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The Role of Geography in Determining the Inequality between Italians*

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The Role of Geography in Determining the Inequality between Italians*

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Abstract

Regional disparities play a marginal role in determining inequality between Italians, both in cross-section and in a lifetime sense. In spite of large differences in average income between provinces, less than 4% of cross-sectional inequality can be attributed to between-province differences. In contrast, information on industry of similar level of detail can explain roughly a quarter of earnings and wage inequality. The share of between-province variance in lifetime income is 3.4% for the whole cohort and only 1.8% for males. The figure for females is as high as 10.2%, reflecting regional differences in participation. Differences between rich and poor within provinces are orders of magnitude larger than average differences across them. While tackling regional disparities may have beneficial effects, it will not significantly reduce the level of inequality between Italians.

JEL Codes: E24, J3, R1
Keywords: variance decomposition, lifetime income, regional inequality, earnings and wage inequality.

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Il ruolo della geografia nella determinazione della disuguaglianza di reddito tra Italiani

Abstract

La disuguaglianza geografica gioca un ruolo marginale nella determinazione della disuguaglianza di reddito tra Italiani. Nonostante le grandi differenze nel reddito medio tra province, meno del 4% della disuguaglianza trasversale puo' essere attribuita alle differenze provinciali. Al contrario, l'informazione sul settore e' in grado di spiegare circa un quarto della disuguaglianza di salario e reddito. La percentuale della varianza del reddito accumulato nella vita tra province e' il 3.4% per l'intera coorte e solo il 1.8% per gli uomini. La percentuale per le donne pari al 10.2% riflette differenze regionali nella partecipazione alla forza lavoro. Le differenze tra ricchi e poveri all'interno delle province sono di un ordine di grandezza molto piu' grande rispetto alle differenze medie tra le province. MLa riduzione delle differenze geografiche puo' sicuramente avere effetti positivi, tuttavia sembra non essere sufficiente per ridurre la disuguaglianza di reddito tra Italiani.

1 Introduction

If there is a country stereotypical of regional inequality, it is Italy. The relatively late unification of the country and the complex history of the peninsula have created a well-known narrative about the prosperous north and the pauper south. And, as a matter of fact, it is true that the average income in the North is substantially higher than in the South. We find that in our 2018 data the richest province has average annual earnings almost two and half times higher than the poorest province and that the average wage rate is about 47% higher in the richest than in the poorest province[1]. Consequently, one could think that the place of birth is an important determinant of the income of Italians and, as a result, that those born in provinces with higher average incomes play the lottery of life with better cards than those born in the southern provinces. The main result of our paper is to show that this is not the case. The North-South divide plays only a marginal role in determining the inequality between Italians.

Yes, the North is richer (we will even show that the distribution of lifetime income in the North first order stochastically dominates that of the South), but the difference in average income between the rich and poor provinces is much smaller than the differences between individuals who live in any given province. That is: there are many very rich people in the South and many very poor people in the North. These differences within provinces are so large that geography (the difference between provinces) is an irrelevant factor in the general lottery of life. The reduction of regional disparities may be beneficial for many reasons, but it is essentially ineffectual in reducing inequality between Italians.

The absence of a geographical gradient to the structure of inequality in Italy is a fact not only in the cross-section but also, and more importantly, in the lifetime income of individuals. We calculate the lifetime income of a cohort of Italians (born in 1960) and show that knowing the province where a person was born (or resides) is essentially useless in trying to determine

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[1]When considering annual earnings we restrict the sample to only those with attachment to the labour market, as explained in Section ???3.

his or her income. Moreover, the reverse is also true. If you aim to guess the province where a certain Italian was born (or resides), knowing his or her lifetime income is almost useless.

This result may be surprising or not (we surely find it so), but it is by no means obvious, as other salient characteristics of an individual, like education, gender or sector of activity do help to predict income to a much better degree than geography. In a companion paper (Briskar et al. 2023) we show that just the two digit industries (there are 88 of them, compared to around 110 provinces) can on their own explain 25% of the variance of log annual earnings in 2018[2]. In contrast, geography accounts for a mere 1.8% of the variance of lifetime income of men. Education, gender, and sector of activity are much more important drivers of inequality, yet the discussion of inequality in (and about) Italy is dramatically fixated on geographical differences.

Still, the fact that the North-South divide is an irrelevant driver of inequality in Italy has an important qualification. We will show that for women, but not for men, there are very large differences in participation that can be attributed to the province of birth. These differences in participation between provinces translate to differences in female average income between provinces that are able to explain a much larger share of the inequality between Italian women. In other words: the only way in which geography acts as a driver of inequality in Italy is that it helps predict female labor force participation and, thus, income. The effect on the overall population is small, but it explains about 10% of the differences in lifetime income between women.

This paper has important implications for our understanding of the sources of inequality in life outcomes between individuals. Our estimates capture not only the differences in pay for the same kind of work across space, but also differences in worker characteristics (such as education), in industry and occupational structure, and in the likelihood of being employed

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[2]This is in line with Brunello et al. (2012), who show that industry explains approximately 25% of differences in wages, while education explains approximately 16% of differences in wages and 20% of differences in lifetime earnings. In Briskar et al. (2023) we show that firms can explain around one half of the variance of annual earnings and two thirds of wage variance.

across regions. Still, regional disparities are orders of magnitude smaller than inequality within each geographic area. This is to the point that knowing where someone was born or resides in is essentially useless in predicting their lifetime income. We demonstrate this for Italy which is well known for having relatively large regional inequalities and thus a similar result would almost certainly be found in other countries. At the same time, investigations using lifetime income are very rare, mainly due to data limitations[3]. The long time span of Italian social security data is another reason that we focus on the case of Italy. Finally, while we show that province of birth or residence plays only a marginal role in accounting for differences in lifetime income between Italians, other aspects of geography such as urban vs rural wage premium or the specific neighbourhood that a person grows up in might be more important.

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Our interest in this issue has to be placed in the context of the large degree of attention gathered by the secular increase in inequality in most western economies[4], and the role of sorting, segregation, and pay premia[5]. However, much less attention has been paid to the regional dimension of individual earnings inequality. There are, of course, a myriad of papers referring to regional differences in average income, but very few put them in the context of general inequality between individuals.

Florida and Mellander (2016) examine the geographic variation across US metros distinguishing between wage and income inequality (finding that wage inequality is closely associated with skills, human capital, technology and metro size, while these factors are only

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[3]An important paper in this regard is Guvenen et al. (2022) that compares median lifetime earnings across many cohorts in the USA.

[4]Atkinson et al. (2011), Piketty and Saez (2007), Acemoglu and Autor (2011), Katz and Autor (1999), Piketty (2018)

[5]Song et al. (2019), Haltiwanger et al. (2022), Card et al. (2018, 2013). There is also evidence that some firms pay workers with similar skills more than others (Krueger and Summers 1988, Van Reenen 1996) and, controlling for differences in observed and unobserved worker characteristics between firms, it has been described how these differences in wage premia contribute to the distribution of earnings (Abowd et al. 1999, Goux and Maurin 1999, Abowd and Kramarz 1999, Holzer et al. 2011, Alvarez et al. 2018, Card et al. 2013).

weakly associated with income inequality). Breau (2015) shows that in Canada, the labor market, socio-demographic and institutional variables are key factors explaining differences in increasing regional inequality. Moser and Schnetzer (2017) find a strong positive correlation between regional income levels and inequality in Austria, where high-income municipalities exhibit a larger spread in the income distribution.

For us, of course, the Italian context has particular relevance, Acciari et al. (2013) being among the first to investigate the spatial dimension of inequality in Italy using tax records from 2000 to 2011; showing (i) that inequality was higher in the South due to a smaller share of income held by the lower tail of the distribution, while higher in major metropolitan areas, and (ii) that inequality has increased over time. These results are in line with the more recent findings of Acciari et al. (2021), who single out Italy as one of the counties with the strongest decline in the wealth share of the bottom 50% of the adult population. Using Italian social security data, Belloc et al. (2022) compute the within-between area variance decomposition of nominal and real wages in 2005, focusing on the urban/rural wage premia (they find none for employees subject to collective bargaining, but identify a large premia for self-employed individuals, not subject to collective bargaining). Along this line, Boeri et al. (2021) show that in the cross-section Italy exhibits limited geographical wage differences in nominal terms (controlling for differences in worker characteristics and industry mix across provinces), due to the nationwide sectoral contracts, which are binding and allow only for limited local wage adjustments. However, when taking into account nominal prices, real wages turn out to be higher in the South, where productivity is lower, thus generating lower employment and income in the South.

To the best of our knowledge, none of these puts the geographic differences in the context of the general inequality within the country, and certainly, none looks at it from the perspective of lifetime earnings.

The remainder of the paper is organized as follows. We first describe the data (Section 2). In Section 3 we present evidence on cross-sectional inequality, and next we present lifetime

inequality, our main results (Section 4) and the role of gender (Section 5). In Section 6 we perform an experiment called "guess the province". Finally, we conclude the paper with a general discussion of the results.

2 Data

We use two main sources of data both provided by the Italian Social Security Institute (INPS), the largest administrative organization at the European level. The first source is a longitudinal administrative employer-employee dataset that collects data on the working histories of the universe of private sector employees in Italy, who represent more than 70% of Italian workers. The data are structured as an unbalanced longitudinal sample at the individual (and firm) level at yearly frequency. Together with earnings and employment histories, the INPS data include socio-demographic information regarding age, sex, nationality, as well as province of birth and residence of individuals and location of firms.

The second data source collects the records of all social security contributions ever paid by workers and by firms on behalf of the workers for a sample of individuals who represent approximately 13% of the whole population (Social Security Histories). In terms of labor outcomes, the dataset contains information on earnings and all types of benefits ever received by the individuals, including maternity and paternity leave benefits, unemployment allowance, sick leave benefits, short-term work programs (STW). We are able to infer whether the income the worker received came from her occupation as an employee in the private sector, in the public sector or whether she was self-employed when she paid the contributions.

While the first dataset has the advantage of collecting information on the universe of private sector employees, it does not include public sector, self-employed, agricultural workers, and caretakers and does not contain information about benefits, but only on earnings. The second dataset includes all records of social security contributions (wages and benefits), and all individuals independent of the job setting (private, public or self-employed), and it

represents 13% of the population. We use the first data source to decompose inequality at cross-section level, while we use the second dataset to compute the lifetime income.

Specifically, in order to compute lifetime income, we focus on the cohort of individuals born in 1960: these workers were fifteen years old in 1975 (the year in which the data are first available), and 56 years old in 2016 (the year in which our analysis terminates). This selection leaves us with a total of 113,388 individuals. We exploit the information on the province of birth in order to assign workers to geographical areas. In order to control for migration issues and for robustness purposes, we also use the last province where the contributions were paid to decompose inequality. It is important to mention that this dataset includes only individuals who have worked at least one day or have received some benefits in their lifetime, while individuals who have never worked do not show in the records.

3   Cross-Sectional Inequality

In order to assess how much geography matters in explaining inequality in Italy, we start by performing a simple variance decomposition. We use the INPS matched employer-employee dataset that covers the universe of private sector employment in Italy. We select a cross-section of individuals in one year, we compute the variance of log daily wages in the given year and then we decompose the overall variance into two components: within- and between-province dispersion. Let w_{ip} be the log of the wage earned by individual i born in province p and let $\bar{w}$ be the average wage in Italy, we compute:

$$\underbrace{\frac{1}{N}\sum_{\forall i}(w_{ip}-\bar{w})^2}_{\text{total variance}} = \underbrace{\sum_{\forall p}\frac{n_p}{N}(\bar{w}_p-\bar{w})^2}_{\text{between province variance}} + \underbrace{\sum_{\forall p}\frac{n_p}{N}\frac{\sum_{\forall i|i\in p}(w_{ip}-\bar{w}_p)^2}{n_p}}_{\text{within province variance}},$$

where w_p is the average wage in province p, N is the total population in Italy and n_p is the population in province p. This equation provides a simple way to decompose the

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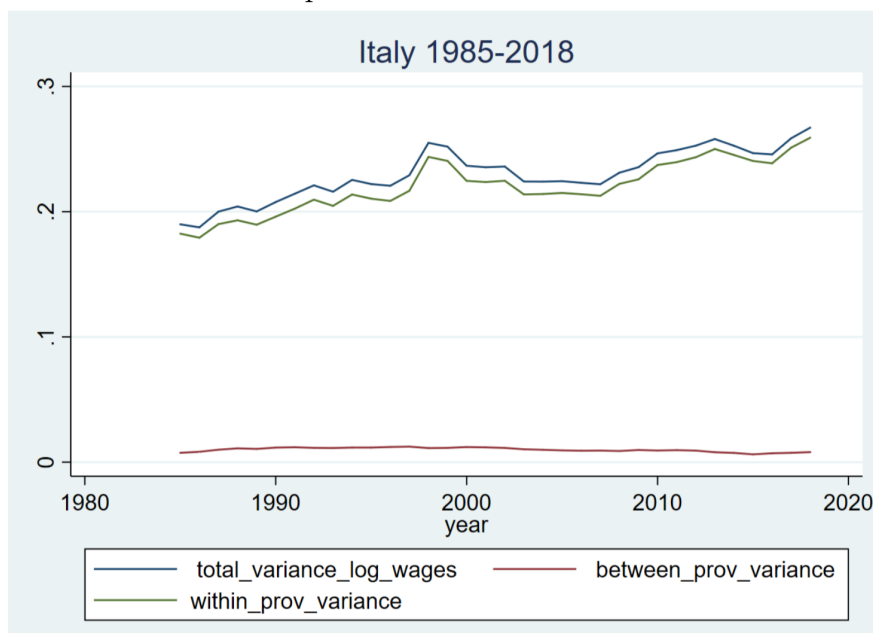**Table 1:** Decomposition of (log) variance of daily wages of full-time employees.

	Total variance	Between province variance	Within province variance	Between province share	Within province share
1985	0.195	0.008	0.187	**4.1%**	95.9%
2018	0.253	0.009	0.244	**3.7%**	96.3%
Change	0.058	0.001	0.057	-	-
% of total increase	100.0%	1.7%	98.3%	-	-

total wage dispersion in the economy into the between-province component (variability of average wages across provinces) and into the within-province component (weighted average of within-province dispersion using population shares as weights).

Table 1 reports the total variance and its decomposition in 1985 and 2018. In approximately 30 years, the total wage variance increased by about 30% from 0.195 to 0.253, however, the between province component has played a negligible role, while a large increase is ascribable to the change in the within province component. Specifically, the between province share accounted for 4.1% of the total variance in 1985 and for 3.7% in 2018. The increase in the within-province variance accounted for 98.3% of the increase in the total variance in the period considered. This is shown in Figure 1, which displays an approximately flat line representing the between province variance in the period 1985-2018, while the lines representing the total and the within province variance are both increasing. In Table 1 and Figure 1, we decompose the variance of log daily wages of full-time employees. However, using other measures of income results in nearly identical results (displayed in the Appendix, Tables A1-A3). Specifically, we perform the same analysts with log daily wages of all employees and log annual earnings, both with and without a minimum earnings threshold[6]. We also

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[6]We follow the usual practice in the literature that studies earnings inequality e.g., Song et al. (2019) and Haltiwanger et al. (2022) and impose a minimum earnings threshold. The rationale for this is to focus only on the workers with an attachment to the labour market. We restrict our sample to individuals with annual earnings above the threshold for that year. The minimum is set at 1200 Euros in 2016 and is adjusted for inflation for the other years using the Italian country-level CPI index.

Figure 1: Evolution of cross-sectional inequality of privately employed individuals and its decomposition between and within provinces.

perform the analysis separately for men and women. In all cases, almost all of the variance increases occurred within provinces. Furthermore, in all the years, with all of the definitions of income and all splits of sample based on gender, over 90% of total variance takes place within provinces[7].

Note that the share of the between-province variance in total variance is equivalent to the R^2 of regressing individual income on provincial dummies. Thus, these are the results of regressing log daily wages of full-time employees on 104 dummies (one per province), which yields an R^2 of less than 4% in 2018. A way to shed light on the irrelevance of geography in explaining inequality is to compare it with the R^2 of alternative regressions. With our data, it is immediate to regress wages on the sector of the firm. When we use NACE sector of activity at 2 digit level (88 categories), and nothing else as an explanatory variable, we obtain an R^2 of 28% in 2018[8]. That is, by ordering people by sector of activity (even if using

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[7]Results for different definitions of income are reported in Tables A1-A3. Results for men and women separately are available upon request.

[8]25% in the case of annual earnings.

8

20% fewer dummies) one is able to explain one order of magnitude more than when ordering people by province. Sector of activity gives order and structure to the data, in this sense explaining it; geography does not.

Thus, geography seems an irrelevant driver of cross-sectional inequality: average income might be different in the North and in the South, but the differences within each geographic area dwarf that difference in averages. Nevertheless, inequality in the distribution of cross-sectional income at a moment in time may not be the relevant variable to consider for our problem.

Firstly, because the dataset we use is by definition restricted to people who work, while unemployment rates are different in southern and northern provinces. It might be the case that the accumulated lifetime income is actually much lower in southern provinces, as their inhabitants suffer unemployment spells with more frequency. Thus, geography could be a bigger driver of inequality if we consider a lifetime notion of income.

The second reason is that while the variance of cross-sectional income needs to be larger than the variance of lifetime income (insofar as there is a mean-reverting component in the income processes that agents face) the mapping between both does not need to be the same between provinces. Imagine a province where the unemployed are always the same people and another where the people who suffer unemployment change over time. In the first province, lifetime inequality would be larger than in the second, even if average unemployment is equal in both provinces.

In addition, it is self-evident that inequality in lifetime income is a better account of the inequalities in welfare than cross-sectional inequality. It is a better account of how differently life treats different individuals on top of and beyond the serendipity of small, passing, and ultimately irrelevant vicissitudes. Thus, we turn to the measurement of lifetime income in the next section.

4 Inequality of Lifetime Income

We want to abstract from issues of heterogeneity between cohorts. Thus, we focus on the cohort of individuals born in 1960, who were fifteen years old in 1975 (the first year in which the data are available), and 56 years old in 2016 (the year in which our analysis terminates). This leaves us with a total of 113,388 individuals.[9]

We compute the lifetime income, using the INPS dataset, which includes all the social security contributions of a representative sample (13%) of the Italian population. The lifetime income is computed as the logarithm of the sum of all income received during the individual working life. In each year we compute the real value of income using the annual national CPI. Following the literature (Song et al. 2019), we do not use an interest rate to compute the present discounted value of income. In years in which no income is recorded we manually add that year's equivalent of one euro in 2016, in order to obtain a balanced panel.[10]

We use four definitions of lifetime income. The first one sums only income coming from private sector employment over an individual's life. The second one sums income from both private and public sector employment. The third one sums all earnings, thus it also includes income from self-employment. Finally, in our most comprehensive definition, we also include all benefits received by the individual over their life, such as maternity and paternity benefits, unemployment subsidies, sick leave benefits etc.

Finally, we exploit the information on the province of birth in order to assign workers to geographical areas. In order to control for migration issues and for robustness purposes, we also use the last province where the contributions were paid to decompose inequality. We use the same decomposition as in Equation 1, substituting daily wages for lifetime income.

Table 2 reports the total variance of the lifetime income of the cohort of 1960 and its

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[9]Remember that this database consists of a random sample of 13% of the population, and consequently, of the 1960 cohort.

[10]We do this because some individuals in the dataset have received no income in certain years (and we want to take logs). Moreover, as it will be clear later, we also generate artificial data to control the bias of representation in the database across genders for those individuals with no participation.

Table 2: Decomposition of variance of (log) lifetime income.

	Total variance	Between province variance	Within province variance	Between province share	Within province share
Province of Birth					
All Sources	11.040	0.377	10.663	**3.4%**	96.6%
Only Males	11.169	0.198	10.971	**1.8%**	98.2%
Only Females	10.758	0.929	9.993	**7.1%**	92.9%
Artificial Women	14.790	1.504	13.286	**10.2%**	89.8%
No Benefits (inc. Self-Employed)	12.271	0.547	11.724	**4.5%**	95.5%
Private and Public Employment	12.273	0.547	11.726	**4.5%**	95.5%
Private Employment Only	14.144	0.752	13.393	**5.3%**	94.7%
Province of Residence					
All Sources	11.029	0.468	10.560	**4.2%**	95.8%

Notes: In the Artificial Women sample, the number of females is artificially increased to be equal to the number of males in every province of birth.

decomposition between and within provinces. In different rows, we assign individuals to either their province of birth or residence, and we account for different income sources. The overall result is clear: geography is a marginal driver of inequality. Nevertheless, the different exercises teach us some interesting lessons.

In the first row we assign individuals to their province of birth, and the between share component accounts for only 3.4% of the variance, while in the last row we assign them to their province of residence (the last province where they received income) and the between share component still accounts for just 4.2% of the total variance. Thus, not only is the province of birth irrelevant in the overall picture of inequality, but it is also clear that this is not because of migration.

In the other rows we always assign individuals to their province of birth, but we consider different sources of income in our measure of lifetime income. Including earnings from public sector employment naturally decreases total variance of lifetime income and including benefits decreases it even further, confirming the role of the welfare state in reducing inequality, while the inclusion of income from self-employment does not change things markedly[11]. In any case, in our focus of interest, when we decompose income into the two components, across all four income structures, we find that the between-province share ranges between 3.4% and 5.3%: the vast majority of the income variance is to be found within provinces irrespective of income source. The share of the between-province variance is slightly smaller when including transfers and income from public employment, but even when looking only at private-sector earnings, the rather limited role of geography in accounting for total inequality of lifetime income is very clear.

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[11]Albeit the incomes reported by the self-employed may not reflect reality, as they are self-assessed and may be included with the only aim to be an investment in pension.

5 Gender and Geography

Interestingly, the role of geography is more prominent when looking at differences across genders. In the second and third row of Table 2 we present the decomposition of lifetime income from all sources for men and women separately. Inequality of lifetime income is higher among men than among women, but the share that is explained by province of birth is much higher among women. Specifically, while the between-province share is 7.1% among women, it is only 1.8% among men. The reason, of course, is that in the South women's participation is substantially lower than in the North, thus resulting in an observable driver of inequality: knowing the province where a woman was born helps predict her degree of participation and, thus, her lifetime income.

Actually, these numbers are an underestimation of the role of geography in accounting for the lifetime income of women. So far we have measured inequality by considering the individuals that appear in our dataset. This includes all individuals who have paid a social security contribution at least once in their lifetime (which could be a voluntary contribution to be eligible for pensions). However, we are fully aware that there are many inactive individuals who have never worked in their lifetime, and are not registered in the social security records. Interestingly, these people are not uniformly distributed, neither across Italy nor across genders. The percentage of males in our data is larger in the southern provinces and correlates very negatively with the average lifetime income of the province (point correlation of -0.48).

To account for this phenomenon we manually add "artificial" females to our data, so that in each province we have a balanced sample of men and women, i.e. 50% men and 50% women. To keep coherence, we attribute to these "artificial" individuals an income equivalent to one 2016 Euro in each year of their life. We report the results in the fourth row of Table 2. Obviously, for men nothing changes, but for women the role of geography increases: the between-province share rises to 10.2% of total variance.

Thus, we can summarize what we have learned so far:

1. In the context of total inequality in Italy, geography has only a marginal role. There are differences between the North and the South, but the differences within each province are vastly larger than any difference between provinces: knowing the province where a male was born does not help predict his income.

2. For women geography has a larger (albeit by no means predominant) role. This is because female participation is substantially lower in the South.

Our claim that geography is not an important driver of inequality has so far been based on the fact that we can not predict income by knowing the province individuals come from.

6   Guess the Province

In this section, we perform the opposite experiment to what we have done so far. Instead of asking how much we know about the income of a person if we know his or her province of birth, we ask what is the probability of guessing the province of birth of a person correctly when knowing his or her income. It is another way of understanding the role of geography in accounting for income inequality.

Imagine a game called "Guess the Province". One province is drawn out of the 104 Italian provinces, each one being selected with equal probability[12]. Then, the lifetime income of one individual is randomly extracted within the province. The game consists of guessing which province has been drawn.

If we did not observe an individual's lifetime income the probability of getting it right would be exactly $\frac{1}{104}$, a bit less than 1%. Knowing the lifetime income of one person drawn randomly from the population of the province might in principle make the guess more accurate. The exercise consists of measuring how much better at guessing the province we get

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[12]This is for simplicity, the probability could be proportional to population, or size, or arbitrary.

by learning about the lifetime income of people randomly drawn from the province. If that number is high, geography would be a very important driver of income. If it is low, it is an indication that it is not.

Notice that the posterior probability that this person is from province $\tilde{p}$ is:

$$P(p = \tilde{p}|w) = \frac{P(w|\tilde{p}) \times Q(\tilde{p})}{\sum_{\forall p} P(w|p) \times Q(p)}. \tag{1}$$

where $Q(p)$ is the prior that the province drawn is p (in our case $\frac{1}{104}$, but in principle this could be different[13]) and $P(w|p)$ is the distribution of income in province p.

People would guess the province with the maximum posterior probability.

$$\tilde{p} = \arg\max_{\forall p} P(p|w) \tag{2}$$

We simulate the game and calculate the percentage of times people get it right and compare it with the percentage of times people would get it right by randomly guessing. We define the success rate as the probability of guessing the province of birth correctly. Without knowing the lifetime income, the success rate is 0.97%, as there are 104 provinces with equal probability. Knowing one observation of the lifetime income, the success rate is 2.2%. That is, knowing one extraction of lifetime income it is possible to get the province right 2.32 times more often than in the scenario with no information, but still, that percentage is very low.

Not surprisingly, when we perform the same exercise by gender, we get something similar to our previous results. Having one observation of lifetime income and the additional information that the person is male, the success rate is 2.65%. The success rate in the case the person is female is 2.83%. That is, knowing one extraction of lifetime income of a male the probability to get the province right is 2.76 times higher than by guessing randomly, and

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[13]For instance, if provinces with larger populations were drawn more often this prior should reflect that probability. We have performed these kinds of experiments and the results are always qualitatively identical.

Figure 2: CDF of the distribution of lifetime income in Lombardy and Campania.
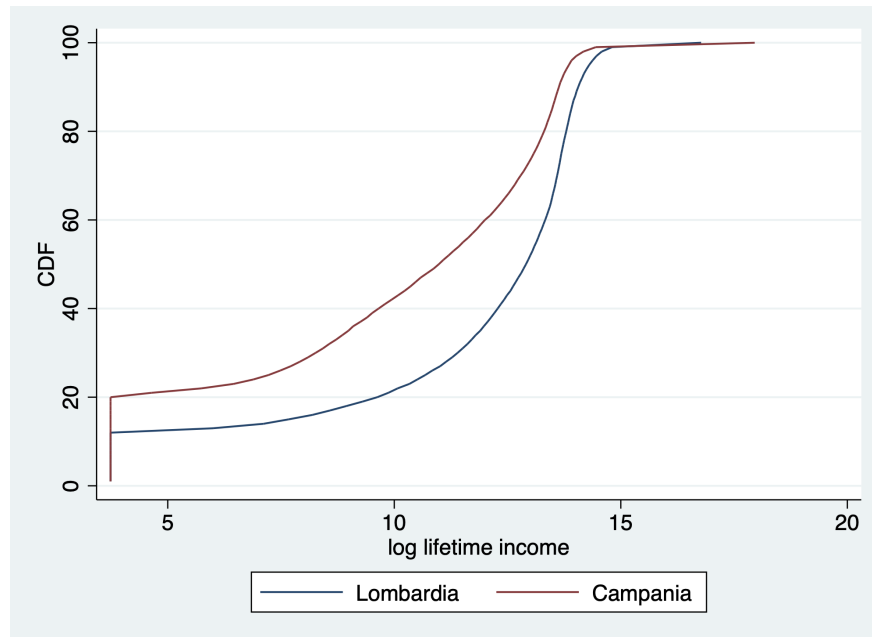
3.03 times if it is known that the person is a woman. It is 3 times better than when there is no information whatsoever, but yet 97.2% of the time the guess is wrong.

Thus, knowing the income of a person does not help in the "guess the province" game, confirming once again that geography is a marginal driver of differences in income among Italians.

7 Conclusions and discussion

Using administrative data for Italy, we have shown that the vast majority of income inequality occurs within provinces, while the between-province component has only a marginal role. Nevertheless, this does not mean that geography has no role in income. It obviously does. The North is richer than the South. The interesting point is, we believe, that in terms of *dispersion*, the role that it plays is minimal when placed in the right context.

Figure 2 plots the CDF of lifetime income in two Italian regions, Campania and Lombardy, the stereotypical poor and rich regions in the country. The distribution of income in

Figure 3: PDF of distribution of lifetime income in Naples and Milan for males and females.
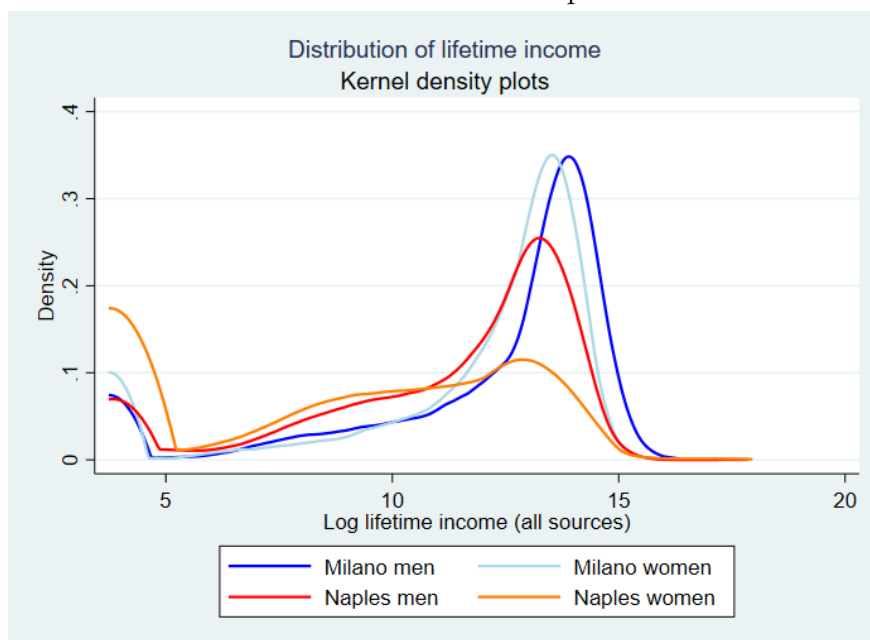
Lombardy essentially first order stochastically dominates the distribution of income in Campania. Without knowing more, and in the hypothetical scenario of being offered where to be born, it seems like a good idea to choose Lombardy. Our point is not that the North-South divide is irrelevant by itself, but that it is essentially irrelevant *for explaining the differences between Italians.* This is because, despite a clearly superior distribution of income in the North, the variance within each is so much larger than the difference in the averages, that in the lottery of life the issue of being born in one place or the other becomes almost irrelevant.

Perhaps the best way of visualizing this is to plot the Kernel density of lifetime income in both the North and the South. In Figure 3 we plot them for the provinces of Milan and Naples, separately for males and females. The spread of income in all four distributions is vastly larger than the differences in the averages. Although the averages are different, the average income of active women in Milan is higher than the average income of males in Naples. Still, the critical point that we are making is that there are many poor people in Milan and many rich people in Naples. The spread of any of the distributions is much larger than the difference between their means.

Consider now two lotteries. In the first one, the geography lottery, two tickets are available, "Naples" and "Milan", and conditional on the ticket you have, an income will be drawn from the lifetime distribution of the corresponding province.

The second lottery is the "relative income" lottery. There are also two tickets, they are called "poor" and "rich". Regardless of which of the two tickets you have, one of the provinces will be randomly drawn for you, and then if your ticket says "poor", you will get the income of a poor person in your province (say, the income of a person in the bottom 10%). If your ticket says "rich", the income of the top 10% in the province will be given to you.

Our point is that if you are playing the "relative income lottery", you should be willing to pay a lot for the ticket "rich", but if you were playing the "geography" lottery, you should not be willing to pay much for the ticket "Milan".

As we have seen, there is a role for geography in the determination of female labor participation, but otherwise (and most certainly for men) in the big lottery of life the effect of being born in any province is marginal, almost irrelevant, at least when placed in comparison with the uncertainty of other aspects, such as being born in a relatively well-off family, having better education relative to others in the same province, or having better luck in finding the first job. Those uncertainties, the within-provinces serendipity, are to a much larger extent what determines an individual's overall welfare. Not the North-South divide.

8   Conflict of Interest

The authors do not have any conflict of interest.

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8.1 Appendix

Table A1: Decomposition of (log) variance of daily wages (all employees).

	Total variance	Between province variance	Within province variance	Between province share	Within province share
1985	0.199	0.008	0.191	**3.8%**	96.2%
2018	0.401	0.018	0.383	**4.4%**	95.6%
Change	0.202	0.010	0.057	-	-
% of total increase	100.0%	5.0%	95.0%	-	-

Table A2: Decomposition of (log) variance of annual earnings (no minimum threshold).

	Total variance	Between province variance	Within province variance	Between province share	Within province share
1985	1.046	0.060	0.986	**5.8%**	94.2%
2018	1.457	0.061	1.396	**4.2%**	95.8%
Change	0.411	0.001	0.410	-	-
% of total increase	100.00	0.2%	99.8%	-	-

Table A3: Decomposition of (log) variance of annual earnings (with minimum threshold).

	Total variance	Between province variance	Within province variance	Between province share	Within province share
1985	0.617	0.041	0.576	**6.7%**	93.3%
2018	0.763	0.041	0.722	**5.4%**	94.6%
Change	0.146	0.000	0.410	-	-
% of total increase	100.0%	0.0%	100.0%	-	-