obtain:

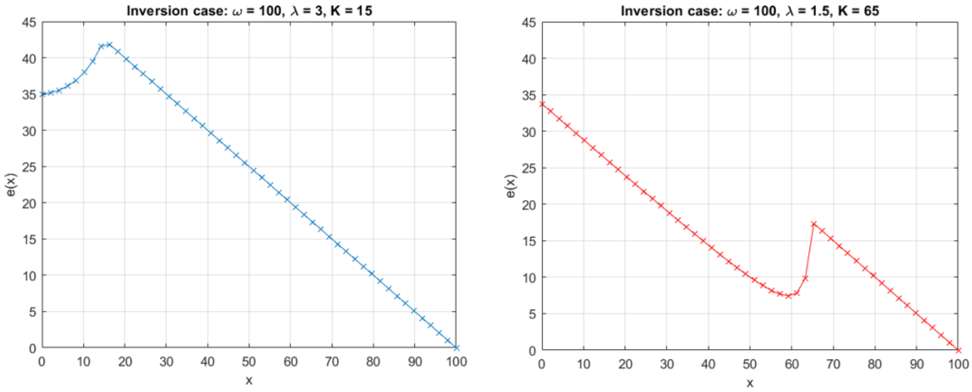
$$x^L_{\lambda>1} < 0 \rightarrow K < \frac{\lambda-2}{\lambda-1}\, K^{Max} \quad (33)$$

---

[4] Note that from (27), we already know that it cannot be greater than K^{Max} and certainly not greater than ω.

Hence, the inversion at all ages (of the first segment, obviously) is possible only if $\lambda > 2$.

Figure 2 – *Inversion of the function e(x) with* $\lambda > 2$ *(left) and* $\lambda \in (1,2)$ *(right).*



4. Conclusions

The present work investigates some theoretical and mathematical properties of the function $S(x)$, highlighting key aspects that are seldom addressed in existing models. A particularly intriguing result is the observed growth of $e(x)$ with age, which appears to be linked to the pronounced angularity of the piecewise linear structure of $S(x)$. Let us add also the importance of $\lambda = 2$ as threshold (this holds true also for $\lambda = 1$, but this was expected); notable also how some final outcome can be seen as a combination of the two original linear functions (see Appendix).

To the best of our knowledge, these behaviours are scarcely explored in current frameworks, suggesting potential avenues for further investigation and possible applications.

Looking ahead, an interesting direction for future research involves the generalization to quadratic or polynomial forms of $S(x)$. Specifically, a rigorous theoretical analysis could aim to determine whether polynomial curves $S(x)$ inherently preclude the growth of life expectancy $e(x)$ with age—or conversely, whether such growth can occur under specific conditions. Addressing this question would deepen our understanding of the interplay between $S(x)$ structure and $e(x)$.

Appendix

Frankenstein function

We can consider the piecewise function as the grafting of two linear functions, one for each segment: from the first one, *A*, we obtain the first line, from 0 to *K*; from the second function, *B*, we obtain the segment from *K* to ω.

A has a maximum age $\widehat{\omega}^A$, different from the global ω: if $S_1(x)$, shown in (7), extended beyond *K*, it would nullify for:

$$S(0)\left(1-\frac{\lambda}{\omega}x\right)=0\rightarrow\;\; x\coloneqq\widehat{\omega}^A=\frac{\omega}{\lambda} \tag{34}$$

From which we can write it as a classic De Moivre with a new longevity:

$$S^A(x)=S(0)\left(1-\frac{x}{\widehat{\omega}^A}\right) \tag{35}$$

In the case of *B* we are looking for that initial contingent $S^B(0)$ that can adapt the second segment of the original piecewise function. We have:

$$S^B(x)\coloneqq S_2(x)\;\rightarrow\; S^B(0)=S(0)\left(\frac{\omega-\lambda K}{\omega-K}\right) \tag{36}$$

Hence we get a De Moivre, with different initial contingent. As we see by rewriting the second line of (7):

$$S^B(x)=S(0)\left(\frac{\omega-\lambda K}{\omega-K}\right)\left(1-\frac{x}{\omega}\right) \tag{37}$$

Moreover, it can be proved, but we omit it due to space limitations, that $e(0)$ is equal to the sum of $e^A(0)$ and $e^B(0)$, weighted with $c_0^A=\frac{\lambda K}{\omega}=\frac{\lambda}{\lambda^{Max}}=\frac{K}{K^{Max}}$ and $c_0^B=1-c_0^A$.More in-depth developments of this idea are currently under investigation.

Acknowledgements

The Authors thank Prof. Carlo Maccheroni for valuable advice.

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DISABILITY TRENDS IN SELECTED EUROPEAN COUNTRIES: AN AGE-PERIOD-COHORT ANALYSIS

Enrico Roma, Rossella Miglio

Abstract. Disability is an important public health issue. Understanding the evolution of disability with age is critical for policy makers and researchers to develop effective interventions and allocate resources efficiently. The aim of this study is to describe disability trends in European countries, focusing on age, period and cohort effects.
We used data from the Survey of Health, Aging and Retirement in Europe (SHARE). The data were pooled from waves 1 to 9 (excluding wave 3) and we considered only Austria, Belgium, Denmark, France, Germany, Italy, Spain, Sweden and Switzerland, resulting in a sample of 72188 respondents and 234946 rows. The response variables were the global index of activity limitation (GALI), the number of limitations in instrumental (IADL) and non-instrumental activities of daily living (ADL). All three variables were dichotomized. A logistic age-period-cohort interaction model was used to estimate the prevalence for each of the three responses. Cohort effects were estimated as the interaction between age and period. The model was estimated using generalized estimating equation with an unstructured working correlation matrix. Gender and individual country-specific wealth quintile were included as covariates. We found that disability prevalence was lower in men than in women and exhibited a non-linear relationship with age. Additionally, prevalence increased over time, peaking in wave 7 (pre-Covid-19) for GALI only, and decreased with higher wealth quintiles. Country-specific differences were also observed. The cohort effect mitigated the impact of age, except in older cohorts for GALI and IADL.

1. Introduction

Disability poses a significant health and economic burden for the individual, the family of the disabled person, as well as for society and healthcare system (Mitra et al., 2017). In addition, disability affects various aspects of life and is associated with negative health consequences, both physical and psychological (Yang et al. 2005), including death (Landi et al. 2010). Given this profound impact, it is crucial to analyse trends in disability to develop public health and policy strategies, especially in European countries where the population is ageing (Eurostat, 2020).

In the literature, several authors have attempted to estimate the trend of disability in relation to age. Ahrenfeldt et al. (2018), for example, used data from the Survey of Health, Ageing and Retirement in Europe (SHARE) to estimate the cognitive and physical functioning of Europeans over the age of 50. It was found that cognitive function has improved across Europe and that there were significant regional differences in physical function. Verropoulou and Tsimbos (2017), also using SHARE, attempted to estimate differences in disability across European countries using 4 waves and 4 different indicators, stratified by gender and two age groups. The results were indicator-dependent but showed a large regional variability. Similarly, Jehn and Zajacova (2019) assessed disability trends using data from the Canadian Community Health Survey (CCHS) collected between 2001 and 2014. Respondents were categorised into two age groups (65 was the cut-off) and the prevalence of disability was examined over time as a function of age and gender. They also reported a reduction in disability in older people respect to older cohort, as previously found by Ahrenfeldt et al. (2018). In a related study using the U.S. National Health Interview Survey (NHIS), Martin and Schoeni (2014) found an overall decline in all but physical disabilities in the over-65 age group.

While interesting, these studies do not offer a complete overview of the phenomenon. Indeed, age is often grouped into broad categories, and it is impossible to distinguish between period effects and cohort effects. There are three papers in the literature that aim to fill this gap by using longitudinal data. The first is by Lin et al. (2012), who use NHIS from 1982 to 2009 to show how disability decreases in younger cohorts and in younger time periods and increases with age as expected. Another notable one is that of Yu et al. (2016), which used data collected in Hong Kong among community-dwelling older adults. In this case, although an increase in the prevalence of disability with age and a gender difference were found, there was no cohort effect. To compensate for the lack of such surveys in Europe, Beller and Epping (2021) estimated an age-period-cohort model using the European Social Survey (ESS) from 2002 to 2016. The main finding of the analysis was a strong U-shaped relationship between the cohort and the prevalence of disability. However, period effect was not significant.

The analysis by Beller and Epping (2021) confirmed the evidence for a non-linear relationship between age and disability prevalence in some of the European countries. Not all the countries participate in the ESS (e.g. Italy was excluded), nor is there a perfect match between the countries participating in the ESS and SHARE indeed. Moreover, the cited papers so far dealt with disability using different indicators. The most prevalent seem to be the Global Activity Limitation Indicator (GALI) (Van Oyen et al., 2006, Galenkamp et al., 2020), the Activity of Daily Living (ADL) (Steel et al. 2002, Yu et al. 2016) and the Instrumental Activity of Daily Living disability indicators (IADL) (Lawton and Brody, 1969, Nicholas et al. 2003). The work of Beller and Epping (2021) is based on the GALI, which is a well-validated single-item indicator. Compared to what has been said so far, SHARE has the advantage to include some of the countries excluded from the ESS, covers similar years and contains all three mentioned disability indicators.

Based on these considerations, the aim of this paper is to estimate an age-period-cohort model to understand the evolution of disability in Europe using SHARE data. The hypothesis is that disability increases with age but changes over time and in different cohorts; a period effect is expected to be detected during Covid-19 pandemic.

2. Data

SHARE is a multidisciplinary longitudinal study that measures health, socioeconomic status and social networks in 27 European countries and Israel (Börsch-Supan et al. 2013, Bergmann et al., 2019). The survey began in 2004 with country-specific sampling strategies. Eligible participants were people aged 50 or older at the time of the survey and living in the sampled household, except for persons who were imprisoned, hospitalized or institutionalized. Data is collected every two years. We used data from waves 1 (2003-2004) to 9 (2022) (SHARE-ERIC, 2024). Wave 3 was excluded as it mainly collected retrospective information and did not include the response variables of interest. For this study, we restricted the sample to individuals with less than 95 years. The inclusion of people older than 95 often caused quasi complete separation in statistical modelling. Moreover, we considered only the countries that participated in all waves, namely Austria, Belgium, Switzerland, Germany, Denmark, Spain, France, Italy and Sweden.

Three response variables were included, i.e. GALI, ADL and IADL, and dichotomized as indicated in the Manual of Scales and Multi-Item Indicators (Mehrbrodt et al., 2019). The GALI measures long-standing activity limitations (six months or more) due to health problems affecting usual activities with a single question with modalities "severely limited," "limited but not severely," or "not limited”. It was then reclassified as "not limited" (0) or "limited" (1). The ADL index assesses limitations in basic self-care activities, including dressing, walking, bathing, eating, getting in or out of bed, and toileting, with a score ranging from 0 (no limitations) to 6 (maximum limitations) and was reclassified as "no ADL limitations" (0) or "1+ ADL limitations" (1). Similarly, the IADL index evaluates limitations in more complex activities, such as meal preparation, shopping, transportation, and financial management, with a score ranging from 0 to 7, and reclassified as "no IADL limitations" (0) or "1+ IADL limitations" (1). Age was calculated based on the year of birth of the respondent while period corresponded to the progressive number of the wave. Gender was also included in the analysis along with country specific quintile of wealth, defined according to Miceli et al. (2019), The selected sample comprised 72188 respondents and 234946 rows. The imputations provided by SHARE were used (Bergmann and Börsch-Supan, 2021). Since the imputation for ADL and IADL were not available, further 1024 respondents were excluded from the analysis of only these variables.

3. Statistical analysis

Dataset preparation and graphical presentation was done with R (Team R. C., 2004, R: A language and environment for statistical computing, R Foundation for Statistical Computing). While model estimation was performed with Stata/SE 18.0 for Windows (64-bit x86-64), revision 25 Apr 2023.

We used a model similar to Luo and Hodges (2022), where the cohort effect was represented by the interactions between age and period, but considering age and period as continuous variables.

$$\begin{aligned} logit(\pi_{i,j}) = \ & \mu_0 + \sum_{l=1}^{4} \alpha_l \cdot ns_l(Age_{i,j}) + \beta \cdot M_i + \sum_{l=2}^{5} \gamma_l \cdot 1_{Wealth_{i,j}} \\ & + \sum_{l=2}^{9} \delta_l \cdot 1_{Country_{i,j}}(l) + \varepsilon \cdot p_{i,j} + \sum_{l=1}^{4} \zeta_l \cdot ns_l(Age_{i,j}) \\ & \cdot M_i \\ & + \sum_{l=1}^{4} \sum_{m=2}^{9} \eta_{l,m} \cdot ns_l(Age_{i,j}) \cdot 1_{\{Country_{i,j}\}}(m) \\ & + \sum_{l=1}^{4} \theta_{l,j} \cdot ns_i(Age_{i,j}) \cdot p_{i,j} \\ & + \sum_{l=1}^{4} \sum_{m=2}^{9} \iota_{q,i} \cdot ns_i(Age_{i,j}) \cdot M \cdot 1_{\{Country_{i,j}\}}(m) \\ & + \sum_{l=2}^{9} \kappa_s \cdot M_i \cdot 1_{Country_{i,j}}(l) \end{aligned} \tag{1}$$

The logistic model in equation (1) was fitted for each response variable. Greek letters represent the parameters to be estimated, the letter i is the index for the individual and j for the repeated measures (varying from 1 to 9). In the linear predictor, $ns_{(\cdot)}(Age_{i,j}, 4)$ indicates a natural spline transformation of age with 4 degrees of freedom (estimated with the R package splines), $\mathrm{M_i} = 1_{Gender}(\text{Male})$, where $1_X(\text{x})$ is an indicator function, and p_{ij} is the wave index of the j-th observation of the i-th participant. The correlation arising from repeated observations of the same respondent over time was handled using generalised estimating equations and assuming an unstructured working correlation matrix. For further details and a non-technical explanation of the model, please refer to the online appendix available at https://osf.io/m4jw8/?view_only=2ef8d42cdac94b1594315cc5e3ab00a1. Another appendix can be found at the same link to complement what is presented in the next section. In the appendix Table A.1 provides descriptive statistics by wave and country, including the prevalence of GALI, ADL, and IADL, calculated only for eligible respondents. Table A.2 presents the prevalence of GALI, ADL, and IADL across wealth quintiles for each wave. Tables A.3, A.5, and A.7 contain the model coefficients for GALI, ADL, and IADL, respectively. Tables A.4, A.6, and A.8 present the estimated working correlation matrices for GALI, ADL, and IADL. Table A.9 summarizes the descriptive marginal effects of the wealth variable on the prevalence of GALI, ADL, and IADL, providing a clear depiction of the wealth gradient in these measures.

4. Results and discussion

The aim of this analysis was to describe the development of disability prevalence in Europe and to shed light on the relationship between the effects of age, period and cohort using SHARE data.

Observing Figure 1, it is immediately apparent how the prevalence of disability increases with age, as expected and confirming what has been described in previous studies (Ahrenfeld et al. 2018, Verropoulou and Tsimbos, 2017, Jehn and Zajacova, 2019, Martin and Schoeni, 2014, Lin et al, 2012, Yu et al. 2016, Beller and Epping, 2021). However, the trend seems to differ from country to country and depending on the indicator used. The GALI asks about the perception of disability in the last six months, while ADL and IADL refer to specific activities. Furthermore, the questions used to determine ADL and IADL score investigate the inability to perform rather simple tasks and therefore refer to more severe forms of disability. In support of this observation, we have evidence that the prevalence of ADL and IADL increases abruptly after the age of 75 in almost all countries.

Another remarkable aspect is the systematic difference in prevalence between men and women in almost all countries, with women showing more disability than men. The exceptions are France, Denmark and Germany, where the gender differences in prevalence in both GALI and ADL is much less pronounced and even almost non-existent in certain ages.

The period effect is represented in Figure 2, but interpretation should be done carefully due to the interaction between period and age. The prevalence increases with wave's number for all three indicators and has a peak corresponding to wave 7 (pre Covid-19). The ε coefficient, which corresponds to the wave effect, is significantly different from zero and positive only in the model for GALI. This finding is apparently in conflict with what have been reported by Beller and Epping (2021), who did not find a period effect. However, their period of analysis was different and ended in 2016, which should be noted. The positive slope of the line representing period effects could be related to a higher prevalence estimate only in one of the most recent periods. In Wave 7, part of the sample participated only to SHARELIFE interview, determining a different sampling strategy. This would be coherent with Beller and Epping (2021), as it would shift the period effect to years later than those investigated by the two authors.

Figure 1 – *Model based prevalence estimates GALI, ADL and IADL by gender and country, marginalized respect to wealth and wave counter.*

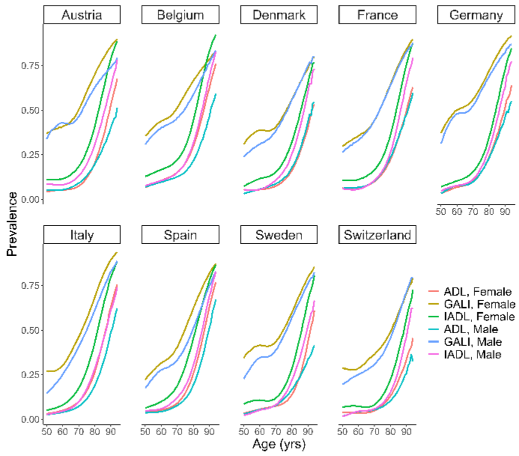


Figure 2 does not indicate a distinct effect of the Covid-19 pandemic, which primarily occurred during wave 8. Instead, it shows a consistent increase across the observed periods, even if not statistically significant for all the response variables. In the model defined in Equation 1, the cohort effect is governed by four parameters. The hypothesis of absence of a cohort effect, i.e. $\theta_1 = \theta_2 = \theta_3 = \theta_4 = 0$, was tested with a Wald test and rejected for all three models (for GALI we had $\chi^2_4 = 34.62, p < 0.0001$, for ADL $\chi^2_4 = 18.75, p = 0.0009$ and for IADL $\chi^2_4 = 27.85, p < 0.0001$). The evidence therefore supports the inclusion of the cohort effect in the model. Then, as explained in Appendix 2, a separate effect measure in the logit scale (namely $\sum_{l=1}^{4} \theta_{lj} \cdot ns_i\left(Age_{i,j}\right) \cdot p_{i,j}$) can be estimated for each cohort in each period of observation. For instance, if a cohort is included in all periods of the analysis (excluding the third wave), it will have eight effect measures.

These effect measures can be visualized in a two-dimensional graph, sorted either by age or by period or by cohort, as all these variables allow a unique ordering. An upward trend in the effect as the age index increases, for example, would suggest an accumulation of cohort deficits with age (Additional examples of interpretation can be found in Luo and Hodges 2022.) In our attempt to interpret the cohort effect, we have therefore resorted to this type of representation.

Figure 2 – *Model based prevalence estimates of GALI, ADL and IADL across the waves of the survey, marginalized respect to age, wealth, country and gender.*

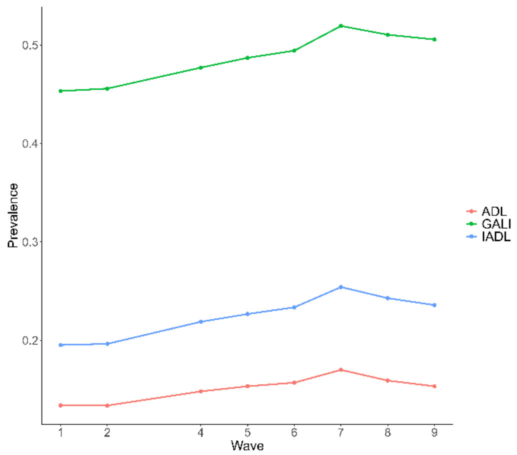
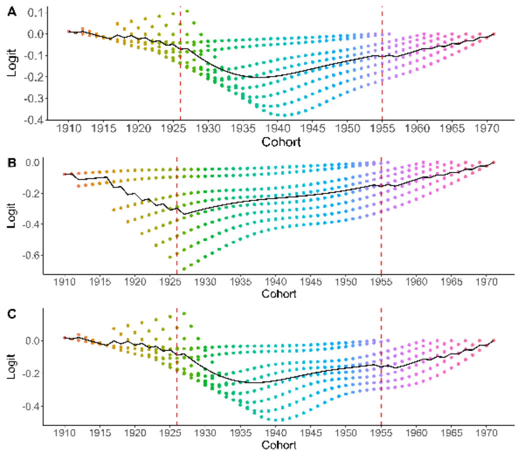


Figure 3 shows the estimates of the cohort effect in the linear predictor scale against the cohort for all three response variables. The continuous black line represents the average size of the effect. The GALI and IADL indicators show an almost identical pattern, with the older cohorts showing a positive effect, the middle and younger cohorts a negative one, albeit quite smaller for the latter. This pattern is very similar to that described by Beller and Epping (2021) for the GALI indicator. However, the cited study includes cohorts up to 2005, and it appears that the increase in reported disabilities is due precisely to these extremely young cohorts, that are not part of our sample. The last cohort examined in our analysis, i.e. those born in 1970, coincides with the lowest estimate of disability in the reference study. However, the size of the effect is hard to compare because our model does not force the intercept and the linear component of the cohort effect to be null (Luo and Hodges, 2020).

The cohort effect found in this study respect to the GALI allows for several interpretations. Firstly, it is possible that older and younger subjects tend to rate their perception of disability higher because the former have potentially severe forms of disability, while the latter have only experienced milder forms. Hence, they may have a different anchor than the middle age groups, who still have sufficient life experience but at the same time have not yet been affected by severe forms of disability (Furnham and Boo, 2011). A second possible interpretation lies in the "failure hypothesis" (Gruenberg, 1977). Essentially, it is possible that older cohorts experienced a stronger selection because most of the people who would have suffered from a disability have died instead. This is not the case in the middle cohorts due to the impact of medical advances. Two other possible competing explanations could be that the selected older people live independently and therefore prove to be a population with a lower level of disability than those living in residential care. In addition, the observation period is quite short, so that some cohorts can only be observed in certain age groups, impacting the prediction process.

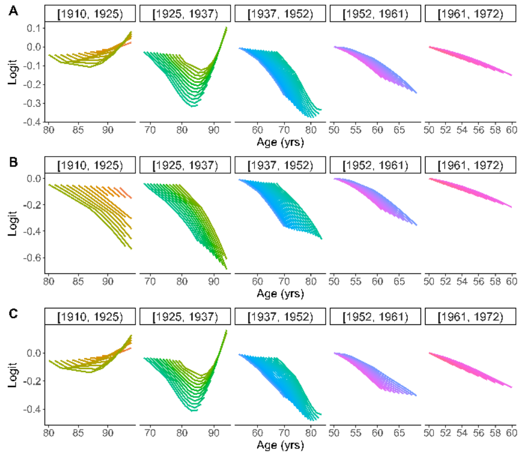
Figure 3 – *Model-based estimates of cohort effects ($\sum_{l=1}^{4} \boldsymbol{\theta_l} \cdot \boldsymbol{ns_i}(\boldsymbol{Age_{i,j}}) \cdot \boldsymbol{p_{i,j}}$) on GALI (Panel A), ADL (Panel B) and IADL (Panel C), on the linear predictor scale. All the cohort borned between 1926 and 1955 (dashed vertical red lines) were included in all the 8 waves of SHARES considered in the analysis. The black line indicates the average cohort effect.*



The ADL indicator, on the other hand, shows a very different pattern: it appears that the older cohorts show a more negative effect while the effect decreases in the younger ones. The older cohorts are the only ones observed at older ages, and the selection of non-institutionalised older people could be a selection bias towards the more resilient individuals, and this could be relevant for ADL where the considered questions are more related to physical limitations.

Figure 4 shows the cohort effect in relation to age. For ease of reading, four cohort groups with similar trends were formed. Note also that the scale of the values on the x-axis is not the same, as no cohorts were observed for any of the age groups considered. As with the previous graphs, GALI and IADL appear to be quite similar. For the older cohorts, it appears that the cohort effect assumes a parabolic relationship with respect to time and therefore there is a reduction in the logit only in the middle age groups where this cohort was observed. For younger cohorts, the effect is decreasing and resembles a straight line. The same is true for ADL, but for all cohorts. The cohort effect is basically higher at older ages and should reduce the logit due to the negative sign. To a certain extent, the cohort effect mitigates the effect of age.

Figure 4 – *Model-based estimates of cohort effects* ($\sum_{l=1}^{4} \boldsymbol{\theta_l} \cdot \boldsymbol{ns_i}(\boldsymbol{Age_{i,j}}) \cdot \boldsymbol{p_{i,j}}$) *on GALI (Panel A), ADL (Panel B) and IADL (Panel C), on the linear predictor scale. Cohorts were separated according to the type of pattern observed.*



Finally, Table A.9 clearly shows how belonging to higher wealth quintiles is associated with a lower prevalence of disability for all indicators, confirming previous results (Makaroun et al., 2017). This can be explained considering that access to healthcare is not free in all included countries and awareness on how to access the national healthcare systems may be low in lower wealth. Additionally, a dose-response relationship between wealth and depressive symptoms in people with disabilities (Torres et al., 2016) may contribute to a higher GALI among lower wealth individuals.

5. Conclusion

This study provides a comprehensive analysis of disability prevalence across Europe, leveraging SHARE data to examine the interplay of age, period, and cohort effects. Disability prevalence increases with age, but the patterns vary by country and the indicator used, reflecting differences in how disability is perceived and measured. Gender differences are evident, with women generally reporting higher disability rates than men, although exceptions exist. The observed period effects suggest an overall increase in disability prevalence, particularly in specific waves, but no clear impact of the COVID-19 pandemic was detected. Cohort effects reveal nuanced patterns, with older cohorts potentially benefiting from selective survival and younger cohorts displaying distinct perceptions of disability. Finally, wealth emerges as a significant factor, consistently associated with lower disability prevalence across all indicators, underscoring the influence of socioeconomic factors. The proposed model has the advantage of adopting a parametric form for the cohort effect, so it can be used to predict future disability trends by including all three components (even if they are out-of-range extrapolations). Therefore, it would allow the prediction of perceived disability trends in Europe taking into account changes in the demographic pyramid of the population.

Acknowledgements

For layout reasons, the full acknowledgement required from SHARE has been included in Appendix 3 (online). We acknowledge funding from Next Generation EU, in the context of the National Recovery and Resilience Plan, Investment PE8 – Project Age-It: "Ageing Well in an Ageing Society" [DM 1557 11.10.2022].

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ISSN ASSEGNATO: 0035-6832

Direttore Responsabile: CHIARA GIGLIARANO

Iscrizione della Rivista al Tribunale di Roma del 5 dicembre 1950 N. 1864

Associazione all'Unione Stampa Periodica Italiana

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