LONGITUDINAL DATA ON LABOUR FORCE IN ITALY: NEW METHODS AND RESULTS FROM 2018 - 2024

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Abstract. The Labour Force Survey - the main official source of information about the Italian labour market conducted by the Italian National Institute of Statistics - in addition to produce cross-sectional estimates, provides longitudinal labor market data. These data are obtained matching the members of the households who were interviewed in different periods due to the rotational scheme of the survey: during 15 months, each sampled household is interviewed for 4 quarters and individual records can be matched to produce 12-months longitudinal data (almost 50% of the total sample). The longitudinal data are built matching those of two quarters and the weights used for providing the estimates are obtained solving two calibration problems. In this contribution, we describe the methodology to measure the accuracy of the longitudinal estimates on annual average and examine, considering the sampling error, the movements in the last years of individuals aged 15-64 among labour market employment status during 2018-2024, drawing a detailed picture also due to the availability of household characteristics.

1. Introduction

The study aims to provide a further perspective on the dynamics of the Italian labor market in the pre-COVID period, during the crisis, and in subsequent years, through the use of longitudinal data. These data, compared to the cross-sectional ones, allow us to understand in more detail the recent evolution of the labour market in relation to its inequalities and critical issues.

The Labour Force Survey (LFS) is the main source of information on the Italian labour market, providing official estimates for a relevant number of indicators based on a two-stage sample design with stratification of the first-stage units – municipalities - and a rotation scheme for the second-stage units – households (Istat, 2006). In addition to cross-sectional data, the LFS also provides longitudinal labour market data (Istat 2024, 2025). These are obtained by matching household members interviewed at different time periods, due to the rotational scheme of the survey (Ceccarelli *et al.*, 2002). Specifically, individual records can be matched to generate 12-months and 3-months longitudinal datasets, covering nearly 50% of the total sample. Since December 2015, the Italian National Institute of Statistics (Istat) has provided 12-months estimates on labour market flows, permanencies and transitions by occupational status (employment, unemployment, inactivity).

In this study, we analyse the 12-month flow data across the four quarters of each year from 2018 to 2024. In particular, we present the methodology used to compute confidence intervals for these main indicators based on annual averages. Furthermore, we illustrate how accuracy measures, such as absolute and relative errors, allow for a more precise analysis of the labour market. The main results on labour market transition are also presented, including the results of logistic regression models used to identify the most important determinants associated with the probability of entering or exiting employment, with a particular focus on different occupations.

The paper is organized as follows: Section 2 provides a brief overview of the longitudinal LFS, discusses the methodological aspects of the weighting procedure, and outlines the proposed methodology for computing sampling errors. The main results are presented in Sections 3 and 4. Finally, Section 5 offers concluding remarks and suggestions for future research.

2. Longitudinal data in the Istat Labor force Survey: methodological aspects

The Italian Labour Force Survey disseminates five main indicators:

- Transition rate
  This is calculated as the ratio between the number of individuals who are in a different occupational status at the end of the period compared to the beginning, and the stock of individuals in the initial status. The rate can be interpreted as the probability of transitioning to a different occupational condition between the beginning and the end of the period.
- Permanence rate
  This is calculated as the ratio between the number of individuals who remain in the same occupational status throughout the period and the stock of individuals in that status at the beginning of the period.
- Workers' Separation Rate (WSR)
  This is calculated, over a given period, as the ratio between the number of individuals entering employment (UE, IE) and the total number of individuals who remain employed (EE), enter employment (UE, IE), or leave employment (EU, EI) during the same period:
  $$WSR = \frac{UE + IE}{EE + (UE + IE) + (EU + EI)}$$
- Workers' Hiring Rate (WHR)

This is calculated, over a given period, as the ratio between the number of individuals leaving employment (EU, EI) and the total number of individuals who remain employed (EE), enter (UE, IE), or leave employment (EU, EI) during the same period:

$$WHR = \frac{EU + EI}{EE + (UE + IE) + (EU + EI)}$$

- Reallocation rate
  This is the sum of the separation and hiring rates. It provides a measure of labour market dynamism, reflecting its flexibility and mobility.

The indicators are computed using data collected from the same individuals, linked through probabilistic record linkage techniques to better address linkage errors (Ceccarelli *et al.*, 2002). The sampling design of the Labour Force Survey (LFS), and in particular its 2-(2)-2 rotation scheme, allows data to be collected from the same units in repeated interviews conducted after 3, 9, 12, and 15 months (Istat, 2006). In other words, households are interviewed four times over a 15-month period. Each quarter, approximately 50% of households are expected to be re-interviewed after 12 months (see Figure 1).

Figure 1 – *Rotating design of LFS and overlapping of a quarterly theoretical sample in two years. Overlapping has been expressed considering the quarter 1 of year 2 as base.*

Year	Quarter	Rotation groups															$o_{q'(\blacksquare)}^{q(\blacksquare)}$
		D	E	F	G	H	I	L	M	N	O	P	Q	R	S	T	
1	4	D4	E3			H2	I1										50%
2	1		E4	F3			I2	L1									---
2	2			F4	G3			L2	M1								50%
2	3				G4	H3			M2	N1							0
2	4					H4	I3			N2	O1						25%
3	1						I4	L3			O2	P1					50%

The indicators listed above are estimated on the linked data using the calibration estimator (Deville and Särndal, 1992). This estimator adjusts the design weights – which reflect the characteristics of the sampling design – to match known population totals, thereby improving the consistency and coherence of the estimates. For a detailed discussion of the calibration system used for longitudinal estimates, see Alaimo et al. (2022).

The sampling variance depends on the stadification and the stratification of the sample, the weight adjustment, the correlation among the observation due to the rotation scheme (Ceccarelli et al., 2017) and the expression of the paramenter (Wolter, 2007) and it is computed using the R-package ReGenesees (Zardetto, 2015).

3. Main results: permanencies and transitions in the labour market status from 2018 to 2024

The computation of the sampling error enables evaluation of the accuracy of the longitudinal estimates. Table 1 shows the relative error and confidence interval of main longitudinal indicators for the population aged 15-64, periodically disseminated by Istat, with reference to the last available data; Figures 1-4 refer to the period from 2018 to 2024.

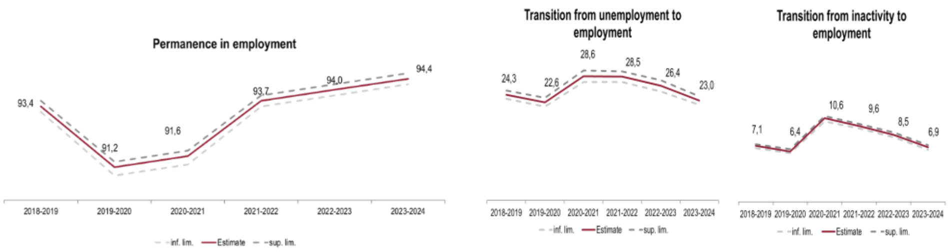
Table 1 – *Permanence and transition rate by occupational status over a 12-month period (estimate, relative error and 95% confidence interval). Population aged 15-64. 2023-2024*

Permanence and transition rate in the professional Condition	Estimate (%)	Relative error (%)	95% confidence interval	
			Lower bound	Upper bound
Permanence in employment	94.4	0.1	94.2	94.6
Transition from employment to unemployment	1.2	4.0	1.0	1.4
Transition from employment to inactivity	4.4	2.1	4.2	4.6
Transition from unemployment to employment	23.0	2.9	21.7	24.3
Transition from inactivity to employment	6.9	2.3	6.6	7.2
Permanence in fixed-term employment	64.3	1.0	63.0	65.6
Transition from fixed-term to permanent	18.0	2.8	17.0	19.0
Transition from fixed-term employment to	4.8	5.8	4.3	5.3
Transition from fixed-term employment to	11.5	3.7	10.7	12.3
Reallocation rate	10.7	1.2	10.4	11.0
Hiring rate	5.4	1.8	5.2	5.6
Separation rate	5.3	1.8	5.1	5.5

Looking at the labour market over the last years, since the period of deepest crisis in 2019-2020, two trends seem to be emerging: the increase in permanent employment and the decrease in entry to employment (Istat, 2025; Istat, 2024; Ciani et al, 2025).

The minimum value of permanent employment, 91.2%, was reached in 2019-2020, and then it steadily grew until reaching 94.4% in 2023-2024. Over time, employment in the longitudinal population has grown due to the positive difference between hiring and separation rates[1]; however, the intensity of this growth has gradually decreased since 2019-2020, following a decline in employment. On the other hand, entry to occupation, after the post-crisis recovery, has decreased in the last three years and the transition from unemployment and inactivity to employment in 2023-2024 is lower than in 2018-2019: respectively 23.0% vs 24.3% and 6.9% vs 7.1%.

Figure 2 – *Permanence employment, transition from unemployment and inactivity to employment. Population aged 15-64. 2018-2019/2023-2024.*



Flow data show an increasing difficulty for fixed-term employees to stabilize their employment status after a year: 18.0% of fixed-term employees in 2023 have a permanent contract in 2024. The value was instead higher respectively by more than 4 percentage points in 2021-2022 (22.2%) and by 6.5 p.p. in 2020-2021 (26.5%). On the contrary, the probability of remaining trapped in precariousness has increased. In 2023, 64.3% of fixed-term employees have the same contract in 2024; this is higher than in previous period (59.5% in 2021-2022 and 51.5% in 2020-2021).

In summary, the Italian labor market shows an increase in the number of permanent workers as a result of their greater permanence in the employment condition, particularly among older workforce, whose exit from the labor market has been delayed over time. The reason is the increase in educational attainment - which has shifted forward entry and exit from employment - as well as the rules that have tightened the requirements for retirement (Istat, 2025). Conversely, entry into employment as a permanent employee is decreasing; in 2024 it concerns less than 30% of new employees. Also the transformation from unstable to stable is decreasing, involves less than 1 in 5 temporary workers in the same year. This leads to a double segmentation between insiders and outsiders, on the one hand, and between standard insiders and unstable insiders on the other, in a context of generalized workforce aging. For the younger generations, which are increasingly reduced in number, it means long periods of non-employment or precarious employment with serious consequences on the

[1] Hiring and separation rates provides a measure of labour market mobility; when the first indicator is greater than the second it means that the longitudinal employed population increases, on the contrary it decreases when the second is greater than the first.

postponement of the transition to adulthood. For older generations, whose demographic weight is increasing, the longer permanence in the labour market could have negative consequences on the new life plans of individuals and on the productivity of the economic system.

Figure 3 – *Reallocation rate of entry occupation (hiring rate) and exit from occupation (separation rate). Population aged 15-64.2018-2019/2023-2024.*

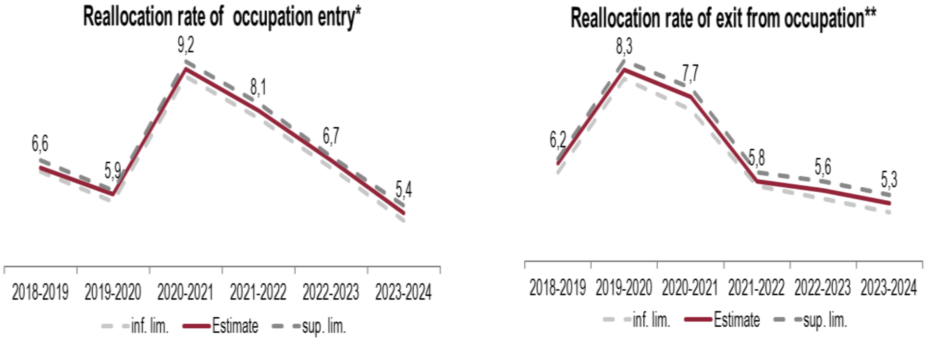
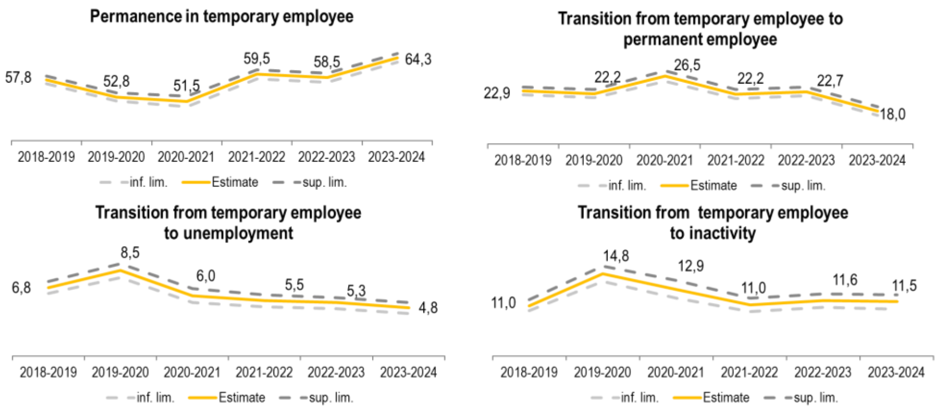


Figure 4 – *Permanence and transition in/from fixed-term employment. Population aged 15-64.2018-2019/2023-2024.*



4. Main results: logistic regression

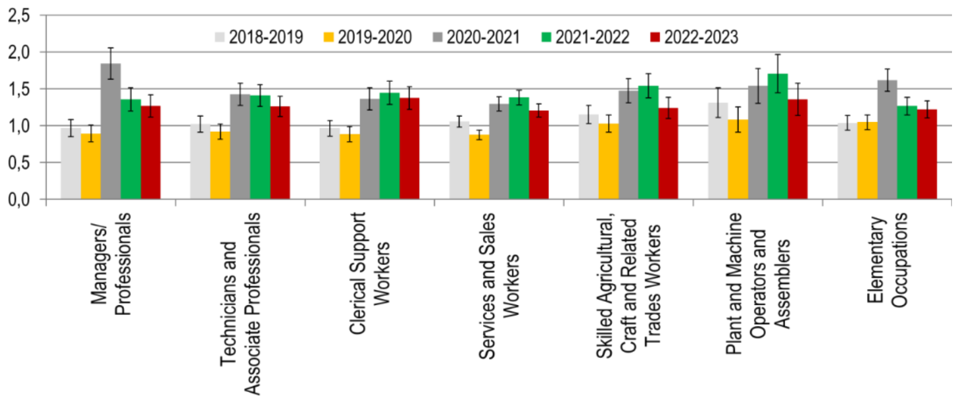
Longitudinal data allow to analyze, in particular, individuals' professional opportunities through their entry into the labour market. This is especially in light of the structural changes in Italy in recent years, which have increased the share of highly skilled employment and that associated with information and communication technologies (Istat, 2025b).

At the same time, analyzing labour market exits completes the study of turnover in Italy by occupation, which represents fundamental elements for corporate and public policies, with particular reference to education and training.

4.1 Probability of entering employment

To identify the main factors associated with the probability of entering employment from 2018 to 2024, a multinomial logistic regression model was applied, taking into account different occupations. Specifically, the analysis focuses on the inactive and unemployed population aged 15–64 at the beginning of each period, excluding members of the armed forces at the end of the period. The outcome variable is the occupational status after 12 months, with employment disaggregated by occupation (ISCO 5-digit). The independent variables are age class, gender, citizenship, educational level, geographical area, non-employment status (inactive or unemployed) at the beginning of the period, and reference period (see Appendix for the results).

Figure 5 – *Multinomial logistic regression: odds ratio and confidence interval of entering employment by occupation, 2018-2024 (versus permanence in not-employment). Reference period versus 2023-2024.*



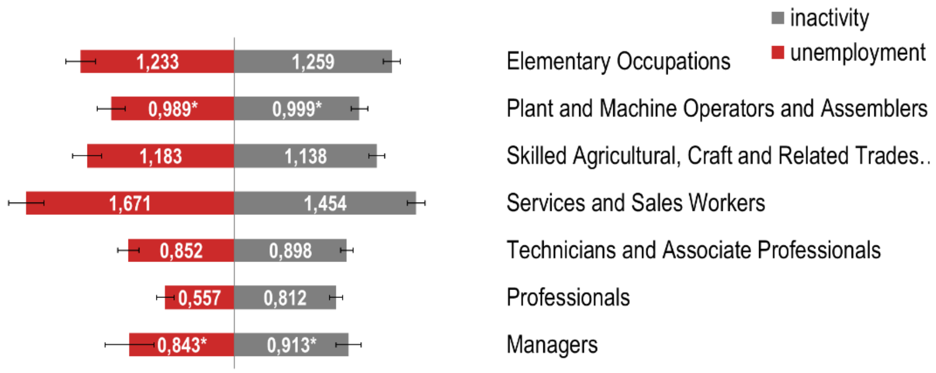
From 2018 to 2021, there was a significant increase in the probability of entering employment for all occupations (see Figure 5). After, a decline was observed for both the most highly qualified occupations (managers and professionals) and elementary occupations - those that had previously experienced the highest growth. From 2021 to 2023, we can observe the highest probabilities of finding employment after 12 months, for each occupation (all odds ratios are significantly above 1). In the last period, the situation was similar to 2018–2020. 2019 is a particular period, because the probability of entering employment after 12 months among service and sales workers reached its lowest point - likely due to the impact of the pandemic.

4.2 Probability of exiting employment

In order to identify the variables associated with the probability of exiting from employment, a multinomial logistic regression model was applied. The population considered includes individuals aged 15–64 who were employed at the beginning of the period (excluding members of the armed forces). The outcome variable is occupational status at the end of the period, classified as employed, unemployed, or inactive. The independent variables include age, sex, citizenship, educational level, geographical area, reference period, and occupation at the beginning of the period (see Appendix for the results).

Service and sales workers have the highest risk of exiting employment: compared to clerical support workers, their risk of becoming inactive is 45% higher, and their risk of becoming unemployed is 67% higher (see Figure 6). Elementary occupations follow, with a risk of exiting employment approximately 25% higher than that of clerical support workers. Professionals have the lowest risk of exiting employment (particularly to become unemployed). Managers follow, whose risk is not significantly different from that of clerical support workers.

Figure 6 – *Multinomial logistic regression: odds ratio and confidence interval of exiting employment, 2018-2024 (versus permanence in employment). Occupation versus clerical support workers.*



** Not statistically different from 1*

5. Conclusion remarks

Longitudinal data have high informational value as they enable a dynamic understanding of labor market trends; it is therefore essential to complement cross-sectional estimates with longitudinal analyses.

The analysis of longitudinal data on labour market has shown that the increase in employment in the last years can only be attributed to the impact of demographic changes on the age composition of the workforce. The increase in permanent workers is primarily a result of their extended tenure in employment, especially among older workers. In the same time, the transition from fixed-term to permanent employment is declining, and the probability of remaining trapped in precariousness increases.

In addition to the reference period, labor market transitions are strongly influenced by occupation; service and sales workers generally have the highest risk of exiting employment, while elementary occupations and the most highly qualified occupations show the most important decline in employment entries from 2020–21 to 2023–24.

In conclusion, the labour force's overall aging encourages contemplation of potential futures, even those that are not too distant, in which making strategic use of the labour force population becomes imperative (Rosina, 2025). Training and employment quality, supply and demand service efficiency, in addition the availability and accessibility of tools for reconciling career paths with life choices, must be a key elements of development policies.

Appendix

Logistic regressions results

Tables A1 and A2 report the results of the multinomial logistic regressions in terms of odds ratio for each category of the independent variables included in the model, according to the order in which they were selected in the stepwise procedure.

Education level is the most important variable for entering employment, followed by occupational status, gender, age, citizenship, and territory (Table A1). The transition from non-employment to qualified occupations is more probably among high education levels, men, Italian young individuals living in central and northern regions. Women have higher probability than men to became clerical support workers or services and sales workers; foreigners, compared to Italians, to be employed in low-qualified occupations. Finally, transitions to employment, for each occupation, are less frequent among individuals living in the South or in the Islands.

The highest risk of exiting employment was observed among term contract and temporary employees, particularly to became unemployed (Table A2). They were followed by young individuals and services and sales workers, during the pandemic period 2019-2021, women, people living in the South or in the Islands, with low levels of education (especially in relation to becoming inactive) and foreign workers.

Table A1 – *Multinomial logistic regression: odds ratio for entering employment (versus permanence in non-employed). Unemployed and inactive persons aged 15-64 at the beginning of the period (excluding armed forces at the end of the period), years 2018-2024.*

	Managers/ Profession als	Technician s and Associate Profession als	Clerica l Suppor t Worke	Servic es and Sales Worke rs	Skilled Agricultur al, Craft and Related	Plant and Machine Operators and	Elementar y Occupatio ns
Education level (vs Low education)							
Medium	6,795	6,484	5,391	2,060	0,912	1,33	1,065
High education	69,589	20,930	9,636	1,106	0,298	0,39	0,439
Occupational condition (vs Inactivity)							
Unemployed	1,548	2,178	3,136	3,393	2,954	3,66	2,762
Gender (vs man)							
Woman	0,774	0,470	1,234	1,185	0,114	0,20	0,509
Age class (vs 15-24)							
25-34	2,306	1,324	1,352	1,375	2,068	1,99	2,638
35-44	1,698	0,986*	1,239	1,050*	2,242	1,59	3,195
45-54	1,250	0,730	0,842	0,782	2,303	1,65	3,102
55-64	0,463	0,260	0,254	0,313	0,885	0,50	1,100*
Citizenship (vs Not Italian)							
Italian	4,477	3,574	3,912	0,824	0,617	0,80	0,369
Geographical area (vs Islands)							
Northwest	1,967	2,752	2,396	1,487	1,193	2,16	1,100
North-East	1,998	2,875	2,634	1,715	1,497	2,78	1,200
Centre	1,674	2,204	2,110	1,561	1,403	1,61	1,079*
South	1,034*	1,207	1,096*	0,972*	1,009*	1,30	0,961*
Reference period (vs 2023-2024)							
2018-2019	0,969*	1,023*	0,966*	1,058*	1,154	1,31	1,039*
2019-2020	0,896*	0,920*	0,885	0,876	1,029*	1,08	1,048*
2020-2021	1,845	1,427	1,367	1,297	1,475	1,54	1,619
2021-2022	1,356	1,410	1,445	1,383	1,544	1,70	1,267
2022-2023	1,271	1,262	1,378	1,209	1,243	1,35	1,221

** Not statistically different from 1*

Table A2 – *Multinomial logistic regression: odds ratio for exiting employment (versus permanence in employment). Employed aged 15-64 at the beginning of the period (excluding armed forces at the beginning of the period), years 2018-2024.*

	Probabily of exiting employment to:	
	unemployment	**inactivity**
Occupational condition (vs Self-employed)		
Permanent employee	1,228	1,020*
Temporary employee	5,840	3,172
Term contract	8,721	6,631
Age class (vs 55-64)		
15-24	2,385	0,769
25-34	1,865	0,439
35-44	1,382	0,315
45-54	1,205	0,289
Occupation (vs Clerical support worker)		
Manager	0,843*	0,913*
Professional	0,557	0,812
Technician and associate professional	0,852	0,898
Services and sales worker	1,671	1,454
Skilled agricultural, craft and related trades worker	1,183	1,138
Plant and machine operator and assembler	0,989*	0,999*
Elementary occupation	1,233	1,259
Reference period (vs 2023-2024)		
2018-2019	1,556	1,089
2019-2020	1,818	1,629
2020-2021	1,657	1,583
2021-2022	1,287	1,116
2022-2023	1,228	1,028*
Gender (vs man)		
Woman	1,139	1,657
Geographical area (vs Northwest)		
North-East	1,152	1,007*
Centre	1,502	1,083
South	1,891	1,495
Islands	1,907	1,380
Education level (vs High education)		
Low education	1,466	1,709
Medium education	1,139	1,310
Citizenship (vs Italian)		
Not italian	1,586	0,894

** Not statistically different from 1*

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