INCIDENCE, INTENSITY AND INEQUALITY OF POVERTY IN ITALY

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1. Introduction

In the economic literature there is a large consensus on measuring poverty according to three specific aspects: incidence, intensity and inequality among the poor (see Sen, 1976). Looking at more than one single index may allow for useful insights in the poverty analysis as well as for better tailored policies aimed at alleviating poverty.

Policy makers are interested in having efficient and unambiguous measures that could better address local policies for eradicating poverty, especially when resources are scarce.

For these reasons, we decide to investigate poverty at subnational level by means of robust instruments, based on decomposable indices and dominance criteria.

For the analysis, we use IT-SILC data for the years 2005 and 2015 to capture the evolution of poverty before and after the 2007-2009 economic crisis.

For the decomposition analysis, we follow Aristondo and Onadia (2018) approach, which is based on the Shapley decomposition (Shapley, 1953). For the two years of analysis, we compute the second member of the family of Foster-Greer-Thorbecke poverty indices (with parameter alpha equal to 2). Then, by applying the Shapley decomposition, we can establish whether changes in the value of the Foster-Greer-Thorbecke poverty measure are due to variations in the size of poor people (incidence of poverty) rather than in their poverty gaps (intensity) or in the inequality among the poor.

Moreover, we integrate the analysis by adding a robust dominance criterion, based on the so-called TIP curves ("Three I's of poverty") introduced by Jenkins and Lambert (1997). TIP curves provide a graphical representation that summarizes the three aspects of poverty in just a picture, allowing for comparison over time and across countries or regions. We trace the evolution of poverty in Italy and in its macro-regions (North, Center and South) between 2005 and 2015, by comparing the resulting poverty curves.

The rest of the paper is organized as follows. Section 2 presents the methodology adopted, describing the decomposition of the poverty indices as well as the poverty curves. Section 3 describes the data used and illustrates the main results with a discussion of policy implications. Finally, Section 4 concludes and points the way for future research.

2. Methodology

The proportion of households or individuals having an income below a fixed poverty line (threshold) is the most used way to measure income poverty. The economic literature refers to this proportion as the *Headcount Ratio* (*H*) or poverty incidence. By denoting with $y = (y_1, y_2, \dots, y_n) \in R^n_{++}$ the vector of incomes of a population of size *n* (*n*≥*2*), with $z \in R_{++}$ the fixed poverty line and with $q = q(y; z)$ the number of units (households or individuals) whose income falls below the poverty line, then the index *H* can be written as:

$$H = H(y; z) = \frac{q}{n}. \tag{1}$$

The main advantage of H is that it is very easy to understand and interpret. However, it also presents some drawbacks. First, H does not capture how poor the poor are (poverty intensity). Second, it ignores the shape of the income distribution among the poor, not considering the inequality among the poor. Consequently, two countries could have the same proportion of poor but exhibit different inequality among the poor group.

Thus, to measure properly income poverty, it is compulsory to introduce indices that take into account the distributional aspects of poverty (Sen, 1976; Shorrocks, 1995). In other words, it is important to have measures that reflect three different but complementary aspects of poverty: the intensity, the incidence and the inequality among the poor.

The *Income Gap Ratio (IGR)* is the simplest measure that accounts for poverty intensity, with the main advantage that it gives more emphasis (weight) to the poorest individuals. *IGR* is defined as the mean of the relative gaps from the poverty line among the poor:

$$IGR = IGR(y; z) = \frac{1}{q} \sum_{i=1}^{q} g_i, \tag{2}$$

where $g_i = \max\{\frac{z - y_i}{z}, 0\}$ denotes the relative poverty gap.

To account for inequality, we use the *Coefficient of Variation (CV),* defined as:

$$CV_p = CV_p(y;z) = \frac{\sqrt{\frac{1}{q}\sum_{i=1}^{q}(y_i - \mu_p)^2}}{\mu_p}, \tag{3}$$

where μ_p denotes the mean income among the poor.

Foster, Greer and Thorbecke (1984) propose a family of poverty indices that includes, as special cases, measures of incidence, intensity and inequality. The FGT family depends on a parameter α that reflects poverty aversion:

$$FGT_\alpha = FGT(y;z) = \frac{1}{n}\sum_{i=1}^{q}(\frac{z-y_i}{z})^\alpha. \tag{4}$$

Assuming α=0, we get $FGT_0 = H$. For α=1, FGT_α reduces to $FGT_1 = H \cdot IGR$, whereas fixing α=2 we get $FGT_2 = \frac{1}{n}\sum_{i=1}^{q}(g_i)^2$. The index FGT_2 can be written in terms of incidence, intensity and inequality, as follows:

$$FGT_2 = \frac{1}{n}\sum_{i=1}^{q}(g_i)^2 = H[IGR^2 + (1-IGR)^2 CV^2]. \tag{5}$$

Aristondo and Onadia (2018) propose a new decomposition of FGT_2, based on the Shapley method (Shapley, 1953). Shapley decomposition is a method extended from game theory to applied economics. It decomposes the overall poverty change between two periods in terms of the percentage changes due to incidence, intensity and inequality. Shapley decomposition approach consists in evaluating the impact of each determinant by eliminating sequentially each of the contributory factors and computing the corresponding marginal change in the statistic. In other words, it allows to estimate the marginal contribution of each determinant to the overall value. In this paper, we want to understand the contribution to a variation in the FGT_2 from 2005 to 2015 that is due to a variation in the intensity, in the incidence or in the inequality among the poor. Thus, following Aristondo and Onadia (2018)[1] the overall poverty change in FGT_2 can be written as an aggregative function of the three determinants, H, IGR and CV, as follows:

$$\begin{aligned} f(H_c, IGR_c, CV_c,) &= FGT_2(H_1, IGR_1, CV_1) - FGT_2(H_0, IGR_0, CV_0) \\ &= c(H_c) + c(IGR_c) + c(CV_c) \end{aligned} \tag{6}$$

[1] See their Proposition 1 and Proposition 2.

where $H_c = H_1 - H_0$, $IRG_c = IGR_1 - IGR_0, CV_c = CV_1 - CV_0$. Moreover, the components $c(H_c), c(IRG_c)$ and $c(CV_c)$ denote the contribution of the three determinants and are given by:

$$c(H_c) = -\frac{1}{6}(H_0 - H_1)[CV_0^2(2IGR_0^2 - 4IGR_0 + IGR_1^2 - 2IGR_1 + 3) + CV_1^2(IGR_0^2 - 2IGR_0 + 2IGR_1^2 - 4IGR_1 + 3) + 3(IGR_0^2 + IGR_1^2)]; \quad (7)$$

$$c(IGR_c) = -\frac{1}{6}(IGR_0 - IGR_1)[CV_0^2(2H_0 + H_1)(IGR_0 + IGR_1 - 2) + CV_1^2(H_0 + 2H_1)(IGR_0 + IGR_1 - 2) + 3(H_0 + H_1)(IGR_0 + IGR_1)]; \quad (8)$$

$$c(CV_c) = -\frac{1}{6}(CV_0^2 - CV_1^2)[H_0(2IGR_0^2 - 4IGR_0 + IGR_1^2 - 2IGR_1 + 3) + H_1(IGR_0^2 - 2IGR_0 + 2IGR_1^2 - 4IGR_1 + 3)]. \quad (9)$$

Jenkins and Lambert (1997) propose a graphical representation to summarize these aspects of poverty through the “three I’s of poverty” (TIP) curves.

TIP curves are cumulative poverty gap curves that plot the cumulated proportion of population (x-axis) versus the cumulated normalized poverty gap among the poor (y-axis):

$$TIP(p, z) = \int_0^{F^{-1}(p)} \left(1 - \frac{y}{z}\right) \mathbf{1}(y \leq z) f(y) dy, \quad (10)$$

where $f(y)$ denotes the income density function, $F^{-1}(p)$ is the quantile function and p the proportion of individuals, $p \in [0,1]$. Figure 1 reports an example of TIP curve.

To construct the curve, gaps are ordered from largest to smallest. For values of p (horizontal axis) greater than the poverty incidence, the TIP curve becomes horizontal. At this point the x-axis value corresponds to the incidence of poverty, the y-axis value indicates the poverty intensity, while the curvature indicates the degree of inequality among the poor. If the curve is a straight line, it means that all the poor are equally poor. The more the TIP curve deviates from linearity, the greater is the degree of inequality among the poor.

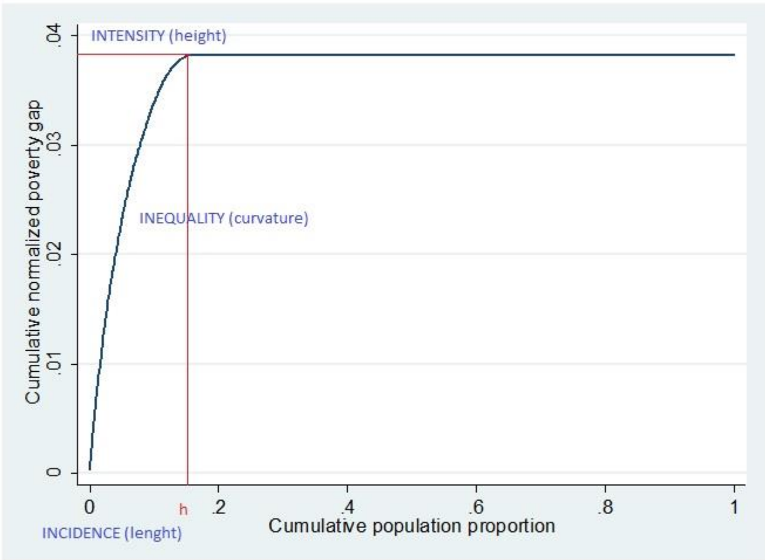
Jenkins and Lambert (1997) derive also a dominance criterion based on the TIP curves, showing that it is equivalent to a restricted second-order stochastic dominance. Income distribution A TIP dominates income distribution B for a given poverty line z if TIP_A (p, z) ≤ TIP_B (p, z) for all p ∈ [0; 1] and < for at least one p. It means that in income distribution B there will be more poverty than in A.

Poverty ranking provided by TIP dominance is robust to the choice of poverty line and to a set of poverty measures. If TIP_A (p, z) is always below TIP_B (p, z) for a common z, then the ordering is preserved for any common poverty line smaller or equal to z. This implies the ordering of poverty indices similar to FGT1 and FGT2 (intensity and inequality).

Finally, analogous to the Lorenz curves, when TIP curves intersect, no TIP dominance can be assessed.

Statistical inference about TIP dominance have implemented by Berihuete et al. (2018) following the asymptotically distribution-free statistical procedure in Xu and Osberg (1998).

Figure 1 – *TIP curve: an example.*

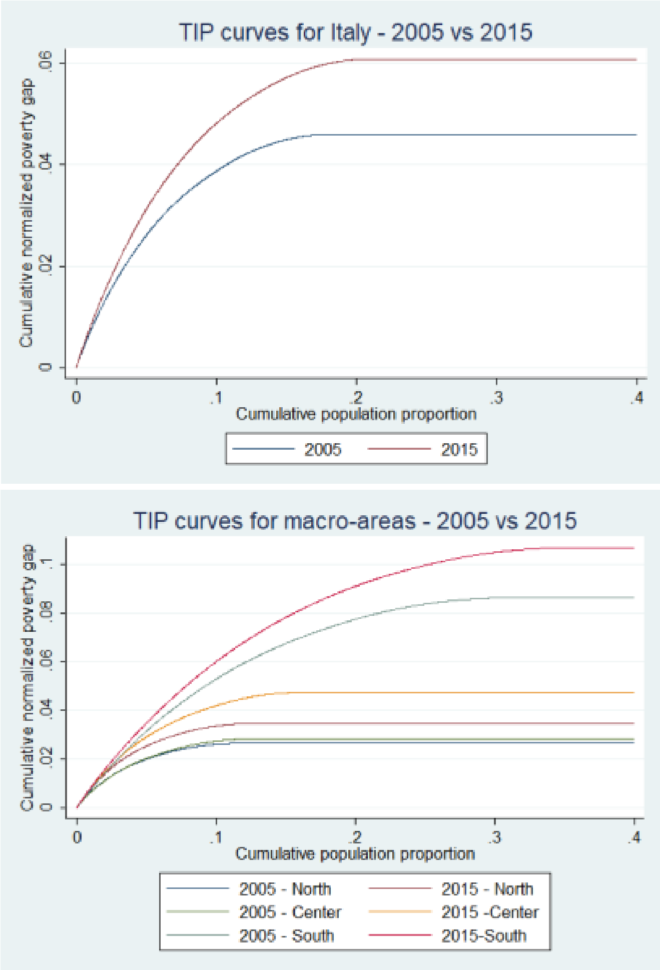


Source: our elaboration.

3. Data and results from empirical application

We use data from the Italian version of European Union Survey on Income and Living Conditions (IT-SILC) referred to the years 2005 and 2015. The variable of interest is the household equivalized disposable income. We compute poverty at household level, considering a relative poverty line equal to the 60% of the median equivalized household income in 2005. Incomes of 2015 have been deflated, so that we keep a fixed poverty line for the two periods of interest. Calculations consider cross sectional sample weights.

Figure 2 – *TIP curves for Italy and macro-regions in 2005 and 2015*



Source our elaboration on IT-SILC data

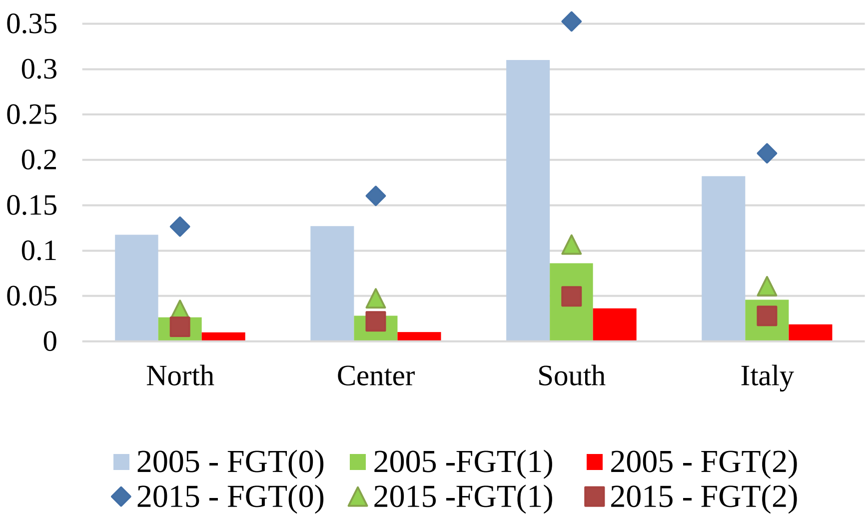
Figure 2 depicts the TIP curves for Italy and its macro-regions (North, Center and South) in the two periods of the analysis.[2]

For Italy, the TIP curve of 2015 dominates the one of 2005, meaning that poverty in 2015 is higher than in 2005. From 2005 to 2015, the incidence coordinate (on

[2] North area includes the following regions: Piedmont, Aosta Valley, Lombardy, Trentino-Alto Adige, Veneto, Friuli-Venezia Giulia and Liguria; the Center includes Emilia-Romagna, Tuscany, Umbria, Marche and Lazio; while regions Abruzzo, Molise, Campania, Apulia, Basilicata, Calabria, Sicily and Sardinia belong to the South.

horizontal axis) has moved to the right and the intensity coordinate (on vertical axis) on the top. Thus, we can conclude that the 2015 the poverty situation is worse than in 2005. The conclusion is analogous for any poverty line smaller than the one chosen.

Figure 3 – *FGT_α for α=0, α=1 and α=2, in 2005 and 2015.*



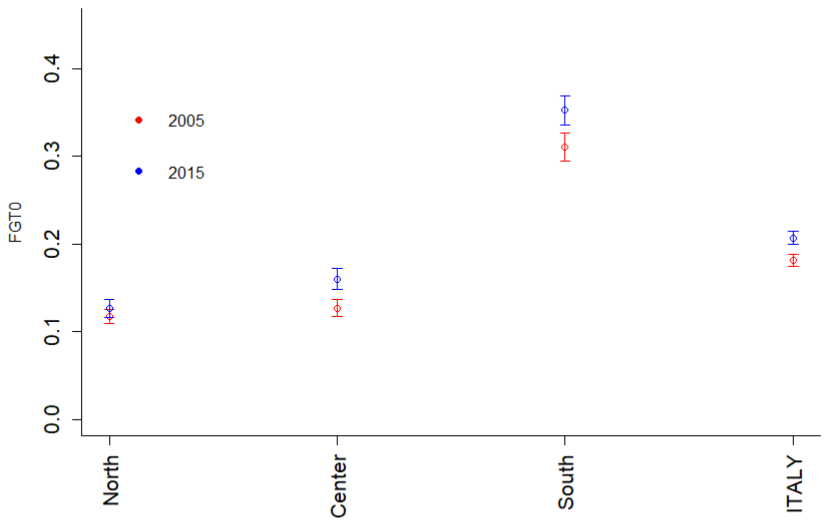
Source: Our elaboration on IT-SILC data.

By looking at the results for the macro-areas (Figure 2 – bottom panel), the first two curves on the top represent the TIP curves for South of Italy in the years 2015 and 2005, respectively. The third curve from above represents the Center in 2015, followed by the North in 2015. The lowest two curves are those of the Center and the North in 2005. It emerges that in all the three macro-areas the situation has worsened over the period of consideration. The level of poverty in the South of Italy remains very far from the rest of the country, while the gap between North and Center increases remarkably.

We now focus on specific indices of poverty, which belong to the FGT_α family, with three values of α, namely α=0, 1 2. Figure 3 compares the values of these indices for Italy and its macro-areas.

Looking at Figure 3, what emerges is that, for all the indices, the poverty values registered in the South are the highest. Moreover, if we compare the results over time, the situation worsened, confirming what already displayed through the TIP curves.

Figure 4 – *95% Confidence Intervals for FGT_0.*



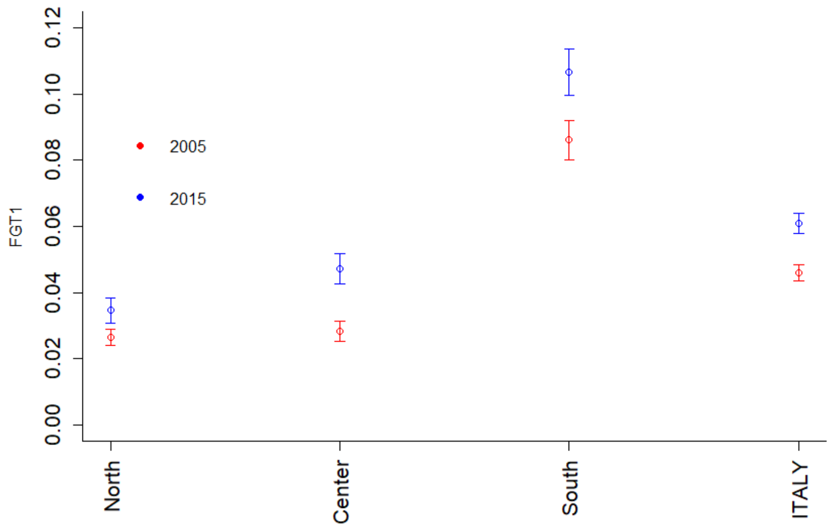
Source: Our elaboration on IT-SILC data.

We also compute 95% confidence intervals, to test if the differences are significant. Figure 4, Figure 5 and Figure 6 summarize the results. The confidence intervals overlap only for the Headcount ratio (FGT_0) for North of Italy. For the remaining indices, the increase in FGT indices from 2005 to 2015 is significant for the three values of the parameter α and for all macro-regions and Italy. Looking at FGT_1, the greatest increase is registered in the Center. The same happens for FGT_2

Finally, we compute the Shapley decomposition, according to equations (6), (7), (8) and (9). Table 1 reports the results of the decomposition.

The smallest variation in poverty (last column of Table 1) is registered in the North (0.0058) whereas Center and South display similar results (0.0116 and 0.0128, respectively). All the contributions have a positive sign, confirming that all the aspects concerning poverty - inequality, incidence and intensity - have increased over the period of interest. For Italy, the three components have almost the same weight (31.67%, 35.48% and 32.85%, respectively). The Center behaves in a similar way. North and South show a different picture: in the North the greatest impact in poverty variation is due to the inequality among the poor (44.06%), whereas for South the highest impact is for the poverty incidence (42.32%). Therefore, the Shapley decomposition constitutes an important source of information, which can help policy-maker understand in which direction poverty-oriented policies should be aimed, whether focused to reduce the number of poor or rather to reduce their inequalities.

Figure 5 – *95% Confidence Intervals for FGT_1.*



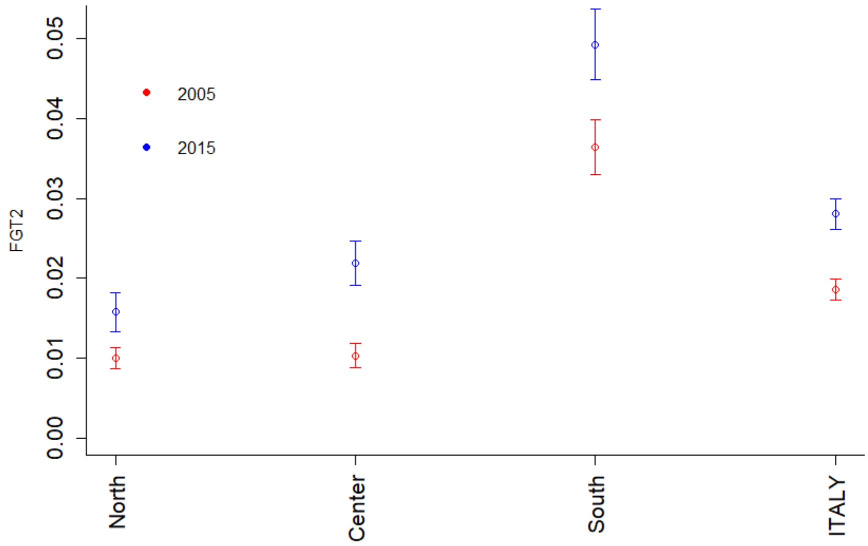
Source: Our elaboration on IT-SILC data.

Table 1 – *Shapley decomposition for the variation of FGT_2.*

	$c(H_c)$	%	$c(IRV_c)$	%	$c(CV_c)$	%	*f(H, IRV, CV)*
North	0.0009	16.17%	0.0023	39.78%	0.0026	44.06%	0.0058
Center	0.0036	31.54%	0.0042	36.38%	0.0037	32.08%	0.0116
South	0.0054	42.32%	0.0038	29.32%	0.0036	28.36%	0.0128
Italy	0.0030	31.67%	0.0034	35.48%	0.0031	32.85%	0.0095

Source: Our elaboration on IT-SILC data.

Figure 6 – *95% Confidence Intervals for FGT_2.*



Source: Our elaboration on IT-SILC data.

4. Concluding remarks

The TIP curves, in combination with the Shapley decomposition, allow to highlight different aspects of poverty that the use of a single poverty index could hide. We believe that the conjunction of these different approaches could be a useful instrument in a period of tight resources. Moreover, the support given by the dominance criterion and inference (using confidence intervals) could add more robustness to the analysis.

There is room for improving the work in several directions. First by considering the local dimension at a deeper degree of granularity: we are planning to extend the results at regional level. Second, we are planning to replicate the analysis to more recent data with the aim of capturing the evolution in poverty intensity, incidence and inequality and help policymakers in identifying the aspects that affect the most the level of poverty. Finally, we are interested in comparing different inferential approaches to TIP curves (see, e.g., Barrett et al., 2016) and in developing inferential results to the Shapley decomposition.

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SUMMARY

Incidence, Intensity and Inequality of Poverty in Italy

Aim of the paper is to analyse unidimensional poverty in Italy and in its macro-regions. In a period of tight resources, the sub-national dimension in measuring poverty is crucial. Indeed, information on household income distribution and poverty at sub-national level may help policymakers focus their efforts and enhance the effectiveness of public interventions. Moreover, high disparities between macro-regions in a given country might undermine national economic growth and lead to ever-increasing regional imbalances over time.

To achieve our aim, we use data from the Italian version of the Statistics on Income and Living Conditions (IT-SILC) for two different years, 2005 and 2015.

The so-called TIP curves, a statistical tool for representing the three different aspects of poverty - incidence, intensity and inequality, provides poverty orderings consistent with a large class of poverty indices and of poverty thresholds.

Finally, we also decompose the variation of poverty index over time to better understand what are the main factors that influence poverty levels.

The main conclusion from the empirical application is an unambiguous increase in poverty levels from 2005 to 2015, both in the entire Italian population as well as its macro-regions.

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