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The Geography of Intergenerational Education Mobility in Italy: Trends and Mediating Factors

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The Geography of Intergenerational Education Mobility in Italy: Trends and Mediating Factors

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Abstract

Using survey data, we contribute to the literature on temporal evolution of educational attainment by parental background by providing the estimates of the intergenerational education mobility in Italian regions across seven birth cohorts. Results of intergenerational correlation between parents and children's education show that in the last fifty years mobility increased in almost all regions, although for the youngest cohorts this decline seems to have ended. Northeast regions and Central regions are the most mobile, followed by Northwest and South regions. This pattern is robust to alternative measures of relative mobility. As expected, we find that - at least for the youngest cohorts - there is a negative correlation between mobility and economic factors such as unemployment and poverty. This suggests that credit constraints explain bottom tail persistence in education. A positive correlation between the intergenerational education mobility and the degree of inequality as measured by the GINI coefficient exists across Italian regions, consistent with the "Great Gatsby curve" documented across countries. In addition, we find a positive association between mobility, indexes of social capital and the number of graduates in the regions. Measures of school quality (PISA test) are positively correlated with regional educational mobility.

Keywords. Intergenerational Mobility, Education and Inequality, Italy, Geography

JEL Codes: J62, I21, I28.

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1 Introduction

Starting from the after-war period onward, the development of publicly provided compulsory education, as well as public funding on education in general, has promoted education upgrading for all children. Education upgrading contributed to increase intergenerational social mobility and to decrease inequality in the distribution of human capital in the world. [1] However, socio-economic background remains important in determining educational outcomes and educational gaps persist among children belonging to different social groups not only in developing countries but also in advanced economies.

Wealthy family can better afford to provide their children with marketable factors like books, private courses, study travels, which are very important in human capital accumulation. This suggests a strong role for public provision or financing of education to equalize opportunities. While public education funding can partially offset the advantage of wealthy families in the acquisition of marketable factors, there are no-purchasable factors that are equally important (if not more) in determining educational attainments. Factors like parental education, provision of social connections, installation by parents of preferences and aspiration in children cannot be easily compensated by public policy (Mejía and St-Pierre, 2008). In addition, the social context in which children grow up might play an equally important role in educational outcomes: for example, neighborhood and peer effects, distance to schools and different qualities of schools.[2] Taken as a whole, social and familiar backgrounds affect the opportunity cost in investing in education. All these factors contribute to the persistency of inequalities in the distribution of human capital.[3]

The purpose of this paper is to document patterns in the intergenerational correlation of educational attainment in Italy across both time and geographic regions. Differently from the study of intergenerational income mobility, that is the object of recent contributions such as Barbieri et al. (2020) and Güell et al. (2018), we focus on patterns in education mobility. This investigation provides, more than the study of income mobility, which is affected by factors intervening later in life, precise insights on the degree of equality of early life opportunities. Notably, a high index of persistency, generally measured through the correlation coefficient between the years spent in education by parents and by offsprings, might indicate that the society has failed in assuring equality of opportunities to children from different familiar background. Our results show that in the last fifty years mobility increased in almost all Italian regions, although for the youngest cohorts this decline seems to have ended. Northeast regions and Central regions are the most mobile, followed by Northwest and South regions. This pattern is robust to alternative

[1]The inequality in the distribution of education in the world has halved in about fifty years: the average Gini coefficient for human capital inequality dropped from 0.55 in 1960 to 0.28 in 2005 (Castelló-Climent and Doménech, 2021).

[2]Chetty and Hendren (2018) show that neighbourhoods have substantial childhood exposure effects: every additional year of childhood spent in a better environment improves a child's long-term outcomes in terms of income but also in terms of college attendance. Evidence of neighbourhood effects has also been found in Europe (Goux and Maurin, 2007).

[3]This topic is important not only for evaluating the level of "equality in opportunities" reached by a society, but also in relation to the economic efficiency. A growing literature, in fact, has begun to stress the role of the distribution of human capital in economic growth (Sauer and Zagler, 2012).

measures of relative mobility. Exploiting the heterogeneity across Italian regions, we study how education mobility correlates with a number of socio-economic variables, without necessarily making causal claims. We find that educational mobility is negatively correlated with economic variables like unemployment and poverty indexes. This confirms the expectation that bottom tail educational persistency is mainly motivated by financial constraints. Additionally, we find a negative correlation with Gini index, confirming the existence for Italian regions of a "Great Gatsby curve" (Corak, 2013). Data also show a weak positive correlation between mobility and social capital and quality of the K-12 school system, as measured by PISA test. Interestingly, geographical location matters more for children growing up in low-income families. Indeed, the geographical variation of the expected rank of children whose parent belongs to the 25th percentile is greater than the variation of the expected rank of children whose parent belongs to the 75th percentile.

The remainder of this paper is organised as follows. Section 2 presents a brief literature review; section 3 discusses data and methodology; evidence at the national level is presented in section 4; section 5 discusses the geographical variation of educational mobility and section 6 the factors that might explain such heterogeneity. Finally, the last section concludes and highlights policy implications.

2 Related Literature

Models of human capital formation and accumulation were developed by Becker and Tomes (1976, 1979) and Solon (1999), building on the notion of human capital defined by Becker (1964). Notably, the Becker–Tomes–Solon' s analysis is focused on the intergenerational dynamics of human capital. Many possible underlying mechanisms lead to a direct effect of parental education on child education. First, higher educated parents generally have higher income, which affects educational attainment through education expenditure. Second, parental education may affect parental time allocation and the productivity of the parent's child-enhancing activities (Glomm and Ravikumar, 1992, 2003). To measure the intergenerational mobility in education it is generally used the correlation between the years spent in education by children and by their parents. Considering the correlation instead of the regression coefficient allows to factor out the dispersion of education in the two generations. This is important when comparing different cohorts since there have been large increases in educational attainment in recent decades and these have tended to cause a secular increase in the variance of education (Black et al., 2011). Hertz et al. (2008) provide correlations and regression coefficients for a sample of 42 countries, analysing cohorts from 1920 to 1980. They document the decreasing intergenerational of persistence of educational attainment as measured by regression coefficients, but substantially stable correlation coefficients and explain this result pointing to the fact that the variance of offspring education has increased relative to the variance of schooling in the first generation. As for Italy, they document a slow decline in the intergenerational persistence of educational attainment, whose level, however, remains high compared to similarly developed countries.

Chevalier et al. (2009) for a more limited sample of European countries and the U.S. confirms Hertz et al. (2008) results. Likewise, Heineck and Riphahn (2009) find no significant change in the intergenerational persistence in education in Germany over half a century. Checchi et al. (2013) note that if the use of correlation coefficients allows accounting for different dispersion of education of different cohorts, it does not allow to disentangle differential intergenerational mobility of subgroups of the population. Focusing on Italian data (1930-1980 cohorts), they suggest a decomposition of the correlation coefficient of education, focusing on the probability of one's educational attainment given that of one's father. They argue that the observed very slow decline of the intergenerational persistence of educational attainment is mainly due to the fact that higher educational attainments are more likely to be obtained by children with highly educated fathers. Brunetti (2021), also working on Italian data, confirms Checchi et al. (2013) results. Brunetti (2021) analyses the intergenerational mobility in education using transition matrices to better disentangle differential intergenerational mobility of subgroups of the population and finds that despite the many educational reforms observed in the last fifty years, the intergenerational transmission of education is still highly polarized. Those coming from a high-educated family are more likely to enter and remain in high positions, while children coming from disadvantaged background will likely remain in the same position. In addition, she observes a reduction in movement between classes that are not immediately adjacent for the cohorts of the youngest. Working on UK data, Blanden and Machin (2004) find similar results: in the U.K., the recent higher education expansion has disproportionately benefited children from higher income (and presumably, higher education) parents. Güell et al. (2007) in Spain confirm the polarization in education transmission.

Karlson and Landersø (2021) trace educational attainment and mobility for cohorts born over the course of the 20th century in Denmark. They find that despite the very generous public education support which allowed free access to colleges and universities, the mobility of Danes born in the 1970s and 1980s, has declined. Karlson and Landersø (2021) explain such phenomenon referring to stagnating high school completion rates and increasing college and university completion rates that are mainly driven by children born to well-educated parents.

Beside the previous contributions, which have focused on national data, a new literature, starting with Chetty et al. (2014), has argued that the intergenerational social mobility process in a country might be heterogeneous by geographical areas. By focusing on intergenerational income mobility, Chetty et al. (2014) provide estimates for US counties and census tracts and find important differences. They find that segregation and income inequality negatively affect the intergenerational income mobility, while they find a positive correlation with social capital and quality of the K-12 school system. Interestingly, geographical location matters more for children growing up in low-income families, suggesting that a good social environment influences behaviour by shaping norms and providing environmental opportunities that favour mobility. Connolly et al. (2019) tackle the same type of analysis for Canadian census tracts, confirming that inequality strongly correlates with intergenerational immobility. Eriksen and Munk (2020) for Denmark municipalities find the highest intergenerational income mobility within middle-income rural municipalities and the lowest intergenerational income mobility within urban and poor rural municipalities. Acciari et al. (2022), by using Italian administrative data on tax returns, show that intergenerational income mobility is lower in the regions of Southern Italy compared with those of the Centre and the North. Provinces in Northern Italy display mobility levels three times as large as those in the South. This regional variation appears to be correlated with local labour market conditions, indicators of family instability, and school quality. Güell et al. (2018), adopting a strategy based on the variability of economic conditions associated with surnames, confirm Acciari et al. (2022) results for Italian provinces.

This new stream of research is very important as might give more precise insights on the causal drivers of intergenerational mobility than between-country comparisons (Connolly et al., 2019).[4] Similar studies that look at the intergenerational transmission of education by geographical areas are still few. An exception is the contribution of Fletcher and Han (2019) that documents differences in educational mobility across time (1982-2004) and geography for the U.S. states. They identify local community and policy factors, such as the existence of high school exit exams, which are correlated with educational mobility. Card et al. (2022) confirm that upward mobility in educational attainment in the US is significantly related to differences in local public education policies that allow for flexibility in school curriculum, funding or management. Likewise, Bell et al. (2022)) find evidence of significant differences in educational mobility across areas in England and Wales for multiple cohorts.

These works point to the evidence that the role of family background can be attenuated or enhanced by the place where children grow up. Building on this idea, Arenas and Hindriks (2021), extend the standard parent–child transmission model 'a la Becker–Tomes–Solon by allowing for unequal school opportunities. They show that unequal school quality shifts parental investment towards the richer families, exacerbating the parenting gap and therefore persistence. These authors underline that differences in school quality could arise also in states where education policies are centralized; this can happen for a variety of reasons, such as differences in peers and in the surrounding community. This argument is consistent with the idea that school inequality is a natural result of broad neighbourhood effect (Chetty and Hendren, 2018).

Against this background, our goal is to evaluate relative mobility and examine its trends and geographic distribution in Italy for birth cohorts from 1920 to 1980. Italy, as opposed to the U.S, is a highly centralised state where institutions and education policies are 'de jure' the same in all provinces. The finding of regional variation in intergenerational education mobility might suggest that environmental factors beyond policy differences can shape school opportunities and educational investment decisions which in turn affect the intergenerational evolution of education by enhancing or attenuating the role of family background (see for example Bratti et al., 2007 and Ballarino et al., 2006).

[4]Connolly et al. (2019) argue that the variation of intergenerational mobility within a country cannot be explained by differences in values and institutions that shape the nature and size of the welfare state, particularly between continental Europe and North America.

3 Data and Methodology

3.1 The Survey on Household Income and Wealth

The Survey on Household Income and Wealth (SHIW) developed by the Bank of Italy contains useful information for computing national mobility in education as it is a household survey drawn from the total Italian population with data on socio-demographic background, income and wealth of family members. [5] The household is the unit of analysis of the survey and its reference member is the householder, defined as the person responsible for the economic decisions of the family.[6]

Unlike studies that focus on the probability of achieving a certain level of education, the aim of this work is to evaluate the intergenerational transmission of human capital based on the highest educational attainment of individuals. We use the waves from 1993 to 2020 as since 1993 respondents of the SHIW were asked to report not only the educational attainment of their parents when they were the same age, but also the education of their spouse's parents, except for 2008, 2010 and 2012 waves when the educational attainment of the spouse's parents is unavailable. To reduce the risk of having respondents without completed degrees, we keep individuals aged at least 28 in every wave and delete the students still present in our dataset.[7] In addition, with reference to the panel component, we select the last available observation to account also for those who achieved higher levels of education later in their life.

The categorical variables representing the educational qualification of family heads, spouses and offsprings range from none to post-graduate. Given the very limited numbers of post-graduates, we pool them with the university degree holders.[8] The final sample contains almost 69,000 child-parent pairs divided in seven ten-year cohorts according to the child's birth year. The first cohort spans the years from 1920 to 1929, the last from 1980 to 1992 with the size of the cohorts varying from 2,958 of the 1980s to 15,164 of the 1950s cohort (see Table 1).

While the SHIW has been used to compute intergenerational mobility in education, either the authors consider only the family heads and their parents (Brunetti, 2021) or the family heads, their spouses and their respective parents (Cannari and D'Alessio, 2018 and Checchi et al., 2006, 2013). In addition to householders and spouses, for the cohort 1980-92 we exploit also the answers of the respondents' first born offspring.[9] As a result, we have an enlarged data set with new observations, the firstborns, that can be used to compute national and regional

[5] Until 1989 the SHIW has been conducted annually as repeated independent cross-sectional surveys. Since then, the Bank of Italy began to follow several families over time, therefore the SHIW is a split sample now, with a cross-sectional and a panel component. For a detailed discussion of the history and the structure of the SHIW see Baffigi et al. (2016).

[6] To belong to the household, persons ought to live permanently in the householder's dwelling and contribute at least partially to the income of the household in the year of the survey.

[7] Recent data on newly graduated from master's degree (laurea magistrale) suggest that 28 is still a conservative choice as graduated are on average around 27 years old. For further details see the 2021 Almalaurea report available at `https://www.almalaurea.it`.

[8] According to the ISCED codes, the complete scale is the following: no qualification, primary school certificate (ISCED 1), lower secondary school certificate (ISCED 2), upper secondary school diploma (ISCED 3), university degree (ISCED 5-8).

[9] The analysis is limited to firstborns to avoid correlations among siblings.

intergenerational mobility.[10]

Matching the head of the family with the offspring is common in studies on intergenerational mobility that rely on census data. [11] The pitfall of using this type of data is the potential selection bias due to co-residency of parents and children. Selection arises when children away from home (that are not observed) systematically differ from those living at the household dwelling. It is recognized that observed and unobserved children differ more significantly when the prevalent co-residency rate in the population is low, as it happens for old individuals. Thus, the coresidence rate is negatively correlated with the age of the child and therefore researchers in intergenerational mobility working with samples of coresidents have to make a choice when they select the educational attainment of children. On the one hand, they may choose individuals old enough to have achieved their highest educational attainment, but potentially bias due to co-residence. On the other hand, they may select younger individuals with high co-residency rate and low probability of selection bias, but without having completed their studies (Francesconi and Nicoletti, 2006).[12]

Pooling coresidents with householders and spouses aged at least 28 potentially expose us to co-residency bias in the cohort of the 1980s. In section 4, we show that coresidence bias in our case seems to be not as severe as expected. Our setting is particular since it allows us to compare retrospective data, which can be considered a random sample, and co-residency data. The estimates with and without the offspring may account for the strength of the bias, both at the regional and at the national level.

3.2 Measures of Mobility

One of the issues in computing intergenerational regression and correlation coefficients in education is that variables accounting for human capital accumulation available in public dataset are usually categorical and not continuous. Researchers tried to overcome this problem converting the educational attainment into years of schooling, i.e. a discrete variable, based on the legal duration of degrees (Black et al., 2011). As an example, if an individual attains high school diploma in Italy, the educational qualification is converted into years of schooling by

[10] Firstborns account for around 45% of all the observations of the 1980-1992 birth cohort.

[11] van der Weide et al. (2021) estimate intergenerational mobility for 147 countries, 39 of which were samples with coresidence conditions. Hertz et al. (2008) combine retrospective data with co-residence data to bolster the sample size of the last cohort of their study. A similar approach has been followed by Narayan et al. (2018) who use retrospective data to estimate mobility for several cohorts and co-residence data for the 1980s cohort

[12] Although selection may be problematic, its impact on intergenerational mobility estimates remains unclear, as the literature on this field is still scarce. Using data from the British Household Panel Survey, Francesconi and Nicoletti (2006), evaluate the extent of the co-residence bias in short panels in an early work on intergenerational mobility in occupational prestige. Their setting allow them to compare a random sample, used as a benchmark, to co-residence samples, and they find a severe impact of selection bias to the estimates of persistence. Likewise, Fletcher and Han (2019) document significant differences between a random sample and a subsample of coresidents in a study on intergenerational mobility in education. Conversely, Munoz and Siravegna (2021) report coresidence bias of the order of barely 1 to 10% on estimates of mobility in 18 Latin American countries, although with some variation according to the indicator considered. Emran et al. (2018) discuss the impact on co-residency bias on the intergenerational elasticity coefficient and on the intergenerational correlation coefficient. They conclude that the estimates of the former indicator would be remarkably biased downward and improvements could be achieved using the correlation coefficient as a reference measure.

summing the legal duration of primary school (5 years), lower secondary school (3 years), and upper-secondary school (5 years). Following Checchi et al. (2006), we count no qualification as 0 years of schooling; primary school as 5 years; lower secondary as 8 years; upper secondary as 13 years; and university degree and post-graduate as 18 years of education.

To study the transmission of human capital, researchers adopt several measures of mobility (or persistence) that can be divided into absolute and relative mobility. While the former evaluate the performance of the child with respect to the parent based on a particular scale, the latter accounts for the extent to which the education of children is independent from parental education.[13] We focus mainly on measures of relative mobility throughout the paper, but we show also how absolute upward mobility has evolved across time.

3.2.1 Intergenerational Regression Coefficient

Two of the most popular indicators of educational persistence are the intergenerational regression coefficient (IGR) and the intergenerational correlation coefficient. The IGR is simply the beta coefficient of a regression of the years of schooling of the parent on the years of schooling of the child, and thus it stands for the average increase of the education of the child when the parental education increase by one year. The IGR is therefore a measure of persistence rather than a measure of mobility (which can be defined simply as 1-β). An empirical regularity points to the fact that the IGR ranges between zero and one, with zero indicating lowest persistence and thus highest mobility and one suggesting that the education of the parent perfectly predict the children's education.[14] Denoting Y_i the child i's years of schooling, X_i as the maximum of both parents' years of schooling, and Z_i as a set of control variables such as gender and region of birth, the IGR can be derived by estimating the following linear regression:

$$Y_i = \alpha + \beta X_i + \gamma Z_i + \epsilon_i \tag{1}$$

which is carried out separately for each ten-years-cohort. The coefficient of main interest is β that represents the IGR. The intercept α is a measure of absolute mobility that stands for the expected years of schooling of the child when the parent's years of schooling are zero. We adopt the same model to derive the IGR at the regional level, performing the regression for each region and ten-year-cohort.

3.2.2 Intergenerational Correlation Coefficient

Another measure of relative mobility widely used in the literature is the intergenerational correlaton coefficient (IGC henceforth). The main difference from the IGR is that the IGC tends to be more stable over time as it factors out the dispersion across cohorts. To approximate the correlation coefficient in the context of the regression model presented above, we follow Checchi

[13] Discussion on the difference between these indicators are available in Narayan et al. (2018) and van der Weide et al. (2021). See also Deutscher and Mazumder (2021) for a full discussion of the measures of relative and absolute mobility in the context of income mobility.

[14] Although theoretically possible, there is no trace empirically of countries where persistence is lower than zero or higher than one. See Black et al. (2011) for more details on this point.

et al. (2013) and Aydemir and Yazici (2019) in adjusting our variables for the dispersion across cohorts. We do so by dividing parents' and children's years of schooling by the standard deviation of the parents education distribution and children education distribution in each cohort, respectively.[15] Hence, we estimate the IGC for each ten-year cohort as follows:

$$S_{c,i} = \alpha + \beta_s S_{p,i} + \gamma Z_i + \epsilon_i \tag{2}$$

where

$$S_{c,i} = \frac{Y_i}{\sigma_Y}$$

and

$$S_{p,i} = \frac{X_i}{\sigma_X}$$

The terms $S_{c,i}$ is the standardized education of the child, with σ_X being the standard deviation of the child education distribution, and $S_{p,i}$ is the standardized education of the parent with σ_Y that indicates the standard deviation of the parental education distribution. The coefficient β_s is the IGC and denotes the increase of child's years of schooling when the parent's years of schooling increase by one standard deviation.

From the intergenerational correlation coefficient, we can derive the IGR in the following manner:

$$IGC = IGR * \frac{\sigma_X}{\sigma_Y}$$

This expression clarifies the relationship between the two indicators. Indeed, although both these measures account for persistence among generations, the correlation coefficient factors out the variance across generations, whereas the beta coefficient is sensitive to the relative variance across cohorts (Black et al., 2011). As a result, the IGC is more stable than the IGR over time. As shown in Table 2 in the next section, this relationship provides useful insights about the evolution of mobility. The standard deviation of the child education remained above that of the parent until the 1960s and reversed in the subsequent cohorts. As a result, the IGR was higher than the IGC in the old cohorts and lower thereafter.

3.2.3 Rank-Rank Slope

To further investigate how relative mobility has changed over time in Italy, we study the transmission of human capital in ranks. The main measure of relative mobility using percentiles is the so-called rank-rank slope (RRS), which has become popular after the seminal work of Chetty et al. (2014). They show that ranks can have important advantages in studying intergenerational income mobility as they not only control for inequality in the parents and children distribution but also better approximate the linear relationship between parent-child education. In the education setting, the rank-rank regressions can be useful to account for

[15] Another possibility leading to the same result is to normalize the child and parent education such that they have mean zero and standard deviation one.

changes in the marginal distribution of parents and children, following for example a reform of compulsory schooling.

In contrast to income, however, data on human capital are usually coarse as education is available only as a discrete variable. To overcome the problem of ties when dividing the distribution into percentiles, we follow Fletcher and Han (2019) assuming that human capital in percentiles is transmitted linearly from parents to children. This assumption implies that the marginal change in child's expected rank is constant across the whole parent's education distribution. Starting from the national distribution in every cohort, we attach the education percentile to each parent (child) computed as the fraction of parents (children) with strictly less education, plus one-half the fraction of parents (children) with equal education (Fletcher and Han, 2019). Formally, the percentile rank of child i, born in cohort g and having education e can be derived through the expected probabilities as follows:

$$R_{i,g} = Pr[u_{i,g} < e_{i,g}] + \frac{1}{2} * Pr[u_{i,g} = e_{i,g}]$$

with $u_{i,g} \leq e_{i,g}$.

Parental education rank can be derived in the same way from the parental education distribution. For each cohort we want to estimate the following equation:

$$R_{c,i} = \alpha + \beta_r R_{p,i} + \gamma Z_i + \epsilon_i \tag{3}$$

where $R_{c,i}$ and $R_{p,i}$ are the child rank in the education distribution of children and the parent rank in the education distribution of parents, respectively. Z_i is the same set of controls as in equations (1) and (2). The constant α_i yields the expected rank of a child whose parent is at the bottom of the education distribution. The parameter of our interest is β_r that denotes the rank-rank slope. A RRS equal to zero means that children stay in the median rank of the distribution regardless of the parental education, while a rank-rank slope equal to one means that children have the same education percentile as their parents. Given that we know that persistence varies between these two bounds, if the RRS is equal to 0.5, a difference of ten percentiles between parents education is associated to five percentiles difference in education between children.

3.2.4 A Measure of Absolute Mobility: the Conditional Expected Rank

When we analyze the temporal evolution of mobility within Italy, we derive from regression (3) estimated at a regional level the mean rank of a child whose parents belong to the $25th$ percentile of the national distribution (CER25). Since we use national rank to derive the expected rank for each region and cohort, the CER25 can be considered a measure of absolute upward mobility (Deutscher and Mazumder, 2021). The CER25 is equal to

$$CER25 = \alpha + 25 * \beta_r$$

The expected rank at the national level would depend directly on the slope of the curve and therefore it would not provide any additional information on mobility. The same would be true if we estimated the rank-rank slope and the CER25 using ranks at the regional level. Note that using the national distribution to derive ranks is essential to make meaningful comparisons among regions. Indeed, the interpretation of the coefficients both across time and across geographic areas would be hard had we consider regions with different education distribution and therefore different reference percentiles. The analysis of the CER25 provides an alternative view on intergenerational mobility among regions as its variation arises because it reflects not only changes in the rank-rank slope but also movements of the curve due to the heterogeneous distribution of national human capital across the country (Heidrich, 2017). As a result, two curves may have identical slope, namely the same relative mobility, but different CER25 due to the different position of the regions in the national human capital distribution. This information would be overlooked if we did not consider the expected rank.

4 Intergenerational Education Mobility in Italy

4.1 Descriptive Statistics

Table 1: Unconditional Distribution of Children's and Parents' Education

Cohort	Education of the child					Education of the parents					Obs.
	NQ	PR	LS	US	UD	NQ	PR	LS	US	UD	
1920-29	19.6	51.3	15.2	9.7	4.2	51.1	38.3	4.7	4.3	1.6	6,398
1930-39	11.6	50.2	21.4	12.1	4.7	39.1	47.7	6.3	5.3	1.7	11,420
1940-49	3.7	35.5	31.8	19.6	9.4	26.2	54.2	10.1	6.7	2.9	14,612
1950-59	1.1	15.7	39.7	29.6	13.9	18.3	54.7	14.4	8.8	3.8	15,164
1960-69	0.5	5.3	44.3	34.6	15.3	11.0	48.7	22.5	12.6	5.2	13,779
1970-79	0.3	2.8	39.3	35.5	22.1	6.0	36.1	30.6	19.8	7.5	5,649
1980-92	0.3	1.4	28.1	36.0	34.1	2.6	16.9	35.9	29.4	15.2	2,958

Notes: Highest completed educational attainment of children and parents by birth cohort of the child. The reference category for parental education is the maximum educational level attained by the parents. NQ stands for No Qualification; PR for Primary Education; LS for Lower Secondary; US for Upper Secondary; UD for University Degree. Obs. stands for the number of pairs of child-parent. Values are expressed as percentages. Source: SHIW Historical Archive.

We begin this section with some stylized facts on the temporal evolution of human capital at the national level. Table 1 provides the unconditional distribution of the highest level of completed education of parents and children at the national level and across time.[16] The portion of children without any qualification or attaining only primary education collapsed between the 1940s and the 1950s and almost disappeared afterwards. This sharp decrease along with the expansion of lower secondary education can be attributed to the 1962 reform of the schooling system - known as Unified Middle School Law - that imposed at least 8 years of compulsory

[16] Unless differently specified, the reference category for parental education is the maximum years of schooling attained by parents.

education to all children. This reform instituted the unified lower secondary school in Italy, which boosted participation rates and therefore average years of schooling. At the same time, the share of children with upper-secondary qualification and university degree steadily grew until the 1960s. The high school diploma then flattened, while the quote of university degree holders kept rising in the 1970s and the 1980s, when almost one-third of children completed college qualification.[17] The pattern followed by the parents is close to the one of the children, when considering the age difference between the two.[18] The share of parents holding primary school qualification decreased by almost 60% is the last generations, while those completing upper-secondary almost tripled.

Along with the stable increase of the average years of schooling, that more than doubled for children and even tripled for parents between the 1920s and the 1980s (Table 2), these stylized facts suggest an expansion towards higher levels of education across the last century. Nevertheless, the expansion did not occur homogeneously across the education distribution, as illustrated in Table 1. In fact, consistent with the findings of Karlson and Landersø (2021) for educational mobility in Denmark, the education expansion seems to be a sum of small expansions in different level of the education distribution. This is likely due to the way human capital accumulation evolved across the century and, in turn, to the schooling policies adopted in the post-war period. Policies extending compulsory schooling enhance equality of opportunities, as all individuals - and notably the poor - obtain at least a minimum level of education. In contrast, the 1969 reform, which opened university to all types of secondary schools seems to have benefited only children from advantaged families, as liberalizing tertiary education does not imply that individuals with a upper-secondary degree decide to engage in a university program (Bertola and Sestito, 2011). The limited expansion of university degree among the children from disadvantaged background contributes to explain the sluggish education mobility that characterizes Italy since the 1960s.

4.2 Educational Mobility in Italy

This section summarizes the results of educational mobility at the national level based on the models presented in section 3. The results reported in Table 3 suggest a general increase in mobility (lower persistence) during the "Economic Boom", the period following WWII, for the three measures here adopted. Not surprisingly, the IGR (column 1) varies more than the other two indicators across time. In the 1980s a one-year increase in the education of the parent is associated to a 0.45 years increase in the child's education. Mobility summarized by

[17]The 1969 Codignola Law reformed the requirements to access university, liberalizing the rigid post-war tertiary schooling system. As opposed to today's rules, the attended high school determined the enrollment into university. Only those studying at the classical liceo could have enrolled into all university programs before the reform, while those enrolled at the scientific liceo had access only to scientific courses, and those studying at technical schools did not have access to university. Thus, school tracking had an overwhelming impact on the student's career.

[18]The cohorts of birth of the parents are unknown. However, we can reasonably assume that there is a twenty-to-thirty years lag between parents' and children's years of birth. For example, the share of children with primary qualification in the cohort 1940-49 is very close to the quote of parents with the same education level in the cohort 1970-79.

Table 2: Summary Statistics

	Child		Parents	
Cohort	Avg.	Std. Dev.	Avg.	Std. Dev.
1920-1929	5.80	4.35	3.13	3.88
1930-1939	6.65	4.23	3.87	3.91
1940-1949	8.57	4.42	4.90	4.07
1950-1959	10.31	4.25	5.72	4.17
1960-1969	11.06	3.92	6.80	4.28
1970-1979	11.88	4.05	8.18	4.42
1980-1992	13.15	4.12	10.27	4.53

Notes: Average years of schooling and standard deviation of the education of parents and children by birth cohort of the child. The reference category for parental education is the maximum level of education attained by the parents. Source: SHIW Historical Archive.

standardized years of schooling slowly decreased between the 1920s and the 1960s and remained stable in the subsequent cohorts. Note that before the 1960s the IGR was higher that the IGC and lower later, suggesting that dispersion in the education of parents and children had some impact on the estimated mobility.[19] In the last cohort, a one-standard deviation increase in parents' education is associated to a 0.49 standard deviation increase in children's education. [20] The last column in Table 3 presents the estimates of the rank-rank slope. Accounting for changes in the marginal distribution of education seems confirm the findings reported above with the trend followed by the RRS that is close to that of the IGR and the IGC, except for a slight rebound of persistence in the last cohort. The slope in the cohort of the 1980s implies that ten percentiles difference in the generation of parents is associated to a 4.8 percentiles difference in the generation of children.

Our estimates of the correlation coefficient are in line with previous results of Checchi et al., 2013, who found a similar trend over time and a correlation coefficient of 0.50 for the 1975-1979 birth cohort. In absolute terms, we find estimates that confirms Italy as one of the most immobile country in the Western world (Hertz et al., 2008).[21][22]

It is important to stress that the estimates reported here need caution as they do not identify a causal mechanism in the transmission of education from parents to children and have therefore a mere descriptive purpose. We do not have data in the SHIW dataset regarding parental characteristics besides education, thus the estimates may be affected by an omitted

[19]Narayan et al. (2018), discussing the difference between the IGR and the IGC, highlight that the standard deviation of the years of schooling follows a reversed U-shape, meaning that it is lowest either when many individuals have low education or high education.

[20]We find similar results when taking father's and mother's education as a reference category for parental education. See Table A1 in the Appendix.

[21]The trend we document is consistent also with that found by Cannari and D'Alessio (2018). Using the wave from 1993 to 2016 of the SHIW and a log-log model, they report that persistence in education decreased over time but slightly increased in Italy in the last decades.

[22]Recent studies on intergenerational income mobility based on large administrative data show, however, that Italy seems more mobile than what actually thought, although with dramatic differences within the country (Acciari et al., 2022).

Table 3: Educational Mobility in Italy over the 20th Century

	Years of Schooling (1)	Standardized Years of Schooling (2)	Rank-Rank Slope (3)	Obs.
1920-29	0.636	0.567	0.528	6,398
	(0.016)	(0.015)	(0.014)	
1930-39	0.592	0.547	0.535	11,420
	(0.012)	(0.011)	(0.011)	
1940-49	0.581	0.534	0.541	14,612
	(0.011)	(0.01)	(0.01)	
1950-59	0.527	0.517	0.522	15,164
	(0.009)	(0.009)	(0.01)	
1960-69	0.463	0.505	0.486	13,779
	(0.009)	(0.01)	(0.01)	
1970-79	0.448	0.488	0.467	5,649
	(0.014)	(0.015)	(0.015)	
1980-92	0.446	0.491	0.482	2,958
	(0.021)	(0.023)	(0.022)	

Notes: Regressions are estimated using sample weights. Robust standard errors are in parentheses. Control variables: gender and region of birth of the child, year of the survey. Source: SHIW Historical Archive.

variable bias. However, the validity of the mobility trend would not be undermined, as long as the bias does not vary across cohorts of birth (Checchi et al., 2006).

4.3 Coresidents in the cohort of the 1980s

To study intergenerational mobility in Italian regions in the 1980s, the subsample of the offspring is combined with that of householders and spouses. The offspring in our sample, whose age range between 28 and 40, still resides in the same dwelling as the respective parents. As a consequence, it may represent a non-random sample, as the offspring that leave away from home is unobserved and likely differ in several dimensions to the co-residents. This example of selection bias is well-known in the literature as co-residency bias. Selection typically arises when age constraints are imposed to account for children's highest level of education. The higher the bound, the more the probability of having a selected sample because of the negative relationship between age and co-residence rate, that is the percentage of children still living with their parents. To avoid co-residence, researchers who estimate mobility in education with census data or data without retrospective questions on parental education usually focus on measures of intermediate levels attainment, such as the probability of achieving high school diploma (Card et al., 2022). They do so because people normally achieve upper-secondary degree at the age of 18 or 19, when the co-residence rate is very high, and then the risk of selection bias is relatively low.[23]

[23] One exception is Hilger (2015) that analyzes intergenerational mobility in education across time in the U.S. using census data and individuals aged 26-29 still living with their parents. Selection is addressed by building a semi-parametric adjustment that relies on two assumptions, namely that parental group share does not change across cohorts and, more important, that the conditional expectation function of schooling of dependent and

In contrast to other developed countries, we observe high co-residence rate in Italy even in people in their early thirties.[24] Consequently, we may expect the offspring not to differ so much from their peers. We have verified our null hypothesis of no-bias by testing whether adding the co-resident change the intergenerational mobility estimates of our three indicators. A Wald test is performed with the null hypothesis being that the beta coefficients are statistically equal in the equations with and without the offspring. This is a convenient approach given that the sample of householders and spouses rely on retrospective data and therefore can be considered a random sample.[25] As the null hypothesis cannot be rejected, there is not statistical difference between the coefficients. As reported in Table 4, the numerical difference of the coefficient of the complete sample (column 1) and the sample of family heads and spouses (column 2) is around 1-2%. This tiny difference can be explained by the age composition of the sample of the offspring. Indeed, almost 90% of the offspring are between 28 and 34, a period in which the co-residence rate is still high in Italy.

Table 4: Coefficients with and without the Offspring in the 1980 Cohort

	Incomplete (1)	Complete (2)
Parent's Education	0.44	0.446
	(0.028)	(0.021)
Std. Parent's Education	0.484	0.491
	(0.031)	(0.023)
Rank-Rank Slope	0.48	0.482
	(0.029)	(0.022)
Obs.	1495	2958

Notes: Column (1) refers to the sample containing only householders and spouses. Column (2) is estimated pooling the offspring with family heads and spouses, as in the last row of Table 3. We estimate the regression using sample weights. Control variables: gender and region of birth of the child, and year of the survey. Wald test for equality of the coefficients: p = 0.66 for years of schooling, p = 0.66 for standardized years of schooling and p = 0.87 for ranks. Source: SHIW Historical Archive.

5 Geographic variation across regions

In this section we study the geography of intergenerational mobility in education focusing on Italian regions. Our study is related to the contributions of Güell et al. (2018) and Acciari et al. (2022), who document remarkable heterogeneity in intergenerational income mobility across Italian provinces, and the work of Barbieri et al. (2020) who report estimates of mobility in earnings in Italian macro-regions.

independent children has the same slope.

[24] Eurostat data show that the share of Italian adults aged 25-34 living with their parents in 2018 is 49%, more than three times that of Germany, four times that of France and almost ten times that of Norway. See `https:ec.europa.eu/eurostat/databrowser/view/ILC_LVPS08__custom_5003548/default/table?lang=en`.

[25] Assortative mating is not addressed here. However, considering the difference between the sample of only householders and the sample composed by householders and the offspring lead to similar results.

In the last century, Italy has experienced significant differences across geographic areas not only in economic development and growth, but also in human capital accumulation (Bertola and Sestito, 2011). Evidence from PISA tests suggests a high degree of polarization of schools' outcomes within the country, with students from the regions of the North that perform on average better than the regions of the South (Giancola et al., 2010). Focusing on adult competencies, Baldissera and Cornali (2020) found similar results, although with more nuances, with the North-East that achieve better results in every field of the PIIAC tests than the Southern regions. These disparities occurred despite the highly centralized public school system and the limited role of local governments in affecting schooling policies. Our aim is to document differences in educational mobility across generations and investigate potential factors that help explain such variation.

To document the evolution of mobility over time, we estimate our three measures of relative mobility for each region of birth of the child and for each birth cohort.[26] We assume that the region of birth is the region in which the child grows up and where the schooling cycle is completed (childhood location).[27] According to this assumption, childhood exposure effects are better described by the region of birth than that of residence. As mentioned in section 4, to compare regions both across time and space, the rank-rank slope is computed using national ranks. The estimated intergenerational regression coefficient, the intergenerational correlation coefficients and the rank-rank slopes are displayed in Figure 1 (see also Table A3 in the Appendix). Consistently with national data shown in Table 3, we observe a decline in persistence from the period prior to World War II to the youngest cohorts in most of the regions, although with some degree of variability. The most dynamic regions are concentrated in the Northern and Central areas of Italy. Emilia-Romagna, Marche and Umbria show a strong decrease in persistence over time, which is in contrast to the evolution of the regions of the South. Indeed, mobility estimates suggest at best a slow decrease over time in Sicily, Campania and Calabria.

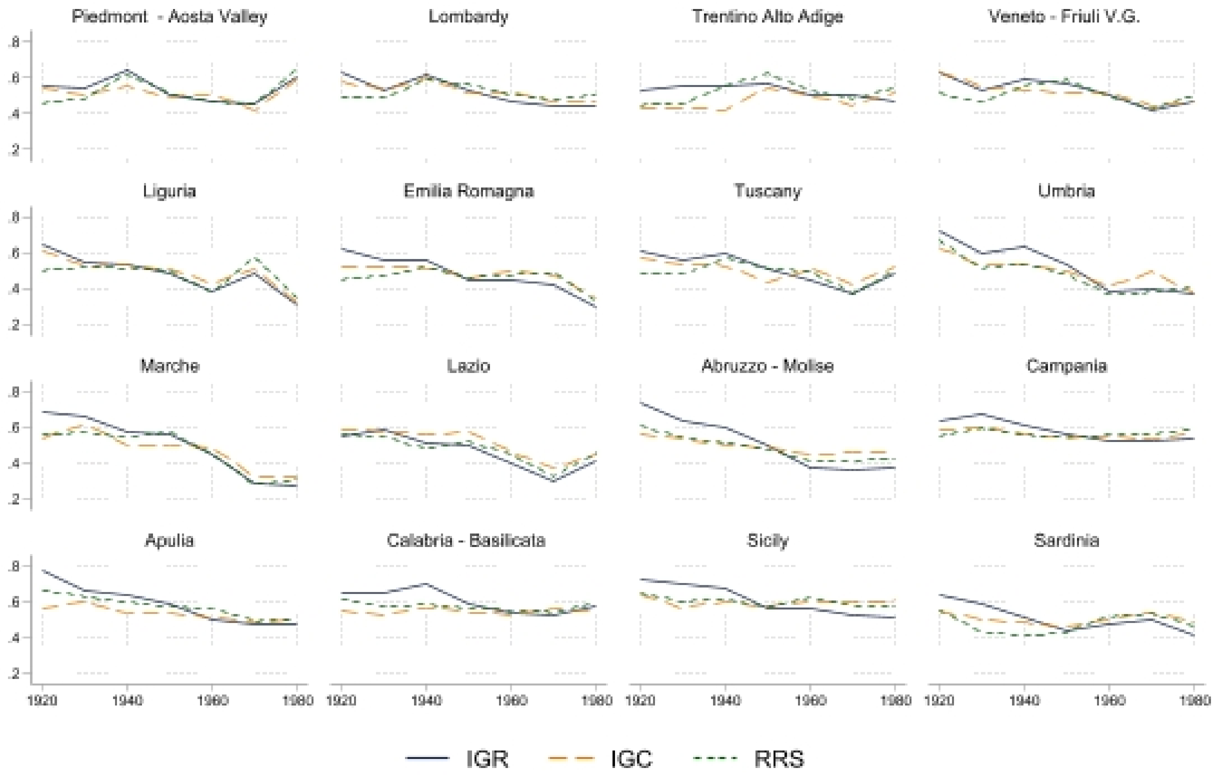
In absolute terms, the socio-economic background tend to be stronger in the South, especially in Sicily, Calabria and Campania. This result is robust to the three specifications selected, but it is strongest when considering the intergenerational regression coefficient. Indeed, Figure 1 shows that in Sicily, in Calabria and in Campania persistence is the highest in almost all the cohorts considered. Results that are more heterogeneous are obtained factoring out variance and controlling for changes in the marginal distribution of parents and children education, suggesting a role for educational inequality in explaining the observed pattern. There are important exceptions in the regions of the South. The case of Sardinia seems at odds with the rest of the Southern regions as its mobility is closer to the one of the most mobile regions. As

[26]Due to the small sample size of Aosta Valley, Molise, Basilicata and Friuli Venezia Giulia, we merge them to Piedmont, Abruzzo, Calabria and Veneto respectively, as they are neighboring regions with similar characteristics. Moreover, we delete children born abroad that account for almost 10% of the sample in the 1980 cohort.

[27]We do not have data on the geographic location of the child at the age of childhood. However, the portion of children living in a region different from the region of birth is around 10% in the last cohort and between 15 % and 20% in the older cohorts. Overall, taking into account inter-regional movements does not change the main results of Figure 1.

suggested by Bertola and Sestito (2011), in the last century Sardinia may have benefited from a long lasting effect of the educational system of the Savoy's Kingdom. Another exception is Abruzzo whose mobility is closer to that of the central regions rather than that of the South.

Figure 1: Relative Mobility across Italian Regions



Notes: IGR is the intergenerational regression coefficient. IGC is the intergenerational correlation coefficient. RRS is the Rank-Rank slope. See Table A3 in the Appendix for further details.

In addition, findings suggest that mobility has reversed or flattened in some regions in the cohort of the 1980s. In Tuscany, Calabria, Lazio and Piedmont seems to have bounced back. However, we need to be cautious in concluding that mobility has worsened in these areas, as for the 1980 cohort we have too few observations. A reasonable conclusion points to the stagnation of mobility, a result that is also observed at the national level since the 1960s.[28] Overall, these findings suggest a substantial degree of heterogeneity in intergenerational mobility estimates in Italy.[29]

[28]We address here the issue of children's mobility within the country. The model is enriched with a dummy variable that accounts for mismatches between the child's birth region and the region of residence, an approach similar to that adopted by Barbieri et al. (2020). The coefficients tend to diminish, suggesting that the association of child-parent human capital is explained, at least partially, by internal mobility. The phenomenon of migrants characterized especially the regions of the South (Sicily, Calabria - Basilicata and Sardinia above all) in the post-war period. It is worth noting that the negative sign of the dummy variable for the older cohorts reversed for the youngest generations, indicating that those who migrate are no longer the poorly educated but rather the highly educated.

[29]We test whether the regional coefficients of each of our indicators are jointly equal and we reject the null, thereby reinforcing the idea that intergenerational mobility varies within the country.

To provide a better picture of the intergenerational transmission of human capital, we report the estimates of the expected rank of a child whose parent belongs to the 25th percentile of the parents education distribution (CER25). We predict the values of the expected rank at the regional level directly from the rank-rank regression based on national ranks. Because of this fixed national scale, this indicator is affected not only by the steepness of the rank-rank curve but also by the movements of this curve to the right or to the left. It may happen, indeed, that regions having the same slope register different CER25, likely due to the different evolution of human capital accumulation relative to the distribution of human capital at the national level (Heidrich, 2017).

Table 5: Conditional Expected Rank of Children with Parents at the 25th Percentile

	1920-29	1930-39	1940-49	1950-59	1960-69	1970-79	1980-92
Piedmont - Aosta Valley	0.433	0.407	0.361	0.391	0.384	0.371	0.305
Lombardy	0.453	0.429	0.366	0.378	0.396	0.407	0.39
Trentino-Alto Adige	0.373	0.382	0.337	0.332	0.347	0.403	0.375
Veneto - Friuli V.G.	0.371	0.36	0.33	0.334	0.373	0.411	0.416
Liguria	0.454	0.42	0.407	0.407	0.446	0.385	0.394
Emilia-Romagna	0.396	0.414	0.399	0.425	0.41	0.418	0.478
Tuscany	0.399	0.397	0.347	0.383	0.409	0.445	0.395
Umbria	0.308	0.359	0.358	0.403	0.425	0.441	0.392
Marche	0.33	0.35	0.374	0.374	0.431	0.484	0.483
Lazio	0.358	0.396	0.426	0.399	0.403	0.459	0.419
Abruzzo - Molise	0.345	0.369	0.421	0.439	0.456	0.457	0.447
Campania	0.337	0.329	0.33	0.322	0.314	0.319	0.351
Apulia	0.326	0.298	0.328	0.332	0.337	0.39	0.406
Calabria - Basilicata	0.274	0.315	0.341	0.354	0.376	0.39	0.399
Sicily	0.313	0.334	0.343	0.332	0.323	0.35	0.322
Sardinia	0.332	0.372	0.387	0.375	0.365	0.361	0.406

Results of absolute upward mobility shown in Table 5 confirm the pattern observed above for measures of relative mobility. [30] However, the conditional expected rank allows us to detect some improvements for Calabria and Apulia. Indeed, the CER25 has increased constantly in these two regions across decades. This result would have been missed had we used only measures of relative mobility. It has to be stressed, however, that relative mobility is still low as illustrated in Figure 1 and in Table A3, therefore the equality of opportunities for children coming from low educated families is still far from being achieved.

Regarding the Northwest regions, Piedmont, Lombardy and Liguria experienced both high upward and relative mobility compared to the rest of the country in the old cohorts. This might reflect the economic and cultural role of this area in the first part of the XX century. After WWII upward mobility has stagnated or decreased in these regions, and eventually converged towards the mean.[31]

[30] Correlations between the rank-rank slope and the CER25 show a high negative relationship across all cohorts ($\rho = -0.71$), as expected. In general, upward mobility is negatively correlated with all the indicators of persistence in our analysis.

[31] In Piedmont, upward mobility collapses between the 1970s and the 1980s while all the measures of persistence

The geographical heterogeneity of intergenerational mobility, however, has not an equal impact across the children with different background. The impact of the birthplace region seems more important for children whose parent belongs to the 25th percentile than for those whose parent belongs to the 75th percentile (CER75). Indeed, Table 6 shows, across all cohorts of birth, that the standard deviation of the regional CER25 is systematically higher than the standard deviation of the expected ranks of children with parents in the upper-tail of the distribution. This confirms Chetty et al. (2014) result that location matters more for children coming from disadvantaged background.

Table 6: Dispersion across Regions of CER25 and CER75

	Std. Dev. CER25	Std. Dev. CER75
1920-29	0.052	0.030
1930-39	0.040	0.029
1940-49	0.032	0.025
1950-59	0.035	0.024
1960-69	0.040	0.025
1970-79	0.047	0.038
1980-92	0.055	0.051

6 Mediating Factors

In this section, we exploit the heterogeneity across Italian regions to study how education mobility correlates with a number of socio-economic variables at the regional level, without necessarily making causal claims. Indeed, it must be stressed that, because of endogeneity problems, all these socio-economic variables must not be interpreted as causal determinants of educational mobility. However, our findings can provide useful insights for future research on the topic.

We focus on the cohort of the 1980s, selecting the indicators from the Italian National Institute of Statistics (ISTAT) and other sources. The choice of the indicators is aimed at describing the prevailing economic and social conditions of the regions when the children were around 14 or 15 years old.[32] Thus, whenever possible, the indicators are averaged over the late 1990s and the first decade of the 2000s. Given the limited number of observations, we illustrate graphically the relationships between the intergenerational persistence and some of the more interesting mediating factors (Figure 2). Table A4 in the Appendix provides the

strongly increase, suggesting that persistence is strong in the upper-part of the distribution. In contrast, Liguria experiences significant downward mobility as the CER25 remains stable while relative mobility grows significantly.

[32] After having concluded the three-years lower-secondary school, Italian students choose whether to enroll into liceo, an academic oriented high school, into a technical oriented high school. This is a crucial choice for the students' career as data from the Ministry of Public Education, University and Research referred to 2016 show that students coming from liceo have more than twice the probability of enrolling into university than those coming from technical schools - 74% against 33% (MIUR, 2017).

pairwise correlation coefficients between the measures of educational mobility (IGC, IGE, RRS, CER25) and all the socio-economic variables considered.

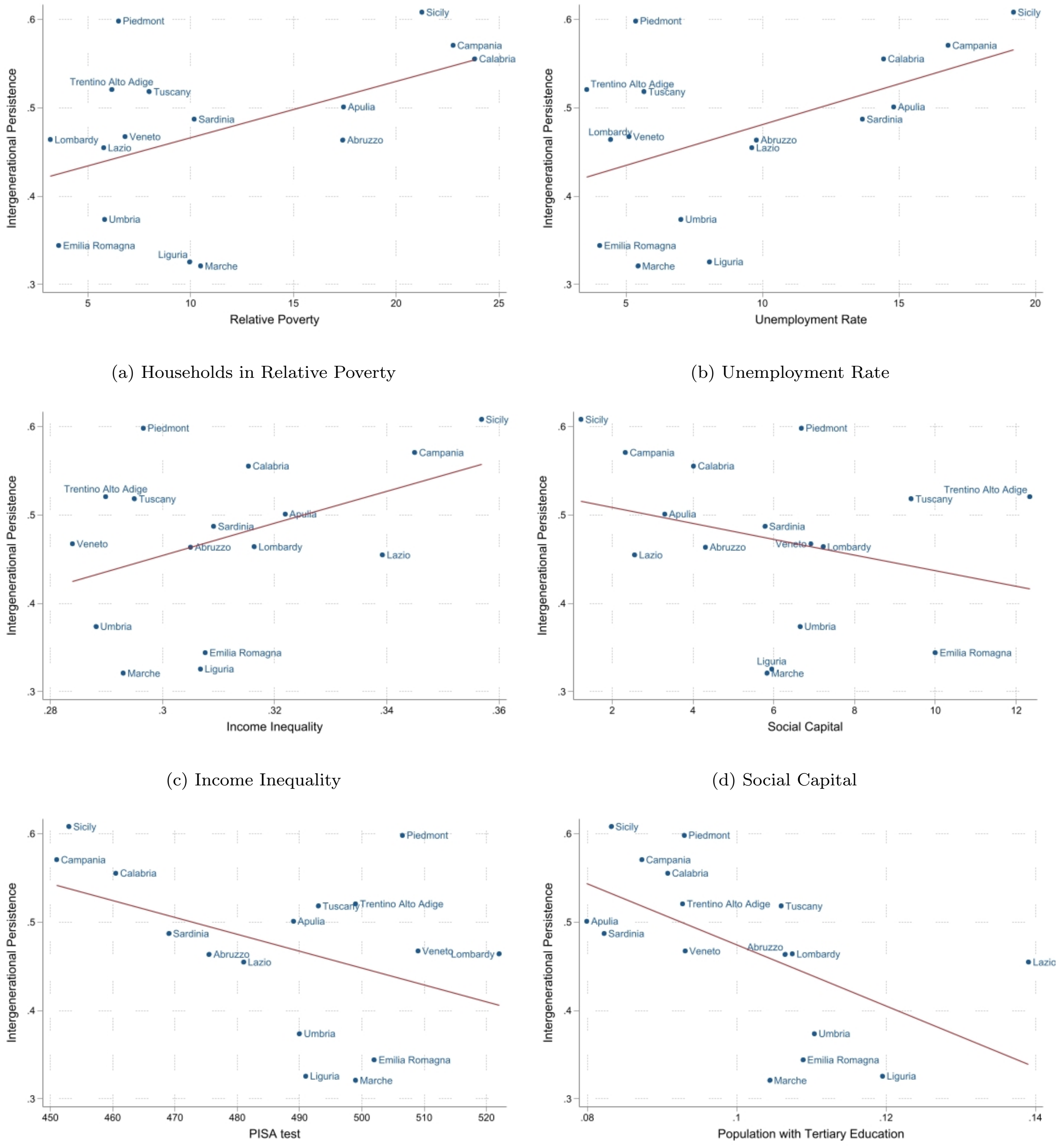
We organize the socio-economic indicators into two groups. The first g roup comprises economic variables such as income inequality, GDP per capita, unemployment rate and an index of relative poverty. The second group contains social indicators that give a picture of the environment outside the stricter family circle. The idea is that human capital accumulation is, along important dimensions, socially determined (Durlauf and Seshadri, 2018). A more advantaged surrounding might be associated with higher cognitive and non-cognitive abilities creating a beneficial synergy with learning at school, thereby improving educational attainment. This creates a strong relationship between the communities in which children develop and human capital accumulation. Thus, we consider the following variables: various indexes of social capital, which proxy the strength of social networks and community involvement in the region; indexes of the quality of institutions and rule of law; proxies for the quality of K-12 school system such as PISA test scores at the regional level, the fraction of students on teachers, the average class size and various measures of public education expenditure per student; population aged over 15 with tertiary education (% total regional population).

As for the economic variables, the relationship between intergenerational persistence and inequality has a special interest. A positive (although not significant) correlation between the intergenerational persistence measures and the degree of cross-sectional income inequality as measured by the GINI coefficient exists across Italian regions, consistent with the "Great Gatsby curve" documented across countries (Corak, 2013). It must be underlined that not considering Piedmont (whose mobility estimated values stand out as outliers in the 1980 cohorts), the correlation becomes statistically significant (see Figure 2). The share of households in relative poverty appears to be positively and significatively correlated with intergenerational persistence, suggesting that bottom tail persistence can be explained also by credit constraints. Note also that the correlation between the poverty index and CER25 is negative as expected.[33] Finally, the unemployment rate appears to be positively and significatively correlated with the persistence measures. As expected, the correlation is instead negative and significant with CER25.

The relationship between intergenerational persistence and GDP per capita deserves a particular attention. From Figure 3 this relationship appears to be U-shaped. Thus, both low GDP per capita and high GDP per capita appear to be associated to high persistence. It is commonly accepted that financial constraints lower intergenerational mobility, mostly for families toward the bottom of the income distribution. This might explain why we find low mobility values in the poorest regions. On the other hand, according to a recent literature on the topic, the efficiency of investments in child human capital increases with income (e.g. Becker et al., 2018). This predicts that the intergenerational persistence of human capital grows stronger as incomes

[33]The government may play a role in improving mobility by introducing a more progressive public investment in human capital or subsidizing education, as stressed by Solon (1999, 2004). We find that more generous scholarships per recipient student are (not significantly) associated with lower educational persistence (see Table A4 in the Appendix).

Figure 2: Correlations between the IGC and some Mediating Factors



(a) Households in Relative Poverty

(b) Unemployment Rate

(c) Income Inequality

(d) Social Capital

(e) PISA Test

(f) Population with Tertiary Education

Notes: Piedmont, Veneto, Abruzzo and Calabria are merged with Aosta Valley, Friuli Venezia Giulia, Molise and Basilicata, respectively. IGC is the intergenerational correlation coefficient for the 1980-cohort. Panel a) index of social capital in 2003; b) PISA reading performance in 2009; c) Gini coefficient between 2002 and 2010; d) population older than 15 with tertiary education between 2004 and 2010 ; e) share of households in relative poverty between 2002 and 2010; f) unemployment rate between 1995 and 2010. Further details are provided in Table A4 and Table A5 in the Appendix.

rise (van der Weide et al., 2021).

As for the second group of variables, we find that the various indexes of social capital correlate negatively with education persistence (as expected). However, these correlations (apart from the corruption index) are mostly not significant. As for the quality of K-12 school system, although in Italy education policies are highly centralized, an important variation in the PISA test scores at regional level is observed, pointing towards the existence of school inequalities across regions. As expected, PISA test scores correlate negatively with the intergenerational persistence measures (IGC, IGE, RRS), and the correlation is significative with IGC (see Table A4 in the Appendix). We consider also the expenditures in public non-tertiary education per student at the regional level. There is low variation between the top region (Trentino-Alto Adige) and the bottom region (Campania) and most of the regions have values of the spending around the mean, as expected given the centralized education system. Thus, we do not find correlation between expenditures and educational persistence. A significant negative correlation is observed instead between the intergenerational persistence measures and the percentage of graduates in the region, confirming the expectation that a "more educated" environment might favour educational investments (see Figure 2).

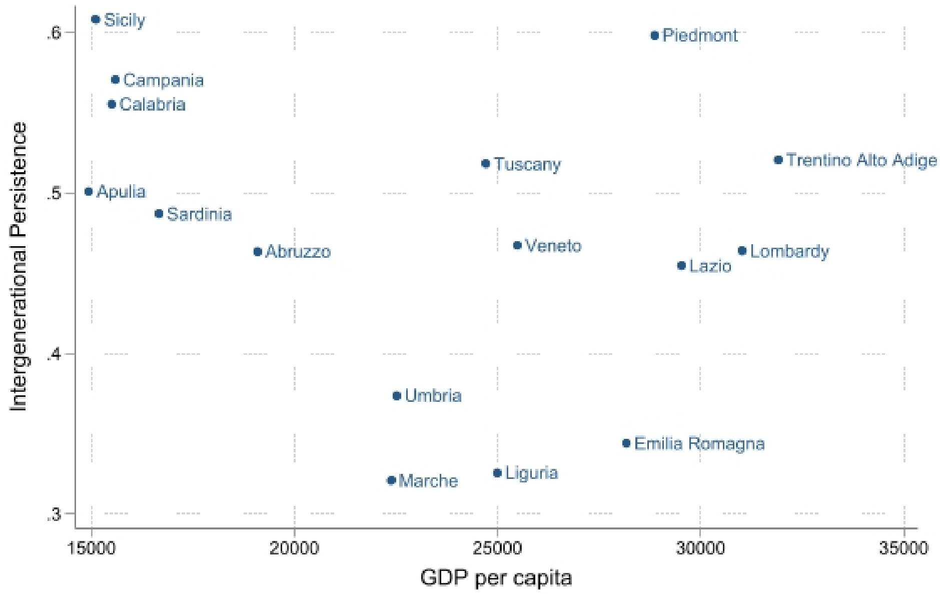


Figure 3: IGC in the 1980s and GDP per capita (1995-2010)

7 Conclusion

An important stream of new research on intergenerational social mobility investigates the geographical variation of various measures of this variable within countries. This paper contributes to this debate by studying the temporal evolution of educational attainment by parental background in Italian regions across seven birth cohorts. We show that in the last fifty years mobility increased in almost all regions, although for the youngest cohorts this decline seems to have ended. Northeast regions and central regions are the most mobile, followed by Northwest and South regions. This pattern is robust to alternative measures of relative mobility. As expected, we find that - at least for the youngest cohorts - there is a negative correlation between mobility and economic factors such as unemployment and poverty. This is a clear evidence that credit constraints explain bottom tail persistence in education. A positive correlation between the intergenerational education mobility and the degree of inequality as measured by the GINI coefficient exists across Italian regions, consistent with the "Great Gatsby curve" documented across countries. In addition, we find a positive association between mobility, some indexes of social capital and the number of graduates in the regions, suggesting that human capital accumulation is, along important dimensions, socially determined, as far as social interactions play an important role in the formation of personality (Durlauf and Seshadri, 2018). Finally, although in Italy education policies are highly centralized, an important variation in the PISA test scores at regional level is observed, pointing towards the existence of school inequalities across regions. Measures of school quality (PISA test scores) are positively correlated with some regional educational mobility measures.

References

Acciari, P., A. Polo, and G. L. Violante (2022). And Yet It Moves: Intergenerational Mobility in Italy. *American Economic Journal: Applied Economics 14*(3), 118–63.

Arenas, A. and J. Hindriks (2021). Intergenerational Mobility and Unequal School Opportunity. *The Economic Journal 131*(635), 1027–1050.

Aydemir, A. B. and H. Yazici (2019). Intergenerational Education Mobility and the Level of Development. *European Economic Review 116*, 160–185.

Baffigi, A., L. Cannari, and G. D'Alessio (2016). Cinquant'anni di indagini sui bilanci delle famiglie italiane: Storia, metodi, prospettive. *Bank of Italy Occasional Paper* (368).

Baldissera, A. and F. Cornali (2020). Geography of Human Capital in Italy: a Comparison between Macro-Regions. *Modern Italy 25*(3), 261–277.

Ballarino, G., D. Checchi, et al. (2006). *Sistema scolastico e disuguaglianza sociale: scelte individuali e vincoli strutturali.* Il Mulino.

Barbieri, T., F. Bloise, and M. Raitano (2020). Intergenerational Earnings Inequality: New Evidence from Italy. *Review of Income and Wealth 66*(2), 418–443.

Becker, G. S., S. D. Kominers, K. M. Murphy, and J. L. Spenkuch (2018). A Theory of Intergenerational Mobility. *Journal of Political Economy 126*(S1), S7–S25.

Becker, G. S. and N. Tomes (1976). Child Endowments and the Quantity and Quality of Children. *Journal of political Economy 84*(4, Part 2), S143–S162.

Becker, G. S. and N. Tomes (1979). An Equilibrium Theory of the Distribution of Income and Intergenerational Mobility. *Journal of political Economy 87*(6), 1153–1189.

Bell, B., J. Blundell, and S. Machin (2022). Where is the Land of Hope and Glory? the Geography of Intergenerational Mobility in England and Wales. *The Scandinavian Journal of Economics*.

Bertola, G. and P. Sestito (2011). A Comparative Perspective on Italy's Human Capital Accumulation. *Bank of Italy Economic History Working Paper* (6).

Black, S. E., P. J. Devereux, et al. (2011). Recent Developments in Intergenerational Mobility. *Handbook of Labor Economics 4*, 1487–1541.

Blanden, J. and S. Machin (2004). Educational Inequality and the Expansion of Uk Higher Education. *Scottish journal of political economy 51*(2), 230–249.

Bratti, M., D. Checchi, and A. Filippin (2007). Geographical Differences in Italian Students' Mathematical Competencies: Evidence from PISA 2003. *Giornale degli Economisti e Annali di Economia*, 299–333.

Brunetti, I. (2021). Istruzione e mobilità intergenerazionale: un'analisi dei dati italiani. *Sinappsi 10*(3), 48–63.

Cannari, L. and G. D'Alessio (2018). Education, Income and Wealth: Persistence across Generations in Italy. *Questioni di Economia e Finanza* (476).

Card, D., C. Domnisoru, and L. Taylor (2022). The Intergenerational Transmission of Human Capital: Evidence from the Golden Age of Upward Mobility. *Journal of Labor Economics 40*(S1), S39–S95.

Carradore, M. (2018). A Synthetic Indicator to Measure Social Capital in the Different Italian Regions: A Before and After Comparison of the Economic Crisis. *Athens Journal of Social Sciences 5*(3), 313–334.

Castelló-Climent, A. and R. Doménech (2021). Human Capital and Income Inequality Revisited. *Education Economics 29*(2), 194–212.

Checchi, D., C. Fiorio, and M. Leonardi (2006). Sessanta anni di istruzione scolastica in Italia. *Rivista di Politica Economica*, 285–318.

Checchi, D., C. V. Fiorio, and M. Leonardi (2013). Intergenerational Persistence of Educational Attainment in Italy. *Economics Letters 118*(1), 229–232.

Chetty, R. and N. Hendren (2018). The Impacts of Neighborhoods on Intergenerational Mobility I: Childhood Exposure Effects. *The Quarterly Journal of Economics 133*(3), 1107–1162.

Chetty, R., N. Hendren, P. Kline, and E. Saez (2014). Where Is the Land of Opportunity? the Geography of Intergenerational Mobility in the United States. *The Quarterly Journal of Economics 129*(4), 1553–1623.

Chevalier, A., K. Denny, and D. McMahon (2009). A Multi-country Study of Inter-generational Educational Mobility. In *Education and inequality across Europe*, pp. 260–281. Edward Elgar Publishing.

Connolly, M., M. Corak, and C. Haeck (2019). Intergenerational Mobility between and within Canada and the United States. *Journal of Labor Economics 37*(S2), S595–S641.

Corak, M. (2013). Income Inequality, Equality of Opportunity, and Intergenerational Mobility. *Journal of Economic Perspectives 27*(3), 79–102.

Deutscher, N. and B. Mazumder (2021). Measuring Intergenerational Income Mobility: A Synthesis of approaches. *FRB of Chicago Working Paper No. WP-2021-09*.

Durlauf, S. N. and A. Seshadri (2018). Understanding the Great Gatsby Curve. *NBER Macroeconomics Annual 32*(1), 333–393.

Emran, M. S., W. Greene, and F. Shilpi (2018). When Measure Matters Coresidency, Truncation Bias, and Intergenerational Mobility in Developing Countries. *Journal of Human Resources 53*(3), 589–607.

Eriksen, J. and M. D. Munk (2020). The Geography of Intergenerational Mobility—Danish Evidence. *Economics Letters 189*, 109024.

Fletcher, J. and J. Han (2019). Intergenerational Mobility in Education: Variation in Geography and Time. *Journal of Human Capital 13*(4), 585–634.

Francesconi, M. and C. Nicoletti (2006). Intergenerational Mobility and Sample Selection in Short Panels. *Journal of Applied Econometrics 21*(8), 1265–1293.

Giancola, O., L. Benadusi, and R. Fornari (2010). Così vicine, così lontane: la questione dell'equità scolastica nelle regioni italiane. *Scuola Democratica: Learning for Democracy* (1), 52–79.

Glomm, G. and B. Ravikumar (1992). Public versus Private Investment in Human Capital: Endogenous Growth and Income Inequality. *Journal of political economy 100*(4), 818–834.

Glomm, G. and B. Ravikumar (2003). Public Education and Income Inequality. *European Journal of Political Economy 19*(2), 289–300.

Goux, D. and E. Maurin (2007). Close Neighbours Matter: Neighbourhood Effects on Early Performance at School. *The Economic Journal 117*(523), 1193–1215.

Güell, M., M. Pellizzari, G. Pica, and J. V. Rodríguez Mora (2018). Correlating Social Mobility and Economic Outcomes. *The Economic Journal 128*(612), F353–F403.

Güell, M., J. V. Rodríguez Mora, and C. Telmer (2007). Intergenerational Mobility and the Informative Content of Surnames.

Heidrich, S. (2017). Intergenerational Mobility in Sweden: a Regional Perspective. *Journal of Population Economics 30*(4), 1241–1280.

Heineck, G. and R. T. Riphahn (2009). Intergenerational Transmission of Educational Attainment in Germany in the Last Five Decades. *Jahrbücher für Nationalökonomie und Statistik 229*(1), 36–60.

Hertz, T., T. Jayasundera, P. Piraino, S. Selcuk, N. Smith, and A. Verashchagina (2008). The Inheritance of Educational Inequality: International Comparisons and Fifty-Year Trends. *The BE Journal of Economic Analysis & Policy 7*(2).

Hilger, N. G. (2015). The Great Escape: Intergenerational Mobility in the United States since 1940.

INVALSI (2011). *Le competenze in scienze, lettura e matematica degli studenti quindicenni: Rapporto nazionale PISA 2009*. INVALSI.

INVALSI-MIPA (2005). ASPIS III - linea di ricerca sull'analisi della spesa per istruzione.

Karlson, K. and R. Landersø (2021). The Making and unmaking of Opportunity: Educational Mobility in 20th Century-Denmark.

Mejía, D. and M. St-Pierre (2008). Unequal Opportunities and Human Capital Formation. *Journal of Development Economics 86*(2), 395–413.

MIUR (2004). *La scuola statale: sintesi dei dati. Anno scolastico 2003/2004*. Ministero dell'Istruzione dell'Università e della Ricerca.

MIUR (2006). *L'università in cifre 2006*. Ministero dell'Istruzione dell'Università e della Ricerca.

MIUR (2017). Gli immatricolati nell'a.a. 2016/2017 il passaggio dalla scuola all'università dei diplomati nel 2016.

Munoz, E. and M. Siravegna (2021). When Measure Matters: Coresidence Bias and Intergenerational Mobility Revisited. *Available at SSRN 3969270*.

Nannicini, T., A. Stella, G. Tabellini, and U. Troiano (2013). Social Capital and Political Accountability. *American Economic Journal: Economic Policy 5*(2), 222–250.

Narayan, A., R. Van der Weide, A. Cojocaru, C. Lakner, S. Redaelli, D. G. Mahler, R. G. N. Ramasubbaiah, and S. Thewissen (2018). *Fair Progress?: Economic Mobility across Generations Around the World*. World Bank Publications.

Nifo, A. and G. Vecchione (2014). Do Institutions Play a Role in Skilled Migration? the Case of Italy. *Regional studies 48*(10), 1628–1649.

Sauer, P. and M. Zagler (2012). Economic Growth and the Quantity and Distribution of Education: a Survey. *Journal of Economic Surveys 26*(5), 933–951.

Solon, G. (1999). Intergenerational Mobility in the Labor Market. In *Handbook of Labor Economics*, Volume 3, pp. 1761–1800. Elsevier.

Solon, G. (2004). A Model of Intergenerational Mobility Variation over Time and Place. *Generational income mobility in North America and Europe*, 38–47.

van der Weide, R., C. Lakner, D. G. Mahler, A. Narayan, and R. Ramasubbaiah (2021). Intergenerational Mobility Around the World. *Development Research*.

8 Appendix

Table A1: Indicators of Relative Mobility with Father's and Mother's Education as Parental Reference

	IGR Father	IGC Father	RRS Father	Obs.	IGR Mother	IGC Mother	RRS Mother	Obs.
1920-29	0.654	0.571	0.539	6291	0.695	0.507	0.504	6282
	(0.017)	(0.015)	(0.014)		(0.02)	(0.015)	(0.015)	
1930-39	0.593	0.544	0.535	11232	0.648	0.496	0.493	11276
	(0.012)	(0.011)	(0.011)		(0.014)	(0.011)	(0.012)	
1940-49	0.577	0.528	0.533	14370	0.625	0.492	0.499	14459
	(0.011)	(0.01)	(0.01)		(0.012)	(0.01)	(0.01)	
1950-59	0.525	0.509	0.511	14933	0.544	0.474	0.48	15016
	(0.009)	(0.009)	(0.01)		(0.011)	(0.009)	(0.01)	
1960-69	0.464	0.499	0.488	13558	0.465	0.459	0.445	13650
	(0.009)	(0.01)	(0.01)		(0.01)	(0.01)	(0.011)	
1970-79	0.439	0.473	0.452	5562	0.462	0.465	0.437	5607
	(0.014)	(0.015)	(0.015)		(0.015)	(0.015)	(0.016)	
1980-92	0.429	0.469	0.461	2709	0.446	0.479	0.466	2876
	(0.024)	(0.026)	(0.024)		(0.022)	(0.023)	(0.022)	

Notes: We estimate the regression using sample weights. Robust standard errors are in parentheses. Control variables: gender and region of birth of the child, year of the survey. Source: SHIW Historical Archive.

Table A2: Average Years of Schooling of Children and Parents and Number of Observations by Region

		1920-29	1930-39	1940-49	1950-59	1960-69	1970-79	1980-92
Piedmont -	Child	7.02	7.54	9.51	11.12	11.42	11.73	12.72
Aosta Valley	Parent	4.18	4.86	6.01	6.76	7.57	8.16	10.31
	Obs.	*431*	*741*	*837*	*804*	*871*	*438*	*152*
Lombardy	Child	7.32	7.94	9.60	11.35	12.05	12.86	14.05
	Parent	3.89	5.18	6.28	7.01	8.16	9.33	11.61
	Obs.	*570*	*1,084*	*1,236*	*1,269*	*1,337*	*530*	*257*
Trentino-Alto Adige	Child	6.75	7.52	8.67	10.55	11.05	12.72	14.00
	Parent	5.36	5.47	5.75	6.55	7.29	8.87	11.69
	Obs.	124	230	379	356	312	149	65
Veneto -	Child	5.88	6.45	8.35	10.27	11.17	12.34	14.10
Friuli V.G.	Parent	3.44	4.15	5.23	6.06	7.08	8.66	10.84
	Obs.	*742*	*1,112*	*1,503*	*1,256*	*1,064*	*396*	*173*
Liguria	Child	7.78	8.19	9.83	11.69	12.20	13.35	13.08
	Parent	4.53	5.38	6.53	7.52	8.41	9.94	10.94
	Obs.	*226*	*429*	*424*	*445*	*530*	*130*	*65*
Emilia-Romagna	Child	5.80	7.12	9.15	11.24	12.08	13.35	14.63
	Parent	2.89	3.89	5.07	6.46	8.16	10.04	12.05
	Obs.	*544*	*865*	*1,044*	*1,018*	*833*	*346*	*169*
Tuscany	Child	6.26	7.23	8.92	10.72	11.92	12.84	13.91
	Parent	3.42	4.34	5.59	6.10	7.84	9.35	11.12
	Obs.	*528*	*864*	*1,079*	*893*	*733*	*304*	*138*
Umbria	Child	4.53	5.75	7.78	10.15	11.10	12.55	13.23
	Parent	2.02	2.69	3.57	4.73	6.41	8.82	10.52
	Obs.	*233*	*408*	*472*	*486*	*372*	*123*	*82*
Marche	Child	4.68	6.13	8.34	10.50	11.40	12.83	14.44
	Parent	1.99	3.13	4.19	5.47	6.20	8.88	11.49
	Obs.	*354*	*565*	*674*	*650*	*428*	*133*	*87*
Lazio	Child	5.29	7.45	9.39	11.06	11.63	13.00	14.28
	Parent	2.78	4.44	5.55	6.46	7.62	9.87	11.76
	Obs.	*270*	*535*	*757*	*830*	*776*	*274*	*177*
Abruzzo -	Child	5.22	6.38	8.97	10.97	11.86	13.00	14.44
Molise	Parent	2.29	3.05	4.17	5.35	6.82	8.94	11.49
	Obs.	*278*	*526*	*554*	*562*	*500*	*170*	*94*
Campania	Child	5.35	6.04	7.77	9.30	9.80	10.41	12.41
	Parent	3.06	3.48	4.34	4.93	5.73	6.67	9.03
	Obs.	*521*	*998*	*1,540*	*1,797*	*1,568*	*540*	*378*
Apulia	Child	5.27	5.46	7.63	9.41	10.13	11.58	13.30
	Parent	2.32	3.17	3.91	4.72	5.58	7.20	9.69
	Obs.	*421*	*773*	*1,186*	*1,215*	*1,066*	*435*	*269*
Calabria -	Child	4.20	5.18	7.42	9.46	10.58	11.97	13.76
Basilicata	Parent	2.29	2.52	3.40	4.28	5.38	7.60	10.06
	Obs.	*364*	*740*	*821*	*928*	*709*	*226*	*127*
Sicily	Child	5.40	5.99	8.26	9.65	10.36	11.28	12.41
	Parent	3.02	3.08	4.46	5.27	6.15	7.31	9.89
	Obs.	*495*	*956*	*1,267*	*1,462*	*1,157*	*455*	*276*
Sardinia	Child	4.53	5.91	7.87	9.54	10.49	11.66	13.49
	Parent	1.79	2.74	3.60	4.69	5.80	7.93	10.24
	Obs.	*202*	*448*	*585*	*664*	*495*	*212*	*113*

Notes: The reference category for parental education is the maximum years of schooling of both parents. Source: SHIW Historical Archive.

Table A3: Relative Mobility across Italian Regions

		1920-29	1930-39	1940-49	1950-59	1960-69	1970-79	1980-92
Piedmont -	IGR	0.562	0.542	0.642	0.5	0.469	0.454	0.604
Aosta Valley	IGC	0.539	0.506	0.558	0.495	0.508	0.421	0.598
	RRS	0.46	0.486	0.622	0.514	0.465	0.454	0.653
Lombardy	IGR	0.63	0.529	0.621	0.529	0.464	0.443	0.444
	IGC	0.576	0.537	0.6	0.514	0.519	0.468	0.464
	RRS	0.488	0.488	0.592	0.563	0.508	0.483	0.508
Trentino-Alto Adige	IGR	0.532	0.559	0.56	0.569	0.51	0.503	0.464
	IGC	0.432	0.43	0.423	0.548	0.498	0.448	0.521
	RRS	0.449	0.456	0.554	0.625	0.532	0.484	0.547
Veneto - Friuli V.G.	IGR	0.63	0.528	0.596	0.567	0.5	0.422	0.471
	IGC	0.636	0.551	0.532	0.52	0.512	0.445	0.467
	RRS	0.513	0.463	0.559	0.589	0.499	0.431	0.503
Liguria	IGR	0.642	0.547	0.53	0.482	0.381	0.483	0.308
	IGC	0.613	0.527	0.53	0.506	0.431	0.505	0.326
	RRS	0.502	0.518	0.513	0.498	0.378	0.572	0.335
Emilia-Romagna	IGR	0.623	0.559	0.563	0.444	0.443	0.425	0.293
	IGC	0.516	0.527	0.514	0.46	0.496	0.476	0.344
	RRS	0.45	0.47	0.518	0.461	0.476	0.488	0.329
Tuscany	IGR	0.609	0.558	0.592	0.504	0.447	0.374	0.478
	IGC	0.566	0.539	0.527	0.428	0.511	0.424	0.518
	RRS	0.478	0.483	0.568	0.512	0.495	0.375	0.501
Umbria	IGR	0.723	0.599	0.634	0.534	0.379	0.392	0.373
	IGC	0.626	0.528	0.539	0.494	0.417	0.491	0.374
	RRS	0.666	0.514	0.539	0.476	0.366	0.379	0.408
Marche	IGR	0.691	0.658	0.568	0.558	0.447	0.282	0.276
	IGC	0.54	0.614	0.501	0.501	0.485	0.324	0.321
	RRS	0.563	0.569	0.544	0.574	0.454	0.281	0.308
Lazio	IGR	0.549	0.587	0.508	0.504	0.404	0.303	0.414
	IGC	0.591	0.578	0.561	0.574	0.463	0.37	0.455
	RRS	0.558	0.549	0.478	0.523	0.444	0.328	0.456
Abruzzo - Molise	IGR	0.742	0.63	0.595	0.498	0.372	0.366	0.374
	IGC	0.563	0.532	0.5	0.483	0.445	0.459	0.464
	RRS	0.606	0.544	0.514	0.478	0.414	0.416	0.422
Campania	IGR	0.632	0.673	0.612	0.563	0.525	0.52	0.532
	IGC	0.583	0.602	0.565	0.539	0.55	0.534	0.571
	RRS	0.554	0.594	0.556	0.551	0.556	0.564	0.588
Apulia	IGR	0.775	0.668	0.641	0.589	0.504	0.471	0.48
	IGC	0.561	0.604	0.537	0.535	0.515	0.487	0.501
	RRS	0.668	0.631	0.599	0.572	0.566	0.494	0.506
Calabria - Basilicata	IGR	0.654	0.655	0.696	0.594	0.539	0.528	0.577
	IGC	0.551	0.532	0.57	0.542	0.532	0.559	0.555
	RRS	0.619	0.572	0.588	0.567	0.556	0.543	0.593
Sicily	IGR	0.724	0.697	0.671	0.569	0.559	0.525	0.515
	IGC	0.64	0.567	0.6	0.572	0.606	0.595	0.608
	RRS	0.647	0.602	0.619	0.57	0.625	0.583	0.581
Sardinia	IGR	0.645	0.586	0.519	0.445	0.475	0.496	0.408
	IGC	0.547	0.505	0.483	0.46	0.504	0.542	0.487
	RRS	0.553	0.434	0.412	0.43	0.519	0.535	0.466

Notes: IGR is the intergenerational beta coefficient as in regression (1). IGC is the intergenerational correlation coefficient estimated using regression (2). RRS is the rank-rank slope. Control variables: gender and year of the survey. All coefficients are significant at 1% with robust standard errors. Source: SHIW Historical Archive.

Table A4: Pairwise Correlations between Measures of Relative and Absolute Mobility and Socio-economic Variables

	IGC	IGE	RRS	CER25
Economic variables				
Unemployment rate	0.5027**	0.3849	0.3732	-0.3428
Household in relative poverty (% total household)	0.4820*	0.4073	0.3695	-0.2271
Gini Index	0.4193	0.276	0.3073	-0.3266
Population with tertiary education (% regional population)	-0.5833**	-0.5287**	-0.5443**	0.3801
Social capital				
Index of Social Capital	-0.2886	-0.2407	-0.2064	0.2064
N. of people registered with EPS / 1,000 people	-0.2363	-0.1866	-0.2443	0.1916
N. of EPS associations/1,000 people	-0.2326	-0.217	-0.2744	0.1598
N. of people registered with CONI / 1,000 people	-0.5228**	-0.5017**	-0.4496	0.2976
N. of CONI associations/1,000 people	-0.4001	-0.416	-0.3603	0.2404
N. of non profit organizations/ regional population	-0.173	-0.2016	-0.1249	0.0693
N. of non-sport daily newspapers sold/1,000 people	-0.3766	-0.36	-0.3053	0.1084
N. of employees in non profit organizations/ regional population	-0.2843	-0.2605	-0.1883	0.0727
Corruption Index	-0.4911*	-0.4082	-0.4339*	0.4099
Regulatory Index	-0.3698	-0.3278	-0.2875	0.2448
Government Index	-0.3946	-0.2364	-0.2387	0.1674
Rule of Law Index	-0.3182	-0.2166	-0.2005	0.232
Institutional Quality Index	-0.4129	-0.2989	-0.2837	0.2697
School quality				
Test PISA reading competence	-0.4256	-0.2776	-0.2729	0.2456
Test PISA reading competence (only Liceo)	-0.4646*	-0.3418	-0.3228	0.2614
Ratio student/Class Upper Secondary	0.3948	0.2771	0.3231	-0.2056
Ratio students/teacher Upper Secondary	0.293	0.2334	0.2759	-0.2898
Education expenditures				
Expenditure per student (Kindergarten)	0.2758	0.2383	0.2718	0.0625
Expenditure per student (Primary education)	0.0398	0.0179	0.1126	-0.0727
Expenditure per student (Lower Secondary)	0.1715	0.1629	0.25	-0.1321
Expenditure per student (Upper secondary)	-0.0172	0.0071	0.0679	-0.0001
Total expenditure per student (Kindergaten to Upper Secondary)	0.0942	0.0794	0.164	-0.0451
Expenditure on university scholarships (per recipient student)	-0.3809	-0.3756	-0.3566	0.3945

Notes: *** p<.01, ** p<.05, * p<.1. Variables in bold format are the mediating factors displayed in Figure 2. The *Corruption Index* measures crimes against the Public Administration overruled by the federal authorities and the Golden-Picci Index. The *Rule of Law Index* summarizes data on crime against persons or property, magistrate productivity, trial times, tax evasion and shadow economy. The *Government Effectiveness* dimension measures the endowment of social and economic structures in Italian provinces and the administrative capability of regional governments in terms of health policies, waste management and environment. The *Regulatory Quality* concerns the degree of openness of the economy, the rate of firms mortality, indicators of business environment and business density. The *Institutional Quality Index* takes into account these four pillars, with also the *Voice and Accountability* dimension, whose components are already contained in other variables considered such as number of civic associations and INVALSI tests (cf. `https://sites.google.com/site/institutionalqualityindex/home?authuser=0` and see Nifo and Vecchione, 2014.)

Table A5: Source of Mediating Factors

Variables	Year	Source
Economic variables		
Unemployment rate	1995-2010	ISTAT
Household in relative poverty (% total household)	2002-2010	ISTAT
Gini Index	2002-2010	ISTAT
Population with tertiary education (% regional population)	2004-2010	ISTAT
Social Capital		
Index of Social Capital	2003	Carradore (2018)
N. of people registered with EPS / 1,000 people	1999	Nannicini et al. (2013)
N. of EPS associations/1,000 people	1999	Nannicini et al. (2013)
N. of people registered with CONI / 1,000 people	1999	Nannicini et al. (2013)
N. of CONI associations/1,000 people	1999	Nannicini et al. (2013)
N. of non profit organizations/ Regional Population	1999	Nannicini et al. (2013)
N. of non-sport daily newspapers sold/1,000 people	2001	Nannicini et al. (2013)
N. of employees in non profit organizations/ regional population	2001	Nannicini et al. (2013)
Corruption Index	2004-2010	Nifo and Vecchione (2014)
Regulatory Index	2004-2010	Nifo and Vecchione (2014)
Government Effectiveness Index	2004-2010	Nifo and Vecchione (2014)
Rule of Law Index	2004-2010	Nifo and Vecchione (2014)
Institutional Quality Index	2004-2010	Nifo and Vecchione (2014)
School quality		
Test PISA reading competence	2009	INVALSI (2011)
Test PISA reading competence (only Liceo)	2009	INVALSI (2011)
Ratio student/Class Upper Secondary	2004	MIUR (2004)
Ratio students/teacher Upper Secondary	2004	MIUR (2004)
Expenditure variables		
Expenditure per student (Kindergarten)	2003	INVALSI-MIPA (2005)
Expenditure per student (Primary School)	2003	INVALSI-MIPA (2005)
Expenditure per student (Lower Secondary)	2003	INVALSI-MIPA (2005)
Expenditure per student (Upper secondary)	2003	INVALSI-MIPA (2005)
Total expenditure per student (Kindergarten to Upper Secondary)	2003	INVALSI-MIPA (2005)
Expenditure on university scholarships (per recipient student)	2003	MIUR (2006)