

From Baby Boomers to X Generation: the evolution of intergenerational mobility in Italy

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Abstract

This paper presents the first estimates on the evolution of intergenerational mobility for cohorts born after Second World War in Italy. We divide sons born between 1945 and 1979 in seven equally-sized birth cohorts and - using a dataset built matching the Italian administrative archives with the Italian component of the EU-SILC 2005 wave - we observe their earnings when there are aged 30 to 40 and a full set of background characteristics. We first derive a measure of intergenerational relative mobility for each cohort regressing sons' earnings on a parental background index, also controlling for possible mediating factors of the association between parental circumstances and sons' outcomes. Then, we also derive a measure of absolute mobility for each cohorts, computing the probability for sons' of moving from the lowest quantile of the background index to the highest quintile of prime age earnings. To obtain a parental background index net of underlying structural changes and thus comparable across cohorts, we exploit a machine learning approach that allows us to rank individuals according to their background characteristics while considering also likely changes over time of the importance of these characteristics. Results show that in the second half of the 20th century background related earnings advantages followed an inverted U-shaped pattern. Moreover, cohort-differences in income relative mobility remain when we control for sons' education, occupation, region of birth and GDP growth occurred in the first phase of the sons' career.

1. Introduction

During the second half of the twentieth century, Italy underwent deep economic and social changes. Just emerged from Second World War, Italy faced two decades of rapid rise in per capita GDP. The GDP rate of growth has been particularly impressive in the period 1958 – 1963, the years of the so-called “economic miracle”. In the post-war period, Italy started the transformation from a largely rural backward country into an advanced industrial economy. Consequently, the structure of employment started to change rapidly, with a decline in agricultural occupation and the rise of new jobs in the expanding industrial sector. This process of occupational upgrading was accompanied by the consequent need of more educated workers. In order to support this process, the State started to invest more in public education and several educational reforms were implemented, thus enhancing school participation rates. However, starting from the 1970s, the economic boom was followed by two decades of sharp deceleration in rates of economic growth that slowed the process of both occupational and educational upgrading. Moreover, from mid-1980s, a process of sustained rise in market inequalities has been registered. In particular, economic improvements for some categories – managers, self – employed, pensioners and rentiers – was contextual to loss for some others – blue collars and employees (Pianta & Franzini; 2016, Franzini & Raitano, 2018).

All these deep transformations occurred over second half of the twentieth century have changed life chances, opportunities and living standard for many people. In particular, chances for children from disadvantaged background to catch up with their luckier peer may have changed. The living standards of children when adults, compared to that of their parents when had the same age, may be different as well. All these factors suggest a possible variation of the degree of mobility over the second half of the last century.

Mobility can be measured in relative and absolute terms. When we refer to relative mobility, we are asking how much of the ranking of sons when adults is tied to the ranking of their parents. Empirical evidence on intergenerational transmission of inequality suggests that the level of relative mobility in Italy is low compared to other countries (Blanden, 2013; Corak, 2013; Barbieri et al., 2020; Bloise and Raitano, 2019). However, evidence on relative income mobility trends over time is scarce and available for very few countries (Stuhler, 2018). If the concept of relative mobility is strictly related to equality of opportunity (we compare economic outcomes of children from a disadvantage background to economic outcomes of children from a more advantaged background), absolute income mobility is connected to the concept of improvement of living standards from one generation to the next. In particular, measures of absolute mobility compare the economic status of children to the status of their parents. According to the little existing economic literature, absolute mobility has declined sharply over the past half century but a significant cross-country variation in level and trends has been estimated among some European countries, Canada and USA (Chetty et al. 2017, Stockhausen 2018, Manduca et al., 2020). Acciari et al (2019) find that in Italy the degree of upward absolute mobility presents significant differences across geographical areas.

However, to the best of our knowledge, because of data limits, no studies have investigated trends of intergenerational mobility in Italy, neither absolute nor relative. Therefore, this paper adds to the relatively small international economic literature on mobility trends over time providing the first evidence of the evolution of intergenerational persistence in Italy after Second World War.

To estimate intergenerational mobility measures, we exploit the innovative longitudinal AD–SILC dataset built matching the administrative archives of the Italian National Social Security Institute (INPS) – which track the working careers of all individuals working in Italy from 1975 onwards– with the 2005 wave of the IT–SILC (the Italian component of the EU-SILC) which records retrospective

information on parental characteristics (e.g., education, occupation, financial distress, while parental income is not recorded).

We select sons born from 1945 to 1979 and group them into 7 different 5-years cohorts. This procedure allows us to observe sons' earnings when aged 30 to 40. However, our dataset suffers from the lack of an identifier that links sons and parents and, therefore, it is not possible to compute measures of parental earnings. Hence, one way forward is to use the background information contained in the retrospective section of the IT-SILC survey. However, using simple background proxies as parental education or occupation may present some problems of comparability and statistical precision that are even more serious when performing a trend analysis. These issues arise because of the arbitrariness of the categorization of qualitative variables and because of changes over time of the distribution of these variables. Older cohorts, for example, are likely to show smaller variation in educational attainment with respect to younger generations. Occupational outcomes may have more variability with respect to education but still we need to take into account the process of occupational upgrading occurred in the second half of the 20th century. In this study we carry out an historical analysis covering a period in which Italy shifted from an agricultural to an industrial society, leading to major changes in the occupational structure and fostering the need of more educated people. Thus, in order to allow for comparability over time, we need to account for this process of structural changes.

When parental income is not observed, as in this case, we could use all the background information available and build a background distribution. Raitano and Vona (2015) and Bloise et al. (2021), building on socio – economic literature (e. g. Granovetter, 1995), create a distribution of parental background using in a hierarchical order a full set of parental characteristics available in the IT-SILC survey. However, this approach presents two main basic issues. First, this approach is characterized by a wide margin of discretion since scholars establish *ex ante* the ordering of the background variables. Second, the influence of a specific background variables (and of categories of specific background variables) may change over time due to an interplay of both compositional and price effects.

Thus, to minimize the margin of discretion and build a measure of family background net of the process of structural changes, we resort to a machine learning approach. The objective is to rank sons in every cohort according to the full set of background characteristics predictive of their earnings. For every cohort we first test different machine learning algorithms (elastic net, ridge regression, LASSO, Random Forest, Boosted regression and OLS) and choose the one that generates the most accurate out of sample predictions. Then, for each cohort, we sort sons according to the predicted earnings and we generate a background measure based on this ranking. Finally, for each cohort we estimate measures of both relative and absolute mobility.

In the first part, intergenerational relative mobility is estimated regressing the percentile of the son's income in his own distribution on the percentile of the parental background distribution build by using ML algorithms. We also analyse changes in the relative importance of intergenerational transmission mechanisms by including among covariates possible mediating factors such as education, occupation, region of birth and GDP growth occurred in the first phase of the career.

Finally, we derive measures of absolute mobility for each cohort. In particular, we derive absolute upward mobility trends as the probability of ending up in the top tercile of log income for those belonging to the bottom tercile of the parental background distribution.

In more detail, the paper is structured as follows. Section 2 reviews the existing literature on trends of intergenerational mobility over time; section 3 and section 4 present the dataset and the empirical strategy, respectively. Section 5 presents preliminary results and section 5 concludes.

2. Main literature on trends of intergenerational mobility over time

A large body of economic research has investigated relative income mobility, i.e. the transmission of inequalities across generations (Solon 2002; Black & Devereaux 2011; Jäntti and Jenkins 2015). Most of this literature has been primarily focused on measuring the degree to which economic advantages are passed on from parents to children, devoting special attention to differences across countries (Blanden 2013, Corak 2013). Economists usually measure the degree of persistence across generations using income as a proxy of the socio-economic status. In particular, the mostly widely used measure is the intergenerational elasticity coefficient (IGE, hereafter), that is the slope coefficient of the regression of sons' log earnings on parental log earnings (Bjorklund and Jäntti, 2009). More recent studies measure the degree of the intergenerational persistence with the rank-rank slope, that is the association between the relative position of parents and sons in their respective generation (Dahl and DeLaire, 2008, Chetty et al., 2014). These are both descriptive measures and do not give any information on casual relationships. However, obtaining these descriptive measures of the degree of intergenerational persistence of economic status is extremely challenging. First, estimating the degree of the intergeneration association has cumbersome data requirements. In particular, to estimate the intergenerational association long panel dataset covering two generations are required, but many datasets do not offer information about parents' incomes. Moreover, the growing body of empirical evidence on intergenerational mobility has pointed out several empirical issues that may question the reliability of the estimates if not properly addressed. First, we should have lifetime income measure for both parents and children, but most datasets give income data only for short time periods. The lack of these data may lead to downward biased estimates of the intergenerational association (Haider and Solon, 2006; Zimmerman, 1992). Moreover, measures of income persistence are sensitive to the age at which income is measured. In particular, estimates of intergenerational persistence are reduced by the so-called life cycle bias that arise when children's earnings are observed when they are too young (Grawe, 2006; Nybom and Stuhler, 2017). To minimize this bias, earnings should be measured when children are around 35 to 45 years old (Haider and Solon, 2006).

All these methodological problems persist when studying trends in intergenerational mobility over time and indeed are exacerbated by the intensive data requirements in both the intergenerational and cohort dimensions. Thus, empirical literature on mobility trends is more scarce and less conclusive. Patterns of intergenerational income mobility in the second half of the 20th century have been investigated in the USA thanks to the availability of suitable data, but mixed evidence has emerged. Hertz (2007) and Lee & Solon (2009) estimate the IGE for cohorts born after 1950 and do not find evidence of significant changes in intergenerational mobility over time. Chetty et al (2014), using rank-based specifications for the 1971 -1986 birth cohorts, confirm that mobility has remained stable. However, other studies find an increase over time of intergenerational persistence (Levin & Mazumder, 2007) especially for those cohorts that enter the labour market in periods of significant rise in cross – section economic inequality (Davis & Mazumder, 2017). Estimates of economic relative mobility patterns are available for very few European countries because of the lack of data. Income mobility has declined in UK for cohorts born between 1950s and 1970s (Blanden et al., 2007; Nicoletti & Ermisch, 2008), whereas it has increased in Norway (Bratberg et al. 2007). Because of the intensive data requirements necessary to estimate the IGE and the IRC, some scholars have considered more feasible estimating sibling correlations, corroborating the hypothesis of declining

mobility in the USA (Levine and Mazumder, 2007) and confirming the findings of a decreasing trend in intergenerational persistence for the Nordic countries (Björklund et al. 2009).

Literature on time pattern of absolute mobility is even more scarce. Absolute mobility seems to have declined sharply over the past half century but a significant cross-country variation in level and trends has been estimated among some European countries, Canada and USA (Chetty et al. 2017, Stockhausen 2018, Manduca et al., 2020).

3. Data and sample selection

We use data from the AD-SILC longitudinal dataset, that has been developed merging the INPS administrative archives with the 2005 and 2011 waves of the Italian sample of the European Union Statistics on Income and Living Condition (IT-SILC). The INPS archives cover workers earnings histories of all individuals working in Italy starting from 1975 up to the end of 2018. For every job relationship experienced during the year the archives provide information on duration (measured in weeks), the pension fund where the worker pays contributions (allowing to distinguish private and public employees and the various groups of self-employed) and gross earnings. The 2005 and 2011 waves of the IT-SILC record instead crucial workers' characteristics not recorded in administrative archives, namely, education and parents' characteristics.

As standard in this strand of literature, we consider only male sons, excluding those without the Italian citizenship. We select male workers born between 1945 and 1979 and partition the sample into 7 equally-sized birth cohorts. The oldest cohort is composed by those born between 1945 and 1949, while the youngest cohort contains individuals born between 1975 and 1979. Table 1 reports the number of sons we have in our dataset for each birth cohort and the time span in which sons' earnings are recorded.

Table 1 Sample size of baseline sample

Cohort	All workers	Employees	Time span in which sons are followed
<i>1945-1949</i>	1,394	1,034	1975-1989
<i>1950-1954</i>	1,298	979	1980 - 1994
<i>1955-1959</i>	1,541	1,160	1985- 1999
<i>1960-1964</i>	1,767	1,302	1990 - 2004
<i>1965-1969</i>	1,882	1,350	1995 - 2009
<i>1970-1974</i>	1,686	1,237	2000-2014
<i>1975-1979</i>	1,374	1,036	2005 - 2019
Total	10,942	8,098	

Source: AD-SILC data

We observe workers real gross annual earnings from employment and self-employment (also including allowances for maternity, sickness and short-time work compensation) from age 30 to age 40 to minimize life cycle bias and deplete from temporary income fluctuations. Multi – year averages of earnings are then computed taking or not taking into account possible zero annual incomes in the 11-year time span. In the baseline sample we also drop the few (6%) individuals in the sample with fewer than 4 annual obs when aged 30-40 and do not consider zero annual incomes. Sensitivity analysis is conducted on children working as an employee only (Figure 1A in the Appendix).

In table 2 and table 3 we report characteristics of our sample. It is possible to notice the process of educational and occupational upgrading occurred over the second half of the last century and how the educational composition has totally changed. The process of occupational upgrading it is striking also looking at table 3 where sons' background characteristics are reported. In particular, for the older cohorts, there is very little variability in the fathers' educational distribution, with the greater share of fathers having only none or basic education. This represents one of the main drawbacks of using fathers' educational outcomes as proxy of parental background when parental income is not observed.

Table 2 Sons' characteristics according to belonging cohort

Cohort	Children' education level				Children mean earnings	
	Primary	Lower secondary	Upper secondary	Tertiary	Total earnings	Employee earnings
<i>1945-1949</i>	35.5	26.7	32.4	5.4	19849.9	22117.6
<i>1950-1954</i>	20.0	33.1	37.5	9.4	21714.0	23609.7
<i>1955-1959</i>	10.5	35.6	43.3	10.5	22797.9	24695.5
<i>1960-1964</i>	6.5	38.8	44.2	10.6	23894.3	24550.0
<i>1965-1969</i>	5.0	36.8	46.9	11.3	24466.2	25266.7
<i>1970-1974</i>	4.2	30.6	49.6	15.6	23882.5	24491.0
<i>1975-1979</i>	2.0	24.4	53.4	20.2	22112.0	22902.7
Total	11.3	32.7	44.2	11.8	22838.8	24046.3

Source: AD-SILC data

Table 3 Sons' background characteristics according to belonging cohort

Sons' cohort	Fathers' level of education				Fathers' occupation		
	Primary	Lower secondary	Upper secondary	Tertiary	Managers	White collars	Blue Collars
<i>1945-1949</i>	86.1	7.5	5.1	1.3	7.3	13.5	79.2
<i>1950-1954</i>	83.1	8.0	6.7	2.2	8.0	15.4	76.6
<i>1955-1959</i>	78.1	12.2	7.6	2.0	10.0	17.8	72.2
<i>1960-1964</i>	71.5	17.2	8.6	2.7	9.8	21.0	69.2
<i>1965-1969</i>	63.7	20.3	12.3	3.7	9.3	23.4	67.3
<i>1970-1974</i>	54.9	23.6	17.2	4.3	9.8	27.8	62.5
<i>1975-1979</i>	44.5	31.3	20.3	4.0	9.7	28.8	61.5
Total	68.4	17.4	11.2	2.9	9.2	21.4	69.5

Source: AD-SILC data

4. Methodology

Building a background distribution when income of parents is unobserved

To the end of estimating the evolution of the degree of mobility over time in Italy, we need to rank sons according to their background when information on parental income is unobserved. To this aim, Raitano & Vona (2015) and Bloise, Franzini and Raitano (2021) build a distribution of parental background using information on parents' characteristics in a hierarchical order. Based on socioeconomic literature (e.g. Granovetter, 1995), they rank individuals by deciding "ex-ante" which parental characteristics are more relevant in influencing children economic outcomes when adult. They first take father and mother occupation, respectively, as a good proxy for the influence of the family on children's outcomes as it encompasses unobservable aspects of human capital, socio-economic status and family networks. They then take, in a hierarchical order, all other parents' characteristics provided by EU-SILC: father and mother education, country of birth of fathers and mothers, the presence of both parents in the household, the number of siblings and the number of income recipients in the household.

However, the previous approach exploited to build a background distribution might have two basic issues. First, within a selected birth cohort, it is difficult to decide ex-ante which background variable (and which categories of a given background variables) are more relevant in predicting economic success of a son when adult. Second, the influence of a specific background category (i.e. having a tertiary graduated mother) on sons' income level is likely to change over time due to an interplay of both compositional and price effects: the structure of the population in terms of educational level changes over time. For this reason, we decided to resort on Machine Learning algorithms to select which background categories are more relevant in a specific birth cohort and thus build the parental background distribution accordingly.

We first assume an unknown data generating process for log income of son i in birth cohort b :

$$\log y_{i,b} = f(\text{back}_{i,b}) + \varepsilon_{i,b} \quad (1)$$

Machine learning algorithms are thus exploited to select and order those background categories included in the vector back_i which maximize the «out-of-sample» capability of the function f to predict economic success of sons when adult. We thus select the model which maximize the «out-of-sample», rather than the «in-sample» r-squared, in order to minimize overfitting and multicollinearity issues. We train and calibrate different potential algorithms (i.e. elastic net, ridge regression, LASSO, Random forest, Boosted regression, and OLS) using the full set of background characteristics of fathers and mothers provided by the 2005 wave of IT-SILC. Table 4 summarize the background variables used by Machine Learning algorithms to rank individuals.

Table 4 Background characteristics exploited

<i>Background variable definition</i>	<i>Background variable name</i>	<i>Nr. of categories (binary variables)</i>
Family composition	Back1	7
Number of siblings	Back2	18

Highest ISCED level of education attained by father	Back3	6
Highest ISCED level of education attained by mother	Back4	6
Activity status of father	Back5	8
Occupation of father	Back6	28
Activity status of mother	Back7	8
Occupation of mother	Back8	27
Financial problems in household when young teenager	Back9	6
Total	9	114

Source: AD-SILC data

Measures of mobility

To provide an estimate of the evolution of relative mobility, for each cohort we estimate the rank-rank slope through the following equation:

$$pct_i^S = \alpha + \beta pct_background_i \varepsilon_i \quad (2)$$

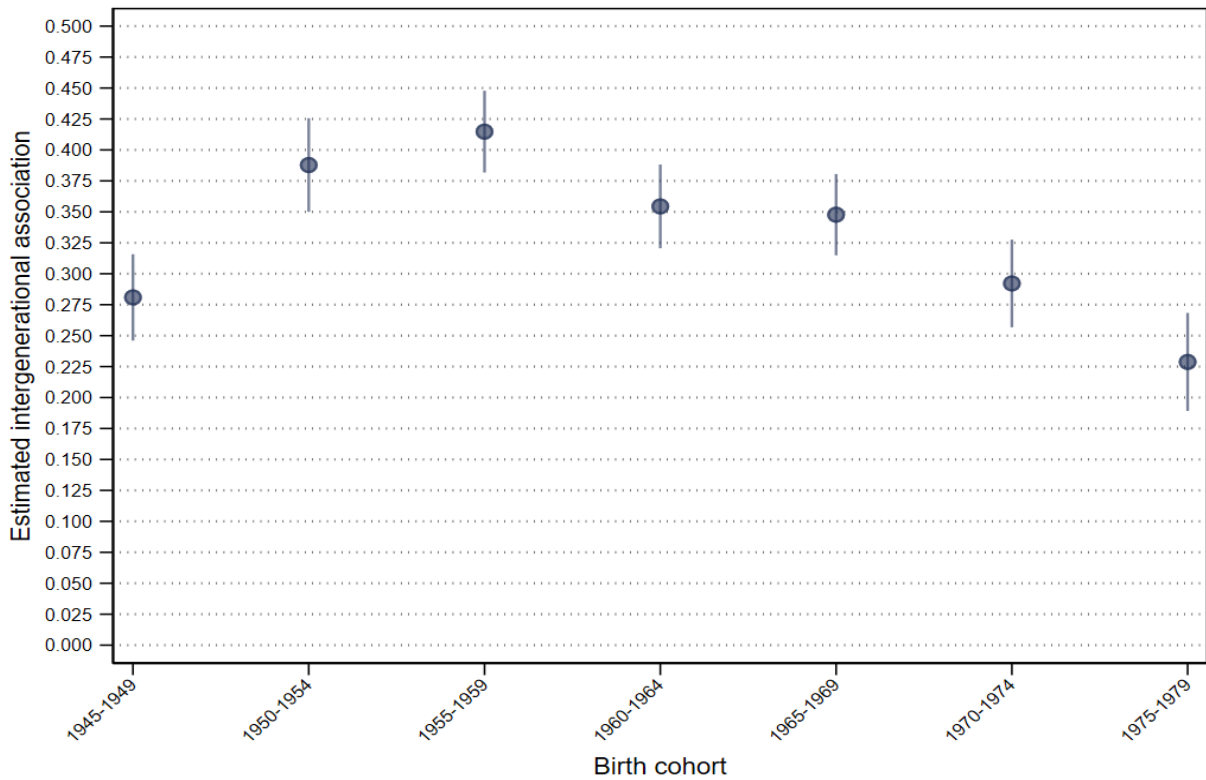
where pct_i^S is the son's percentile of gross earnings in its own distribution and $pct_background_i$ is the percentile of the background measure obtained by using ML algorithms. Further control variables are included in the rank-rank specification: a binary variable which is equal to one for employees; 5 binary variables for the year of birth; 8 binary variables for the number of positive earnings observations recorded between 30 and 40 years old (from 4 to 11).

Then, to measure absolute mobility, we compute the probability of ending up in the best tercile of log income for those belonging to the lowest tercile of the parental background distribution.

5. Intergenerational correlation across cohorts: preliminary results

As first step of our analysis we show the estimated rank-rank slope β (Figure 1) computed regressing percentile of the son's income in his own distribution on the percentile of the parental background distribution built using ML algorithms.

Figure 1 Estimates of the intergenerational association between percentiles of sons' earnings on percentiles of the parental background distribution

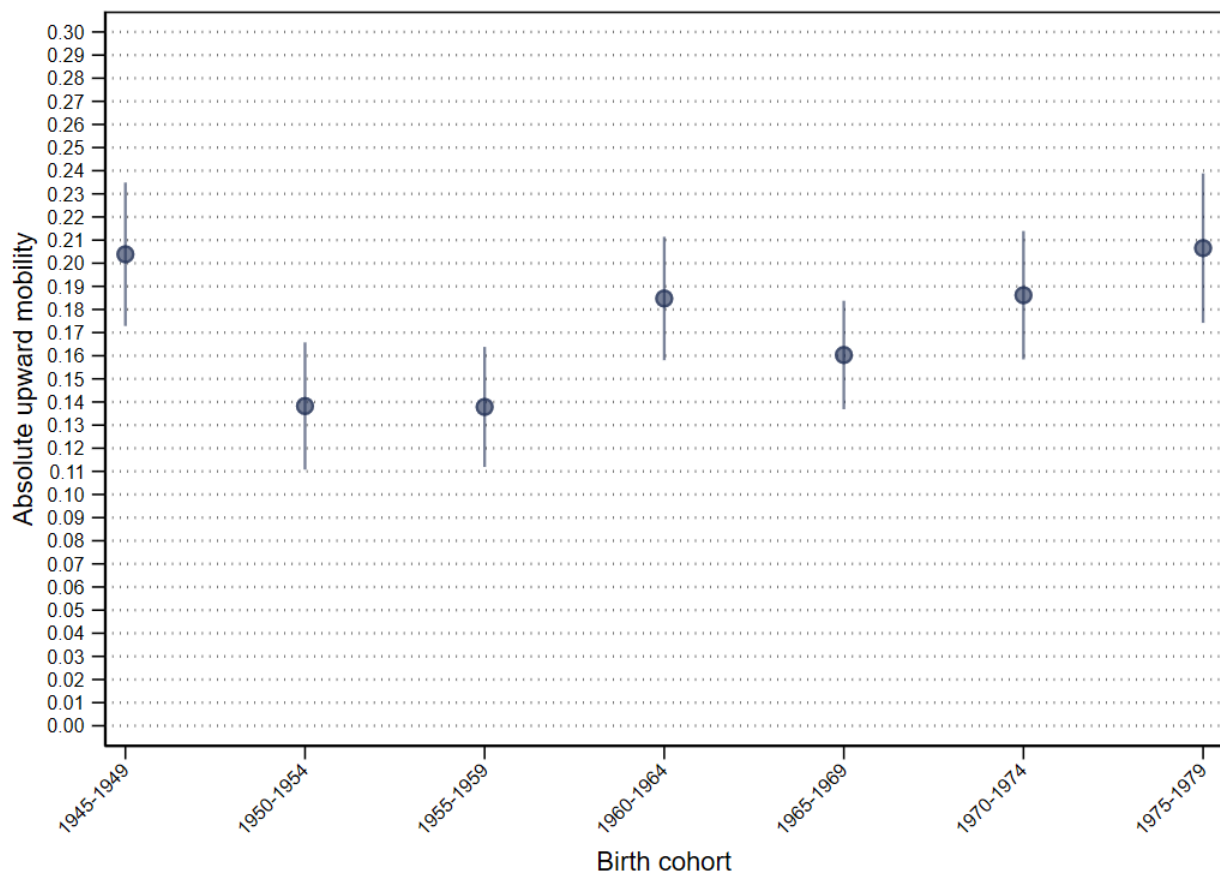


Author's elaboration based on AD-SILC dataset. 90 percent Interval of Confidence. Standard errors are robust to heteroskedasticity.

Results show that a positive coefficient of intergenerational persistence emerges throughout the second half of the 20th century. Moreover, we can observe an inverted U-shaped pattern of rank-rank slopes. The coefficient for the 1945-1949 cohort is not statistically different from the coefficient for the younger cohort. However, individuals born between 1950 and 1974 present higher values of the rank-rank coefficients with respect to the younger and the older cohorts. This means that generations born during the 50's and the 60's experienced a higher level of relative immobility (or a lower level of mobility). Even if these individuals were born during prosperous economic times - the Italian economic miracle -, they entered the labour market during a period in which economy growth started to slow down and, in 1975, entered its first recession after the end of Second World War. For example, those children born in the 1950s are likely to enter the labour market approximately when they are aged around 18-20 years old, thus at the beginning of the 1970s. Their economic outcomes and the degree of association between their earnings and their family background are likely to be associated with economic and labour market condition of the times. Moreover, we measure their earnings when they are aged between 30 and 40 years old that, for

the central cohorts, coincides with the time starting from the 1980s in which cross – section economic inequalities began to rise sharply. The 1975-1979 younger cohorts present a similar level of intergenerational persistence with respect to the older cohort, but a higher level of mobility with respect to the central ones. This result may be related to the circumstance that their earnings are recorded in a period which was affected by the economic crisis consequences which altered the relationship between earnings and family background. Sensitivity analysis on children working as an employee only is conducted and results (Figure A1 in the appendix) confirm our findings.

Figure 2 Estimates of Absolute Upward Mobility



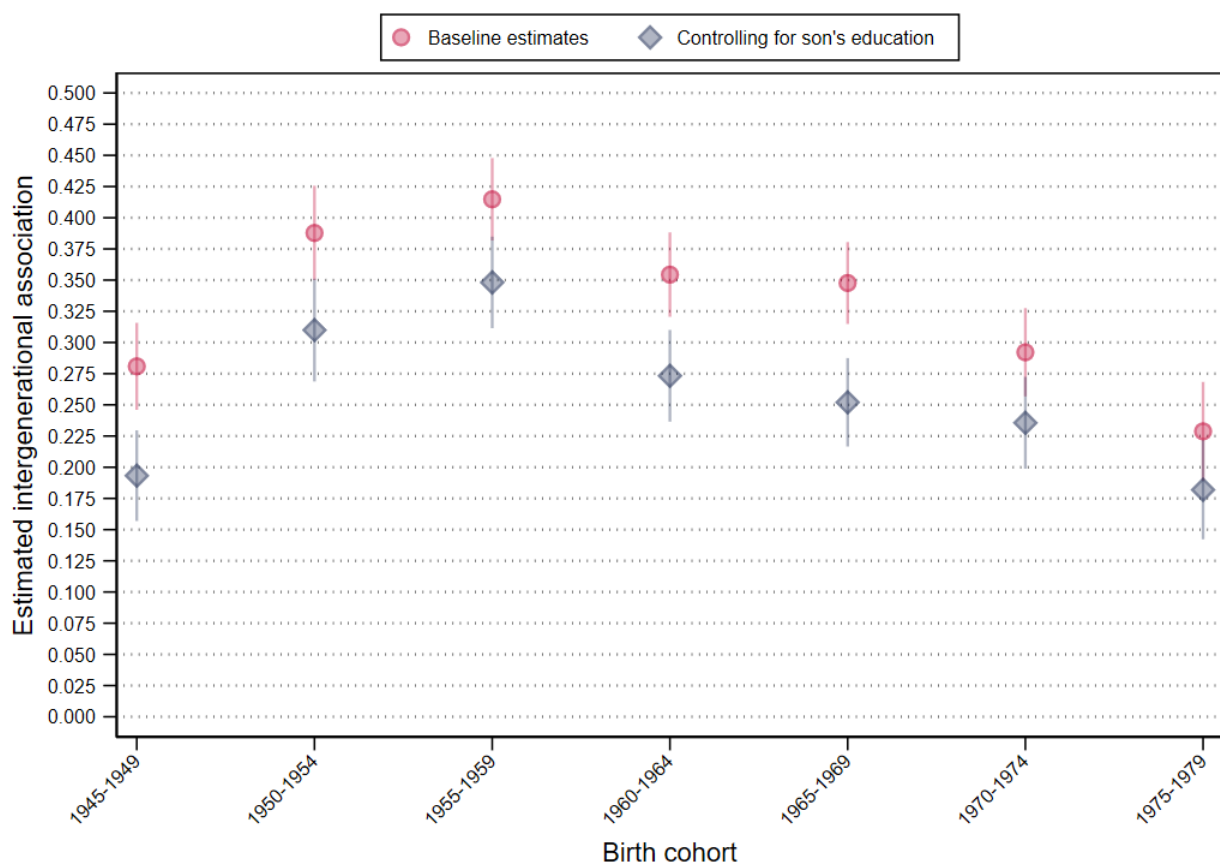
Author’s elaboration based on AD-SILC dataset. 90 percent Interval of Confidence. Standard errors are robust to heteroskedasticity.

The pattern of our absolute mobility measure presented in figure 2 confirms our previous findings. Between the younger and the older cohorts there is not a statistically significant difference in the level of upward mobility that seems to be higher with respect to the level of mobility experienced by those born between 1950 and 1959.

Then, we control for possible mediating effects of the association between parental circumstances and sons’ outcomes. Among mediating variables behind the transmission of advantages from one generation to the next, we analyse the role played by sons’ education, occupation, region of birth and GDP growth occurred in the time span between son’s graduation year and the year the son

turns 40 years old. In figure 3 we present rank-rank slopes obtained controlling for sons' level of education. Results show that the pattern of relative mobility persists when sons' education is controlled for. As expected, since we are now controlling for mediating factors of the intergenerational association, we observe a reduction in the magnitude of the coefficients that is statistically significant only for the first cohort and for those born between in the 1960s. This result points out that the share of intergenerational persistence explained by education has not been constant in time and has decreased for individuals born in the 1970s with respect to those born in the 1960s.

Figure 3 Estimates of the intergenerational association between percentiles of sons' earnings on percentiles of the parental background distribution controlling for sons' education



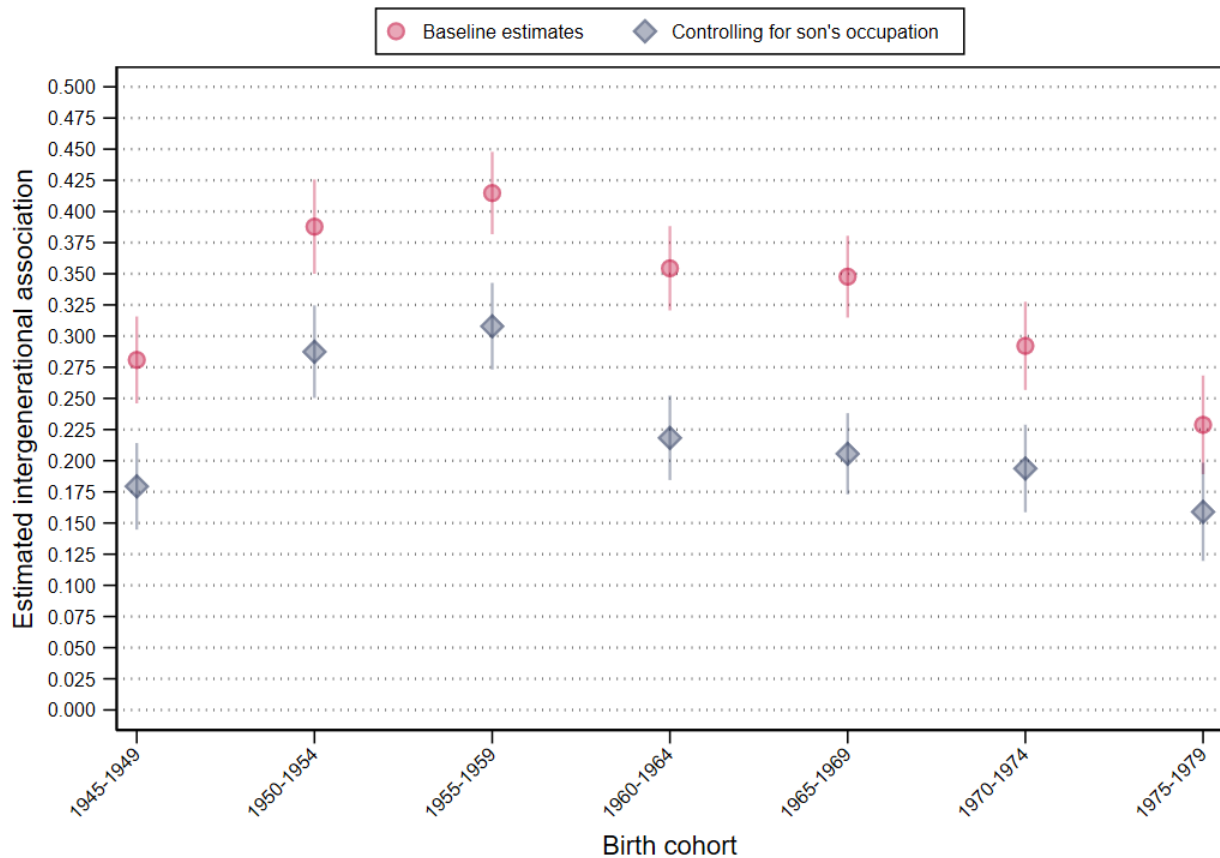
Author's elaboration based on AD-SILC dataset. 90 percent Interval of Confidence. Standard errors are robust to heteroskedasticity.

Results presented in figure 4 show that sons' occupation has a stronger role in explaining intergenerational persistence with respect to education. The role of sons' occupation as mediating factor is particular important for those born in the 1960s. When we control for occupation, differences among cohorts vanish except that for those born in the 1950, whose coefficient stay higher.

After controlling for region of birth (figure A2 in the Appendix) and GDP growth rate (figure A3 in the Appendix), the coefficients do not change. When we control for all our potential mediating

factors (figure A4), the coefficients are reduced but the time pattern of relative mobility is preserved.

Figure 4 Estimates of the intergenerational association between percentiles of sons' earnings on percentiles of the parental background distribution controlling for sons' occupation



Author's elaboration based on AD-SILC dataset. 90 percent Interval of Confidence. Standard errors are robust to heteroskedasticity.

6. Very preliminary Conclusions

Our results show that in the second half of the last century the intergenerational association between sons' earnings and parental background followed an inverted U-shaped pattern. In particular, the degree of mobility is lower for those born in the 1950s with respect to those born in the 1940s and in the 1970s. It is important to stress that for those born in the 1950s, earnings are taken in a period in which cross – section inequalities started to rise sharply. When we add to our baseline model sons' characteristics that might mediate the association between son's earnings and family background (education and occupation) we find that sons' occupation has a stronger role in explaining intergenerational persistence with respect to education. When we control for education,

occupation and more general circumstances as region of birth and GDP growth, a statistically significant intergenerational association persists. Thus, it is likely that behind the residual association between son's earning and family background may act different mechanisms.

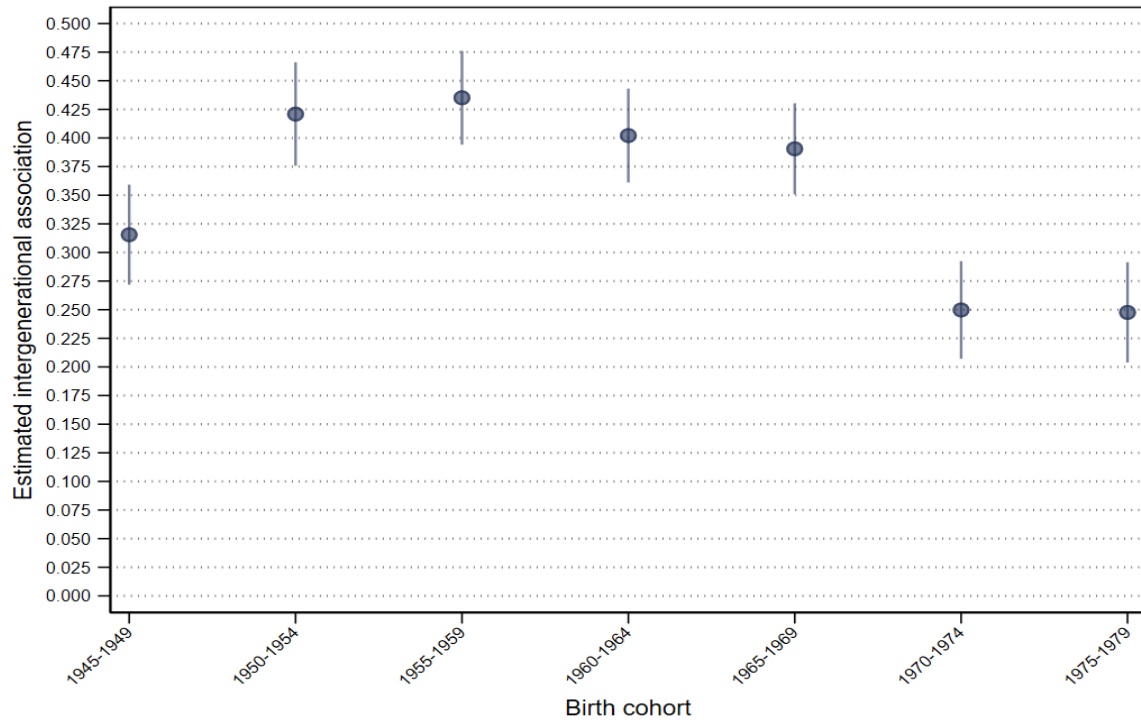
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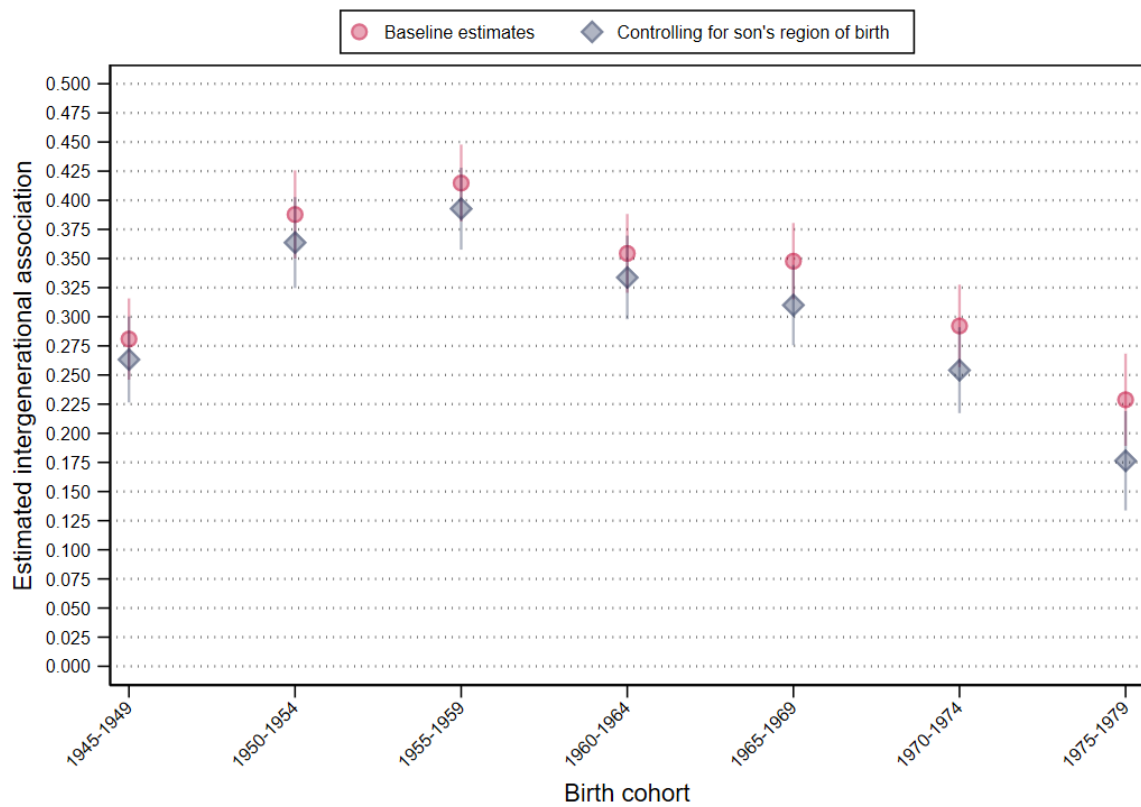
Appendix

Figure 1A. Estimates of the intergenerational association between percentiles of sons' earnings on percentiles of the parental background distribution, sub-sample of employees



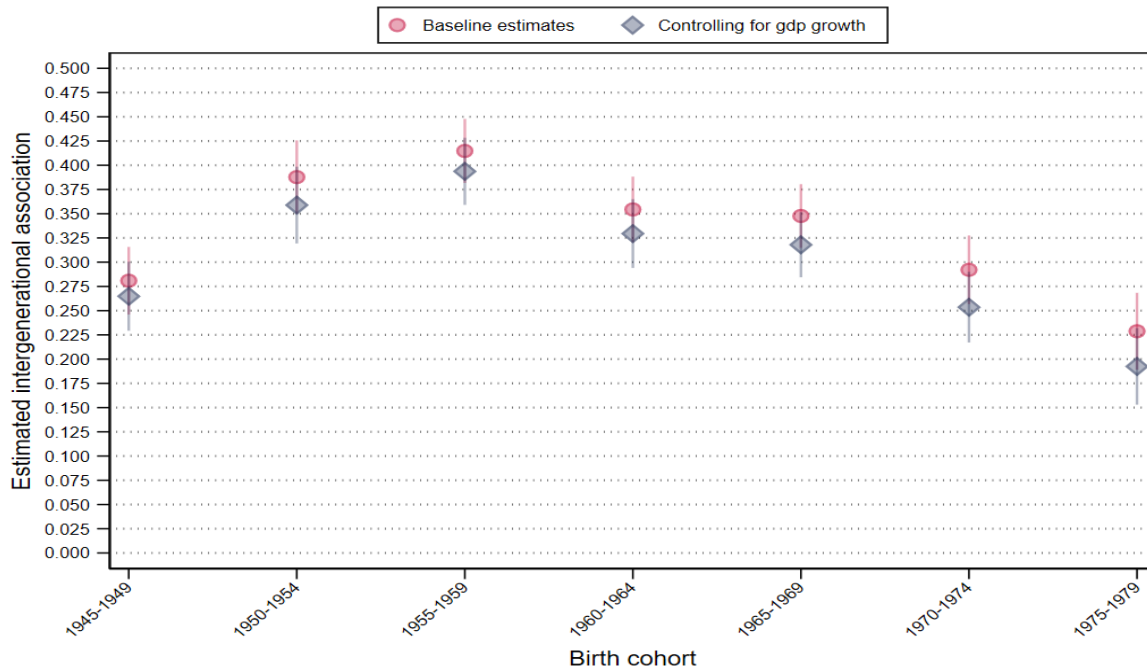
Author's elaboration based on AD-SILC dataset. 90 percent Interval of Confidence. Standard errors are robust to heteroskedasticity

Figure 2A Estimates of the intergenerational association between percentiles of sons' earnings on percentiles of the parental background distribution controlling for sons' region of birth



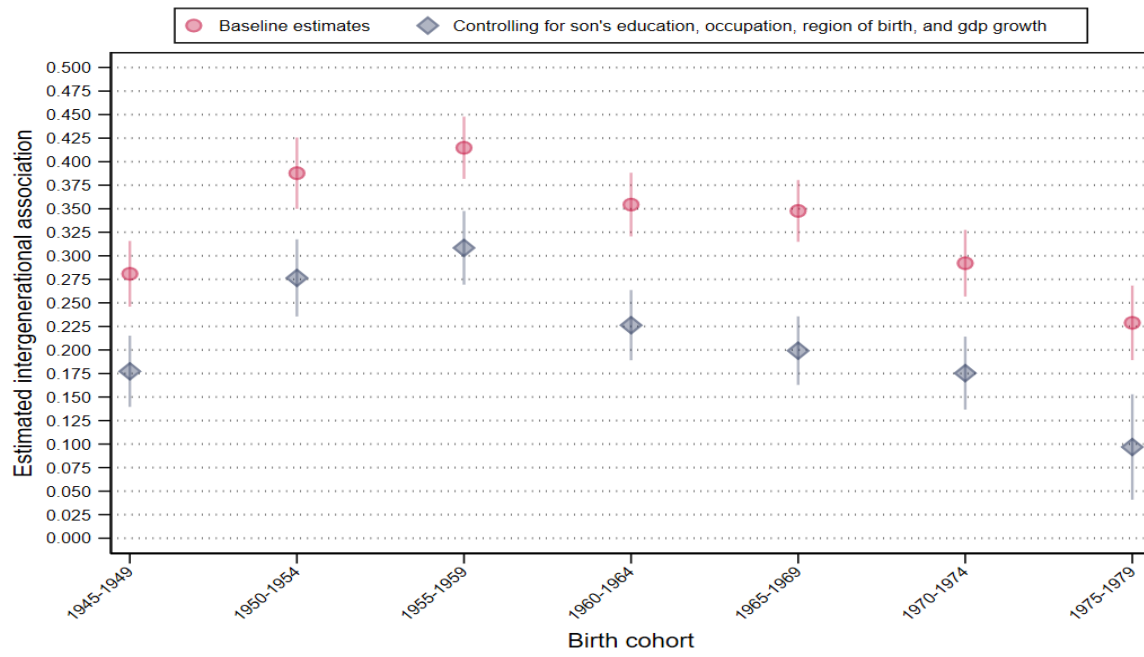
Author's elaboration based on AD-SILC dataset. 90 percent Interval of Confidence. Standard errors are robust to heteroskedasticity.

Figure 3A. Estimates of the intergenerational association between percentiles of sons' earnings on percentiles of the parental background distribution controlling GDP growth rate computed for the period between graduation year and the year the son turns 40.



Author's elaboration based on AD-SILC dataset. 90 percent Interval of Confidence. Standard errors are robust to heteroskedasticity.

Figure 4A Estimates of the intergenerational association between percentiles of sons' earnings on percentiles of the parental background distribution controlling for son's education, occupation and region of birth and GDP growth rate



Author's elaboration based on AD-SILC dataset. 90 percent Interval of Confidence. Standard errors are robust to heteroskedasticity.