THE ACCURACY OF LONGITUDINAL LABOUR FORCE SURVEY ESTIMATES

Leonardo S. Alaimo, Alessio Guandalini, Antonella Iorio, Cristiano Marini, Alessandra Masi

1. Introduction

Besides cross-sectional data, the Italian Labour Force Survey (LFS) also provides longitudinal labor market data. The latter are obtained matching the members of the households who were interviewed in different time periods, due to the rotational scheme of the survey. In particular, individual records can be matched to produce 12-months and 3-months longitudinal data by involving almost 50% of the total sample. Since December 2015, the Italian National Institute of Statistics (Istat) has been providing 12-months estimates on the labour market flows, permanencies and transitions by occupational status (employment, unemployment, inactivity).

In this work, we present the methodology for computing the confidence intervals for these main indicators. Moreover, it is shown how the measures of accuracy, such as absolute or relative error, allow more precision analysis of the labour market.

The paper is organized as follows. In Section 2 the longitudinal LFS is briefly presented, the main problems are listed and the adopted solution are described. In Section 3 the methodological aspects related to the weighting procedure and moreover, the proposed methodology for computing the sampling variance are discussed. The method is applied on real data and some results are shown in Section 4. Finally, concluding remarks and further perspective are in Section 5.

2. The longitudinal data in the LFS

The Labour Force Survey (LFS) is the main source of information about the Italian labour market. It provides official estimates for a relevant number of indicators by using a sample based on a two-stage design with stratification of the first-stage units (municipalities) and a rotation scheme for the second-stage units (households). LFS aims to produce cross-sectional data. However, since each sampled household is interviewed for 4 quarters (rotation scheme 2-(2)-2: two consecutive occasions and, after a pause of two quarters, is then re-included in the sample for two other occasions), the records can be linked together to produce a rich source of longitudinal data at 3-, 9-, 12- and 15-months (Ceccarelli *et al*., 2002). Two-quarter longitudinal data are produced linking the LFS data of each quarter. This can raise a number of methodological issues. In fact, according to the rotation scheme, the 50% of the cross-sectional household sample for each quarter should be re-interviewed 12 months after. A record linkage is carried out. However, some key variables are affected by errors of several types (response, coding, editing, etc.). In this case, a deterministic record linkage is not advisable; on the contrary, a probabilistic procedure is more advisable (Discenza *et al*., 2012).

In order to produce longitudinal datasets and the transition matrix, the following aspects must be considered:

- the longitudinal sample refers only to a specific longitudinal reference population, not to the entire one;
- LFS is not a panel survey, thus persons that move out of the selected households or household which move out of the municipality are not re-interviewed;
- household non-response may occur at subsequent waves due to refusal, non-contact, etc. (attrition);
- longitudinal sampling weights have to account for the longitudinal population, for the total non-response and to ensure coherence with the official LFS quarterly estimates.

For defining the longitudinal sampling weights, the most relevant methodological problems to be addressed are:

- definition of a suitable reference population for the longitudinal sample;
- longitudinal non-responses and eligibility;
- coherence between cross-sectional and longitudinal estimates.

2.1 The Longitudinal population for the Italian LFS

Longitudinal data for the Italian LFS concerns only people who are residents in the same municipality, both at the beginning and at the end of the period. Accordingly, the reference population[1] is defined as the resident population in the same municipality for 12 months or 3 months, thus net of deaths and of internal or international migration. The definition of the reference population directly influences the way in which the transition matrix is computed. The strategy followed by Istat is to provide flows estimates from LFS summing up two transition matrices obtained using a combination of two methods:

[1] There are several possibilities for defining the reference population for the longitudinal LFS. The choice depends on two aspects: the sample design and the availability of population totals for weighting.

- The first transition matrix contains stocks and flows estimates obtained from weighted longitudinal micro-data for the population which is resident in the same municipality both at the beginning and the end of the period. This component represents more than 96% of the total population still resident in the country; it provides very accurate estimates with many possible breakdowns (gender, age groups, NUTS region, level of education, etc.).
- The second transition matrix contains stocks and flows estimates obtained at a macro level for few domains by using retrospective questions from the cross-sectional sample at the end of the period for the population which moves across the country (internal migrants). This component, representing about 2% of the total population, has lower precision and could also contain some bias because it is based on a very small sample and it uses the main status one year before (the only which is known from retrospective questions) to model the transitions between occupational status.

2.2 The Longitudinal non-responses and eligibility

The longitudinal component of the LFS is also affected by units non-response such as:

- *Municipality non-response*: some municipalities are substituted in July at the beginning of a new annual survey cycle and some others may, for different reasons, fail to provide the interviews in subsequent waves;
- *Household and individual non-response*: some people do not fill in the questionnaire because they refuse to respond or the interviewers are unable to contact one or more individuals in a household. This kind of non-response can be assimilated to the "false negative" which occurs when the record linkage fails to match two records because of errors in the key variables.

Unit non-response may reduce the longitudinal component, thus increasing the variance of the estimates. Moreover, it can produce bias if non-respondents have significantly different labour features with respect to respondents.

Given the longitudinal population as defined in the previous pages, it is necessary to classify all the individuals interviewed at the first quarter into two groups:

- *Eligible*: they represent part of the longitudinal population that should be re-interviewed at the second wave.
- *Not-eligible*: they left from the initial population during the observed period thus they do not represent part of the longitudinal population. This is a very important theoretical concept but, since the LFS is not a panel survey, the individuals cannot be distinguished in eligible and not-eligible. Coherence between cross-sectional and longitudinal estimates.

A crucial problem is that the longitudinal component produces both cross-sectional and longitudinal estimates referred to the longitudinal population. The first ones, obtained from the longitudinal data, have to be consistent with the "official" estimates provided by the cross-sectional samples (the full sample) at the beginning and at the end of the observed period. The differences between these two kinds of cross-sectional estimates must be non-negative because they refer to the occupational status at the beginning and at the end of the period for people who left the initial cross-sectional population and for people who entered in the final cross-sectional population.

Since the longitudinal estimates have higher variability than quarterly official estimates, it is not possible to completely control their consistency. However, it is possible to reduce the risk of obtaining inconsistent results by using specific weighting strategy (Discenza, 2004).

2.3 The longitudinal main indicators

Transition rate: it is obtained as the ratio between the number of individuals who are in a different occupational status at the end of the period compared to the status at the beginning of the period and the stock relating to the condition at the beginning of the period. The rate can be seen as the probability of transition to a different occupational condition between the beginning and the end of the period.

Permanence rate: it is obtained as the ratio between the number of individuals who remains in the same occupational status during the period and the stock relating to the condition at the beginning of the period.

Workers' Separation Rate (WSR): it is equal, over a period of time, to the ratio between the people entering the occupation (UE, IE) and the sum of those who remain employed (EE), enter (UE, IE) and leave the occupation (EU, EI) in the same period considered.

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

Workers' Hiring Rate (WHR): it is equal, over a period of time, to the ratio between people leaving employment (EU, EI) and the sum of those who remain employed (EE), enter (UE, IE) and leave employment (EU, EI) in the same period considered.

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

with:

- UE: transition to employment from unemployment

- IE: transition to employment from inactivity
- EE: permanence in employment
- EU: transition to unemployment from employment
- EI: transition to inactivity from employment

Reallocation rate: it is given by the sum of the separation and hiring rates. It measures the well-being of the labour market and its elasticity and mobility.

3. Methodological aspects

The longitudinal data are built matching those of two quarters $\boldsymbol{Q}$ and $\boldsymbol{Q}'$. The weights used for providing the estimates are obtained solving two calibration problems. Calibration (Deville and Särndal, 1992; Särndal, 2007; Devaud and Tillé, 2021) is a widespread practice in National Statistical Institutes for several reasons. The leading reason is that it provides a system of weights that makes the sample consistent with known distributions of selected auxiliary variables. Furthermore, the calibrated weights can be used for providing all the estimates of the survey. This obscured the main reason, highlighted by Deville and Särndal (1992), which is the increase of the accuracy of the estimates when auxiliary variables strongly related with the interest variables and their totals are available.

Basically, calibration changes the design weights of the survey as little as possible for matching the totals of a set of auxiliary variables appropriately chosen. Then, the calibrated weights can be used for producing all the estimates. For longitudinal LFS, the weights of the cross-sectional sample, s, at the beginning of the period, d_k^Q are the starting point. However, the focus is just on the the *matchable* individuals ($s_{matchable}$) in the sample Q, that is, the individuals that are expected to be interviewed also in the quarter Q' because of the rotation scheme adopted in LFS. Their weights are calibrated mainly to reach consistency with quarterly estimates because the transition estimates have to be coherent with the estimates of the beginning quarter already published. Therefore, in the calibration system:

$$\begin{cases} min_{w_k^{(1)}} \left\{ \sum_{k \in s_{matchable}} G\left(w_k^{(1)}, d_k^Q\right) \right\} \\ \sum_{k \in s_{matchable}} w_k^{(1)} \boldsymbol{x}_{\boldsymbol{k}}^{(\mathbf{1})} = \boldsymbol{t}_{\boldsymbol{x}}^{(\mathbf{1})} \end{cases} \tag{1}$$

the auxiliary totals, $\boldsymbol{t}_{\boldsymbol{x}}^{(1)}$, are some estimates from the quarter Q. Then, the weights $w_k^{(1)}$, are determined and used as the starting point for the second calibration in which the consistency with the longitudinal population is aimed. Only those related to the *matched* individuals ($s_{matched}$), that is individuals interviewed both in quarter Q and Q', are considered. The calibration system, in this case, is:

$$\begin{cases} min_{w_k^{(2)}} \left\{ \sum_{k \in s_{matched}} G\left(w_k^{(1)}, w_k^{(2)}\right) \right\} \\ \sum_{k \in s_{matched}} w_k^{(2)} \boldsymbol{x}_{\boldsymbol{k}}^{(\boldsymbol{2})} = \boldsymbol{t}_{\boldsymbol{x}}^{(\boldsymbol{2})} \end{cases}. \tag{2}$$

It is important to point out that in both the calibration system (1) and (2), $G(\cdot)$ is a pseudo-distance that measures the difference between the original and the final weights. In LFS, the truncated logarithmic distance to prevent negative or large weights is used (see, e.g., Deville and Särndal, 1992; Singh and Mohl, 1996).

The weights $w_k^{(2)}$ can be finally used for providing the estimate of a population total t_y,

$$\hat{t}_y = \sum_{k \in s_{matched}} w_k^{(2)} y_k \tag{3}$$

where y_k is the value of y variable observed on a unit k in the sample. Expression (3) refers to the calibration estimator and holds for estimating totals. However, its variance estimator cannot be directly applied to this context.

The first reason is that expression (3) takes into account just the last calibration step while, for properly addressing the variance estimation, it is necessary to consider both of them. A better approximation can be obtained writing the calibration system in (1) and (2) as a unique calibration system

$$\begin{cases} min_{w_k^{(2)}} \left\{ \sum_{k \in s} G\left(d_k^Q, w_k^{(2)}\right) \right\} \\ \sum_{k \in s_{matchable}} w_k^{(1)} \boldsymbol{x}_{\boldsymbol{k}}^{(\boldsymbol{1})} = \boldsymbol{t}_{\boldsymbol{x}}^{(\boldsymbol{1})} \\ \sum_{k \in s_{matched}} w_k^{(2)} \boldsymbol{x}_{\boldsymbol{k}}^{(\boldsymbol{2})} = \boldsymbol{t}_{\boldsymbol{x}}^{(\boldsymbol{2})} \end{cases}. \tag{4}$$

where the final weights $w_k^{(2)}$ are obtained changing the d_k^Q for matching at the same time $\boldsymbol{t}_{\boldsymbol{x}}^{(\boldsymbol{1})}$ on the *matchable* individuals and $\boldsymbol{t}_{\boldsymbol{x}}^{(\boldsymbol{2})}$ on the *matched* individuals. Then, the sampling variance can be approximated by

$$\widehat{AV}\left(\hat{t}_y\right) = \sum_{k \in s} \sum_{\ell \in s} \frac{\pi_{k\ell} - \pi_k \pi_\ell}{\pi_{k\ell}} (\hat{e}_k w_k)(\hat{e}_\ell w_\ell) \tag{5}$$

where π_k and π_ℓ are the first order inclusion probabilities, $\pi_{k\ell}$ are the second order inclusion probabilities and $\hat{e}.$ are the estimated residuals on y_k of the superpopulation model implicitly assumed by the calibration estimator defined by the calibration system in (4).

Moreover, expression (5) holds for the variance of the total, while the main longitudinal indicators described in Section 2.3 are ratios, such as $\hat{R} = \hat{t}_y/\hat{t}_v$. Ratios are non-linear statistics, then, the standard formulas for the sampling variance cannot be directly used and a Taylor linearization is needed before.

The assumption on the basis of the Taylor linearization is that a non-linear statistic, such as ratios, can be approximated by its first-order Taylor. There are several ways for computing linearized estimators. All the methods are of common practice and usually lead to similar results (for further details, see: Wolter, 2007). The expression of the linearized variables for a ratio estimator computed on the sample is

$$\hat{z}_k = \frac{w_k^{(2)}}{\hat{t}_x}\left(y_k - v_k\hat{R}\right). \tag{6}$$

Replacing (6) in (5) the estimated residuals, $\hat{u}_k$, computed this time on $\hat{z}_k$ gives this expression

$$\widehat{AV}(\hat{t}_R) = \sum_{k\in s}\sum_{\ell\in s}\frac{\pi_{k\ell} - \pi_k\pi_\ell}{\pi_{k\ell}}(\hat{u}_k w_k)(\hat{u}_\ell w_\ell) \tag{7}$$

that can be used for approximating the sampling variance of the main longitudinal indicators. From expression (7) the relative error, $\sqrt{\widehat{AV}(\hat{t}_R)}/\hat{R}$, can be easily derived. Furthermore, under the assumption of normality, the 95% confidence intervals can be defined as $\left[\hat{R} - 1.96\sqrt{\widehat{AV}(\hat{t}_R)};\ \hat{R} - 1.96\sqrt{\widehat{AV}(\hat{t}_R)}\right]$.

4. First results

The methodology described in the previous section enables to measure the accuracy of the longitudinal estimates[2]. Table 1 and Table 2 show the relative error and confidence interval of longitudinal indicators, periodically disseminated by Istat, with reference to the last available data (from the 4th quarter of 2019 to the 4th quarter of 2020). Analyzing the professional condition of individuals aged 15-64 in the 4th quarter of 2020 and comparing it with that of the same period of the previous year, we can observe that 92.6% of the employed is still in employment (with an

[2] The estimates and the measures of accuracy have been computed using the package ReGenesees (Zardetto, 2015) of the R statistical software.

confidence interval ranging from 92.1% to 93%) and 21.5% of the unemployed (from 19.6% to 23.5%) and 6.6% of the inactive (from 6.1% to 7.2%) find a job; a third of the reference population (from 30.7% to 35.3%) remain trapped in unemployment. The total reallocation rate, which provides a measure of labor market mobility, is equal to 12.9% (from 12.3% to 13.4%); we observe a decrease of employment, mainly due to the separation rate (from 6.6% to 7.4%), which is significantly higher than the hiring rate (from 5.5% to 6.2%). Only 1 over 5 transits from fixed-term employment to permanent employment (ranging from 18.3% to 22%); on the other hand, more than 1 over 2 (with the upper limit of the confidence interval which is close to 60%) remains trapped in a precarious employment.

Table 1 – *Permanence and transition rate by occupational status over a 12-month period (estimate, relative error and 95% confidence interval). 2019 4th Quarter - 2020 4th Quarter.*

Permanence and transition rate in the professional condition	Estimate (%)	Relative error (%)	95% confidence interval	
			Lower bound	Upper bound
Permanence in employment	92.6	0.24	92.1	93.0
Transition from employment to unemployment	2.1	5.43	1.9	2.4
Transition from employment to inactivity	5.3	3.64	4.9	5.7
Transition from unemployment to employment	21.5	4.70	19.6	23.5
Permanence in unemployment	33.0	3.62	30.7	35.3
Transition from unemployment to inactivity	45.5	2.84	42.9	48.0
Transition from inactivity to employment	6.6	4.16	6.1	7.2
Transition from inactivity to unemployment	6.0	4.32	5.5	6.6
Permanence in inactivity	87.3	0.42	86.6	88.0
Reallocation rate	12.9	2.08	12.3	13.4
Hiring rate	5.9	2.96	5.5	6.2
Separation rate	7.0	2.92	6.6	7.4

Source: Istat, Labour force survey, longitudinal data.

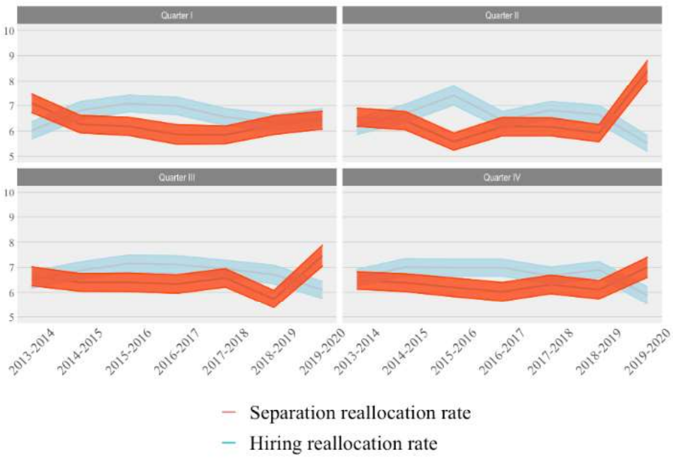
Figures 1 and 2 present the lower and the upper limit of longitudinal indicators from 2013 to 2020. The quarters are considered separately in order to avoid seasonal effects. Figure 1 reports data on hiring and separation rates, from which we can see the slow overcome from the 2013 crisis; starting from the 1st quarter of 2015-2016 and (although not for all quarters) up to 2019, we observe a significant difference between the trends of the two rates (while the hiring rate tends to rise, the separation rate shows a decreasing trend). Since the 2nd quarter of 2020, the significant effect of the economic-health crisis has been very evident (the separation rate returns to be significantly higher than the hiring rate with an important growth with respect to the previous period). Data show trends and gaps according to gender. Permanence rate in employment is always significantly higher for men than for women. For both categories, starting from 2019 and with reference to the 2nd and 3rd quarters, we observe significant decreases in the permanence rate. On the contrary, the transition from employment to inactivity rate is higher for women than for men, with a significant growth for both sex in the 2nd and the 3rd quarters of 2020.

Table 2 – *Transition from fixed-term employees over a 12-month period (estimate, relative error and 95% confidence interval). 2019 4th Quarter - 2020 4th Quarter.*

Transition rate from fixed-term employment	Estimate (%)	Relative error (%)	95% confidence interval	
			Lower bound	Upper bound
Transition to permanent employment	20.2	4.60	18.3	22.0
Transition to self-employed	2.0	17.45	1.3	2.6
Permanence in fixed-term employment	56.1	2.04	53.9	58.4
Transition to unemployment	8.5	7.20	7.3	9.7
Transition to inactivity	13.3	6.17	11.7	14.9

Source: Istat, Labour force survey, longitudinal data.

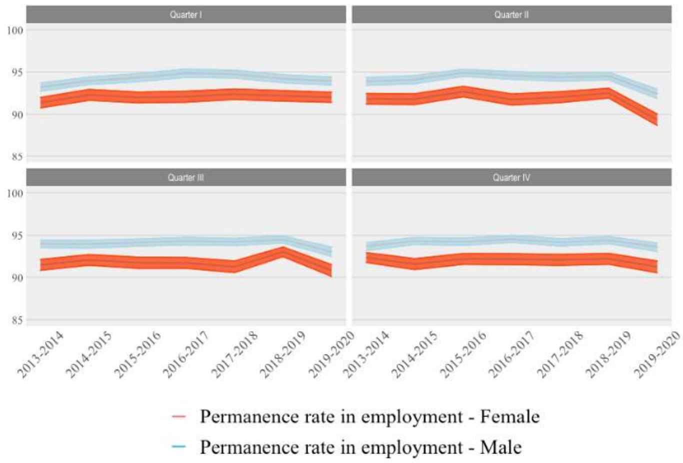
Figure 1 – *Hiring and separation rates (population aged 15-64, 95% confidence interval).*



Source: Istat, Labour force survey, longitudinal data.

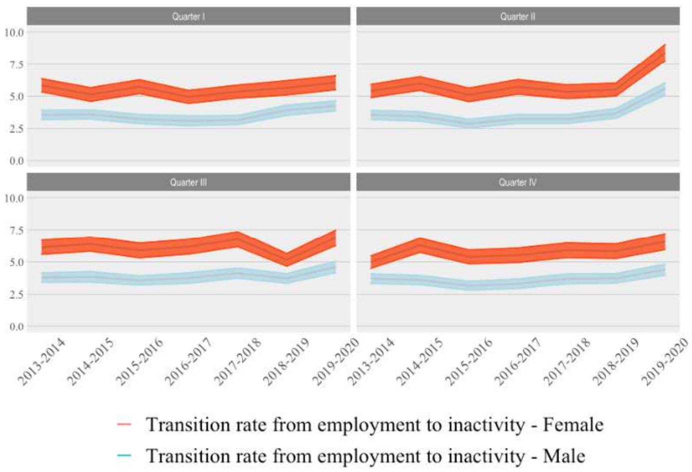
Finally, the transition from inactivity to employment rate is always significantly higher for men than for women, with a significant decrease (rate from 5.8% falls to 4.6%.) only for women in the 2nd quarter of 2020.

Figure 2 - *Permanence rate in employment, by sex (employed 15-64 aged at t_0 = 100; 95% confidence interval).*



Source: Istat, Labour force survey, longitudinal data.

Figure 3 – *Transition rate from employment to inactivity, by sex (employed 15-64 aged at t_0 = 100; 95% confidence interval).*



Source: Istat, Labour force survey, longitudinal data.

Figure 4 – *Transition rate from inactivity to employment, by sex (employed 15-64 aged at t_0 = 100; 95% confidence interval).*

Source: Istat, Labour force survey, longitudinal data.

5. Concluding remarks

Accuracy is one of the main characteristics of a standardized measure, i.e., of a measure based on uniform procedures to collect, score and report numeric results. Those procedures must be subject to a verification of its proper functioning allowing to minimize the measurement errors, the random and the systematic one (Alaimo, 2020). Accuracy is a component (together with precision) of the reliability: the higher the random error the lower the level of reliability of the measuring instrument. Variables always contain a random error at different levels; this means that the same measurement process introduces this type or error and its effect of on reliability can only be estimated. The effects of random errors are totally a-systematic; an instrument affected by such an error may overestimate or underestimate the size measured in a certain object. From these considerations, we understand the importance of this study, which allows to measure the random error of LFS longitudinal data.

References

ALAIMO, L.S. 2020. Complexity of Social Phenomena: Measurements, Analysis, Representations and Synthesis. *Unpublished doctoral dissertation,* University of Rome "La Sapienza", Rome, Italy.

CECCARELLI C., DISCENZA A. R., ROSATI S., PAGGIARO A., TORELLI N. 2002. Le Matrici di Transizione della Rilevazione Trimestrale sulle Forze di Lavoro. *Nota metodologica*, Istat, Roma.

DEVAUD D., TILLÉ Y. 2019. Deville and Särndal's Calibration: Revisiting a 25-Years-Old Successful Optimization Problem, *TEST*, Vol. 28, No. 4, pp. 1033-1065.

DEVILLE J.C., SÄRNDAL C.E. 1992. Calibration Estimators in Survey Sampling, *Journal of the American Statistical Association*, Vol. 87, No. 418, pp. 376-382.

DISCENZA A. R., FIORI F., LUCARELLI C. 2012 Weighting Issues in LFS Longitudinal Data, *Rivista Italiana di Economia, Demografia e Statistica,* Vol. 66, pp. 77-84.

DISCENZA A. R. 2004. Weighting Procedure for Longitudinal Data of the Italian Labour Force Survey. *Statistiche Report*, Roma, Istat.

SÄRNDAL C.E. 2007. The calibration approach in survey theory and practice, *Survey Methodology*, Vol. 33, No. 2, pp. 99-119.

SINGH A.C., MOHL C.A. 1996. Understanding Calibration Estimator in Survey Sampling, *Survey Methodology*, Vol. 22, No. 2, pp. 107-115.

ZARDETTO D. 2015. Regenesees: An Advanced R System for Calibration, Estimation and Sampling Error Assessment in Complex Sample Surveys, *Journal of Official Statistics*, Vol. 31, No. 2, pp. 177-203.

WOLTER K. 2007. *Introduction to variance estimation*. Springer Science & Business Media.

SUMMARY

The accuracy of longitudinal labour force survey estimates

Besides cross-sectional data, the Italian Labour Force Survey products longitudinal data. Starting from December 2015, the Italian National Institute of Statistics provides 12months estimates on labour market flows, permanencies and transitions by occupational status (employment, unemployment, inactivity). In the present paper, the methodology for computing the confidence intervals for the main indicators disseminated is presented.

Leonardo S. ALAIMO, Istat, leonardo.alaimo@istat.it
Alessio GUANDALINI, Istat, alessio.guandalini@istat.it
Antonella IORIO, Istat, iorio@istat.it
Cristiano MARINI, Istat, cristiano.marini@istat.it
Alessandra MASI, Istat, masi@istat.it