The Poor Stay Poor, the Rich Get Rich: Essays on the Intergenerational Transmission of Economic Status

SAPIENZA
UNIVERSITÀ DI ROMA

Ph.D candidate: Francesco Bloise

Supervisor: Prof. Maurizio Franzini

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Summary

Persistence of inequality across generations is an important field of research with many implications in terms of policy. Economic inequality related to the intergenerational transmission of economic opportunities may strongly influence policies designed to reduce earnings or wealth concentration. Empirical research has usually focused on the intergenerational persistence of earnings or income, considered as good measures of differences in economic well-being and consumption capacity of individuals. On the contrary, only a limited number of recent studies attempt to estimate the degree of intergenerational mobility by using net wealth as a measure of economic status of individuals.

This Ph.D thesis includes three autonomous chapters regarding the intergenerational persistence of wealth and earnings inequality and their mechanisms. The first one reviews research on wealth inequality and persistence across two or more generations. Broadly speaking, wealth is more unequally distributed than income and unlike other flow variables, may be transmitted across generations directly, by means of bequests or donations. This means that it may be a good proxy of permanent economic disparities. Unfortunately, measuring wealth is not an easy task since data on real and financial assets are incomplete and provided with many differences across countries.

Regarding the extent of correlation in wealth across generations, only a limited number of studies are able to use suitable data on wealth which cover two or more generations. In any case, according to few recent empirical works, intergenerational rank correlations in wealth seem to be usually higher than intergenerational rank correlations in income. These findings derive from the fact that wealth is more representative of cumulate resources and less affected by transitory shocks than earnings or income. Moreover, wealthy parents seem to transmit many resources to their children at the beginning of the adulthood, by making donations. This may explain why, unlike intergenerational correlations in income, intergenerational correlations in wealth seem to be very high also considering children in their 20’s.

The second chapter exploits retrospective socio-economic information about both parents to impute parental wealth in order to assess the degree of wealth mobility across generations in Italy and highlight some of the mechanisms linking parental wealth to offspring's economic outcomes.

Using the Bank of Italy's survey on household income and wealth (SHIW) and two samples of offspring and pseudo-parents in their 40s, I find an intergenerational age-adjusted wealth elasticity (IWE) of 0.451 and a rank-rank slope of 0.349 which appear to be robust to the use of different predictors of parental economic status. These results suggest that Italy is a low mobility country also when wealth is taken as an alternative measure of economic status.

As in the only previous study by Boserup et al. (2016) which analyses the pattern of wealth mobility over the lifecycle, the second chapter shows a U-shaped pattern of the intergenerational wealth correlation as a function of the second generation's age with higher estimated intergenerational correlations when children are taken at the beginning of their adulthood or in their 40's.

Geographical differences in the extent of intergenerational wealth mobility are analysed by estimating elasticities and rank-rank slopes in two different macro-areas of the country. Results suggest that the southern part of Italy is extremely less mobile than the northern part of the country.

Regarding the analysis of the mechanisms behind the intergenerational wealth correlation across two generations, the second chapter suggests that income seems to be the main intergenerational mediating factor. On the contrary, the correlation across generations of saving preferences and attitude to risk seems to explain only a small fraction of the IWE.

Finally, the third chapter (which is part of a research work with Michele Raitano and Teresa Barbieri) provides new and detailed estimates of intergenerational earnings mobility in Italy and sheds light on mechanisms behind the association of gross earnings between fathers and sons.

Being not available panel data following subsequent generations in Italy, we make use of a recently built dataset that merges information provided by IT-SILC 2005 (i.e., the Italian component of EU-SILC 2005) with detailed information about the whole working life of those interviewed in IT-SILC recorded in the administrative archives managed by the Italian national Social Security Institute (INPS).

This dataset allows us to rely on the two-sample two-stage least squares method (TSTSLS) to predict father earnings and, then, compute point in time intergenerational elasticities (IGE) and imputed rank-rank slopes. Furthermore, the characteristics of the dataset allow us to extend point in time estimates considering, for both sons and "pseudo-fathers", average earnings in a 5-year period and observing sons at various ages, thus assessing the robustness of our estimates to attenuation and life cycle biases.

Confirming previous evidence (Mocetti 2007; Piraino 2007), we find that Italy is characterized by a relatively high earnings elasticity in cross country comparison – the size of the estimated β is usually over 0.40 – and the size of the intergenerational association increases when older sons and multi-annual averages are considered.

We then investigate mechanisms behind this association both: i) including a set of possible mediating factors of the parental influence (e.g., sons' education, occupation, labour market experience) among the control variables when regressing sons' earnings on fathers' earnings and ii) following the sequential decomposition approach suggested by Blanden, Gregg and Macmillan (2007). Results show that a limited share of the intergenerational association is attributable to sons' educational and occupational attainment, while the largest part of the association is mediated by sons' employability, i.e., by their effective experience since the entry in the labour market.

Results show that the mediating role of education in Italy is limited, especially if compared with evidence obtained for other countries such as the US and UK.

Chapter 1: Wealth Inequality and Persistence Across Generations: Evidence and Measurement Issues

Abstract

This chapter reviews research on wealth inequality and persistence across two or more generations. Broadly speaking, wealth is more unequally distributed than income and unlike other flow variables, may be transmitted across generations directly, by means of bequests or donations. This means that it may be a good proxy of permanent economic disparities. Unfortunately, measuring wealth is not an easy task since data on real and financial assets are incomplete and provided with many differences across countries.

Regarding the extent of the intergenerational wealth correlation, only a limited number of studies are able to use suitable data on wealth which cover two or more generations. This is the reason why empirical research still focuses on income to measure intergenerational economic mobility. Moreover, most of empirical studies on intergenerational wealth are forced to selected two generations at different ages because of data limitations. Further evidence is thus needed to credibly compare intergenerational correlations in income to intergenerational correlations in wealth.

In any case, according to few recent empirical works, rank correlations in wealth seem to be usually higher than rank correlations in income. These findings derive from the fact that wealth is more representative of cumulate resources and less affected by transitory shocks than earnings or income. Moreover, wealthy parents seem to transmit many resources to their children at the beginning of the adulthood by making donations. This may explain why, unlike intergenerational correlations in income, intergenerational correlations in wealth seem to be very high also when earnings of children are measured at early stages of their careers.

Introduction

The leading character in the studies on economic inequality and mobility across generations is usually income, widely considered as the best measure of the degree of economic well-being and consumption capacity. Wealth, however, is a key indicator of economic status and opportunities since it is able to capture, more than income, differences in permanent, rather than current, economic flows of individuals and households. Moreover, unlike income, wealth can be directly transmitted from one generation to the next by means of bequests and inter-vivos transfers, which are likely to increase the intergenerational component of inequality.

Therefore, in the last few years, both the academic and non-academic debate has been focusing on how wealth is distributed across individuals. For instance, extreme concentration of wealth at the top is investigated by Piketty (2014) in his famous: "Capital in the 21st Century" which has brought again attention to economic disparities and wealth accumulation. Other alarming aspects regarding the degree of inequality that characterise modern economies, have been presented in a recent report by Oxfam which shows that the top 1% of the world population owns a greater amount of wealth than the remaining 99% (Hardoon et al., 2016). On the contrary, there is only a limited number of recent studies which estimate the degree of wealth correlation across two or more generations. This is mainly due to the lack of suitable data on wealth which cover different generations.

The main aim of this chapter is to summarise issues related to the measurement of wealth, its distribution and how it is correlated across generations. Since economic inequality and its persistence across generations is often measured by attempting to capture disparities in lifetime economic resources, it may be useful to introduce wealth as a better proxy of permanent economic status.

However, measuring wealth is not trivial because of the limited availability of good quality data on assets and liabilities. Ideally, when measuring net wealth, one should include all potentially marketable and non-marketable assets and all financial liabilities. Unfortunately, complete information on some specific assets such as valuables or pension wealth is not available in most countries. This is the reason why income is usually preferred over wealth to measure economic inequality and its persistence across generations.

Nevertheless, economic resources may be associated across two or more generations either indirectly because of intergenerational correlations in rewarded abilities, educational attainments and preferences or directly by means of inheritance or donations. Therefore, when estimates of economic mobility are provided by measuring both intergenerational correlations in wealth and income, the former seems to better capture correlations in overall lifetime resources than the latter. This may suggest that intergenerational mobility in lifetime resources may be overestimated when income is used as a proxy of permanent status and suitable data that cover two generations over their lifecycle are not available.

The chapter is organized as follows. Section 1.1 describes concepts and all measurement issues that may arise when measuring wealth. Section 1.2 presents international comparisons of wealth levels and inequality. Section 1.3 summarizes evidence and methodological aspects of empirical studies on intergenerational income mobility. Section 1.4 analyses methodological aspects regarding the intergenerational transmission of wealth. Section 1.5 concludes.

1.1. Wealth inequality: concepts and measurement issues

The relatively little attention dedicated to the study of the distribution of net wealth, computed as the sum of real and financial assets (gross wealth) minus financial liabilities, compared to the study of the distribution of income, is mainly due to the limited availability of good quality data about the value of assets and debts.

There are several reasons why the measurement of net wealth is more insidious than that of income. Ideally gross wealth should include all potentially marketable and non-marketable assets but information on all sources of wealth is not available in all countries. For instance, old-age and occupational pensions or durables other than vehicles are not included in the computation of gross wealth since data on non-marketable assets are often unavailable. To get an idea of how the inclusion or not of pensions can change international rankings, think of what should be the amount of private savings accumulated by individuals working in countries without extensive social security systems. On the contrary, in the presence of generous social security systems, the accumulation of private wealth for old age is less important for most individuals but the wealthy. Therefore, this kind of institutional differences may affect motivations to accumulate wealth and thus its distribution.

The inclusion of pension wealth would decrease inequality indices, especially in countries characterised by public pensions systems, usually more redistributive. For instance, including pension wealth in the computation of net wealth would decrease the Gini index from 0.65 to 0.48 in the United Kingdom in 1993 (Davies and Shorrocks, 2000). However, the redistributive effect of pensions observed in some countries has decreased in the last decades because of the shift from public defined-benefit schemes to public defined-contribution schemes (pensions depend exactly on the amount of contributions paid during lifetime). The result of this shift has not been neutral in terms of net wealth inequality measured without excluding pension wealth (Wolff, 2014).

In most cases, the level of wealth inequality is not a precise indicator of material well-being inequality of individuals or households. Public and welfare policies may, in fact, significantly increase the welfare of the poorest, providing public transfers which reduce the incentive to save and, thus, to accumulate wealth (also in order to purchase real estate properties). For instance, the high degree of wealth inequality in Sweden, which is usually presented as one of the most egalitarian countries in terms of income distribution, might be surprising. The main reason of this apparent contradiction is that a large portion of Swedish own very low or negative levels of net wealth (Davies, 2009). This result, which could also reflect some measurement errors, is mainly due to the high share of indebted households and the low percentage of people living in own house. These two aspects are strongly influenced by strong housing policies, which facilitate the access to mortgages, and by the generous Swedish public pension system. Similarly, the relatively limited wealth inequality observed in Italy is in large part explained by the widespread possession of real estate due to poor public housing policies.

Another aspect that should not be neglected when making international comparisons is the choice of the unit of analysis, which may be the household intended as a group of people who live together regardless of kinship relations, the family understood as a group of relatives that live together, or the individual. Unlike empirical analysis on income inequality, where great importance is given to families or households, studies on wealth should be focused on individuals since the right to ownership is basically an individual right. Unfortunately, even though fiscal data are on an individual basis, most data about net wealth in the surveys take the household or the family as unit of analysis.

Usually, empirical studies that focus on household income inequality make use of equivalence scales such as the square-root scale, which divides household income by the square root of household size, or the modified OECD scale, which assigns a value of 1 to the household head, of 0.5 to each additional adult member and of 0.3 to each member under 14 years old. The application of such scales is essential to compare households of different size and to consider economies of scales in consumption.

On the contrary, the application of equivalence scales to household wealth is more controversial (Sierminska and Smeeding, 2005; Bover, 2010; Jäntti et al., 2013; Cowell & Kerm, 2015). In fact, the relationship between household net wealth and consumption may be interpreted in several ways. Net wealth may be intended as the value of potential future consumption (for instance after retirement). In such a case, it is not the current household composition and the household size that should matter, but the future composition. On the contrary, if net household wealth is interpreted as the ability to finance current consumption, it is better to use equivalence scales as in the case of income. If, instead, net wealth is taken as measure of socio-economic status or power, there is no reason to apply equivalence scales to net wealth.

Finally, data extracted from sample surveys suffer from numerous measurement errors. They are mainly due to sampling and to the shape of the distribution of wealth which is very asymmetric with an extreme degree of inequality in the upper tail. This is the reason why data from surveys may lead to an underestimation of the degree of overall net wealth inequality (Vermeulen, 2014). This issue can be minimized by over-sampling, using sophisticated techniques, the richest portion of the population.

Another category of measurement errors from sampling is related to the missing response from the wealthy. For instance, as reported by the Luxembourg Wealth Study (LWS), in Italy the overall response rate was 53% in 2010.

1.2. Cross-country rankings of wealth levels and inequality

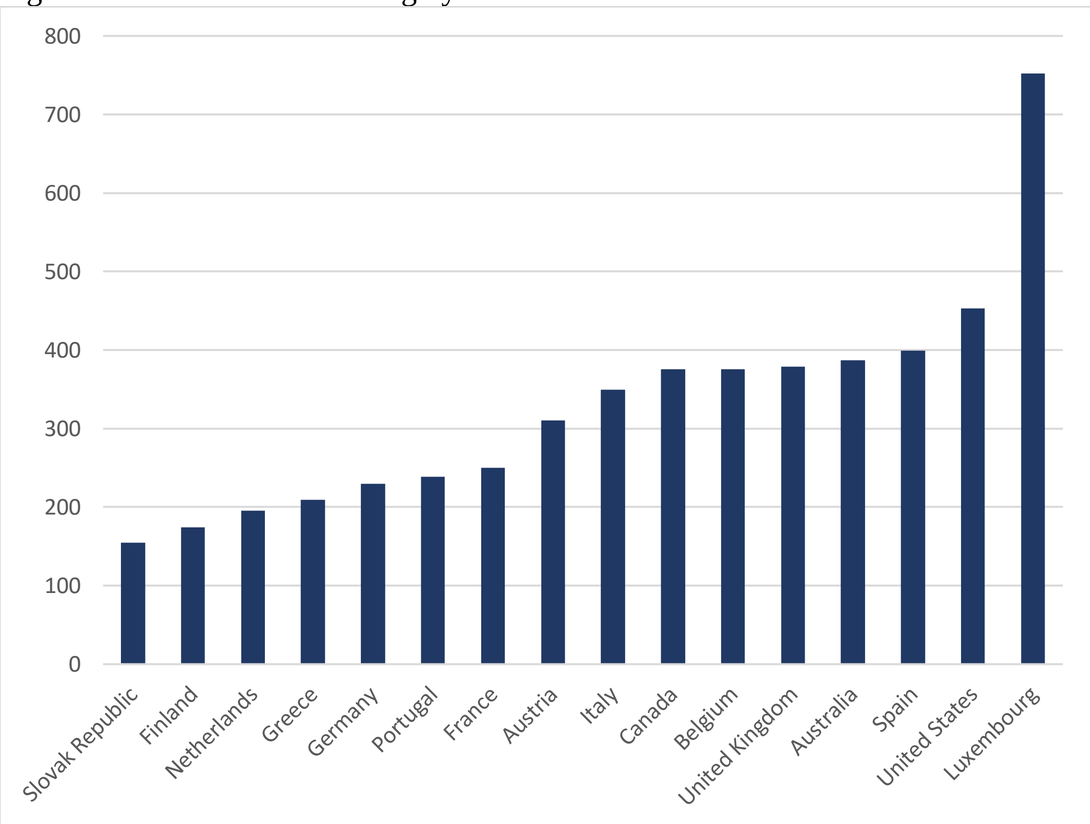
1.2.1. Wealth levels and distribution

Because of all measurement issues described in previous section, it is more difficult to compare statistics on the degree of wealth inequality than on income inequality. Nevertheless, despite many limitations in the availability of good data about wealth, in the last few years empirical research has made a great effort to obtain an international ranking of the degree of wealth inequality. For instance, the Luxembourg Wealth Study (LWS), established in 2004, represents a first attempt to provide harmonized data on wealth and enable international comparisons (Sierminska et al.2006).

Another source of data on wealth is the OECD Wealth Distribution Database, that provides information, for 18 different countries, harmonised according to different guidelines (Murtin & d'Ercole, 2015). However, the harmonization process is still not perfect and some cross-countries differences remain. For instance, there are many cross-country differences in the number of years for which data are available or in the degree of wealthy households over-sampling. Therefore, unlike international rankings on income distribution which are unanimous in considering the Northern European countries as the most egalitarian and the English-speaking and southern European countries as those with the highest level of inequality, the literature on the distribution of wealth has not achieved the same degree of consensus so far (Jäntti et al., 2008).

In any case, when countries are ranked in terms of net wealth levels, it is preferable to use median instead of mean wealth since the latter is likely to be strongly influenced by the high degree of wealth concentration in the upper tail of the distribution. For instance, using the latest OECD data on net wealth expressed in purchasing power parity U.S. dollars (Figure 1.1 and 1.2), the United States, among 16 OECD countries considered, ranks 2th, when countries are classified in terms of mean wealth, and 15th when the ranking is based on median net wealth; Netherlands and Austria drop respectively from the 14th to the last place and from the 9th to the 13th place; Italy ranks 8th using mean wealth and 5th using median wealth; Luxembourg leads the ranking choosing either mean or median wealth as a measure of net wealth levels. Regarding Northern European countries, previous studies report low levels of net wealth in Sweden and Denmark (OECD 2015, Cowell et al, 2013).

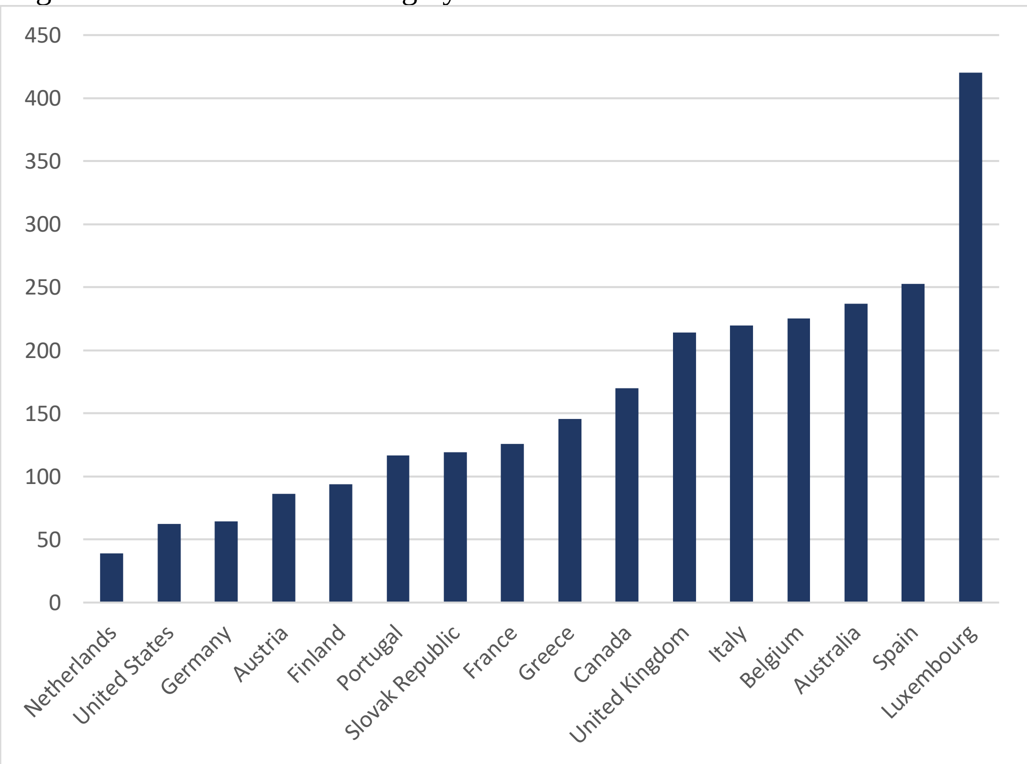
Figure 1.1: International ranking by levels of mean wealth



Source: OECD (Wealth distribution database) Year: 2010 or latest data available.

As stated in the previous section, most of these cross-country differences and lower levels of net wealth in Scandinavian countries are probably due to institutional characteristics. In particular, the presence of universalistic welfare systems reduces the need to accumulate economic resources against unexpected events, such as increased uncertainty over future earnings or unexpected expenses (e.g. health problems or other emergencies).

Figure 1.2 International ranking by levels of median wealth



Source: OECD (Wealth distribution database) Year: 2010 or latest data available

Concerning cross-country differences in terms of wealth inequality, it is possible to take the Gini index as a typical summary measure of concentration. Table 1.1 shows Gini indexes for 16 OECD countries in 2014, using data from different sources presented in the Allianz Global Wealth Report 2015. These data report the United States to be a highly unequal country (the value of the Gini index is greater than 0.8), followed by Sweden, United Kingdom, Austria and Germany that report a Gini index respectively of 0.799, 0.757, 0.736 and 0.733. Conversely net wealth inequality in Greece, Spain, Norway, Australia, Belgium and Italy is the lowest among the OECD countries considered, with a Gini index lower than 0.6.

Table 1.1 Cross-country differences in wealth and income inequality

Country	Gini Wealth	Gini Market Income	Gini Disposable Income
Australia	0.573	0.434	0.327
Austria	0.736	0.426	0.281
Belgium	0.587	0.425	0.266
Canada	0.640	0.411	0.325
Finland	0.645	0.424	0.262
France	0.655	0.445	0.294
Germany	0.733	0.419	0.299
Greece	0.554	0.512	0.353
Italy	0.592	0.445	0.329
Netherlands	0.640	0.406	0.287
Norway	0.568	0.377	0.262
Portugal	0.634	0.496	0.345
Spain	0.563	0.479	0.352
Sweden	0.799	0.383	0.281
U.K.	0.757	0.471	0.353
U.S.	0.806	0.473	0.389

Data sources: Oecd (Database on income distribution and poverty). Allianz Wealth Report 2015 (Wealth)

The extent of economic inequality measured through the Gini of net wealth is usually greater than economic inequality measured by means of the Gini of income. For instance, the Gini index of wealth in the US is nearly twice the size of the Gini index of market income and more than twice the size of the Gini index of disposable income. Even though these two differences are less marked in other countries such as Greece or Italy, economic disparities measured in terms of real and financial assets holding are generally higher than economic disparities in the labour market. This is because economic differences in income and economic disparities in wealth are correlated but this correlation is imperfect. In particular, while economic disparities in terms of income reflect yearly economic differences, wealth differences are related to cumulate economic performances of individuals and to disparities in saving propensity, attitudes to risk and intergenerational transfers.

1.2.2. Wealth inequality over the distribution

International rankings may be controversial not only when comparing levels of wealth, but also when the main goal is to build credible international rankings which make use of the Gini index as a measure of wealth inequality. More specifically, the Gini index does not appear to be the most suitable indicator when considering variables that can assume negative values. In these cases, in fact, the Gini index may also assume value greater than one (Amiel et al., 1996; Cowell, 2013). Moreover, international comparisons based on the Gini index are not suitable to assess whether higher levels of inequality depend on a high concentration of wealth or a high prevalence of debts.

For instance, higher levels of inequality in Sweden or Denmark seem to be strongly correlated to the high incidence of households with negative net wealth (Davies et al, 2009): the latter country is characterised by negative levels of net worth for the lowest three deciles of the distribution (Davies et al, 2014). Therefore, high levels of wealth inequality in the Northern European countries, as well as the high diffusion of loans among young people to finance their university studies, could be explained by institutional characteristics which, as already said, reduce the incentive to accumulate private wealth. Moreover, it is well known in the empirical literature that only a small part of the population holds a large fraction of wealth (Davies and Shorrocks,2000). For all these reasons, it is preferable to use alternative measures of wealth inequality which focus on the on the amount of net wealth held by households at different points of the wealth distribution.

Table 1.2 shows some possible alternative measures of wealth inequality presented in the report “In it together: why less inequality benefit all” (OECD, 2015). For instance, the mean/median wealth ratio is very high in the United States and Netherlands with a value of respectively 7.3 and 5. On the contrary, this ratio is reported to be the lowest, among the OECD country considered, in Greece, Australia, Italy and Spain (column 1).

Table 1.2 shows also the difference (expressed as a share of median wealth) between the amount of wealth held by those above the 95th percentile (the top 5%) and the median wealth (column 2). This ratio, which is useful to evaluate the degree of wealth concentration at the top of the distribution, is reported to be about 70 points higher than the OECD average in the Unites States; Netherlands, Austria and Germany are also reported to be highly unequal considering the upper tail of the wealth distribution.

Table 1.2 Alternative measures of wealth inequality

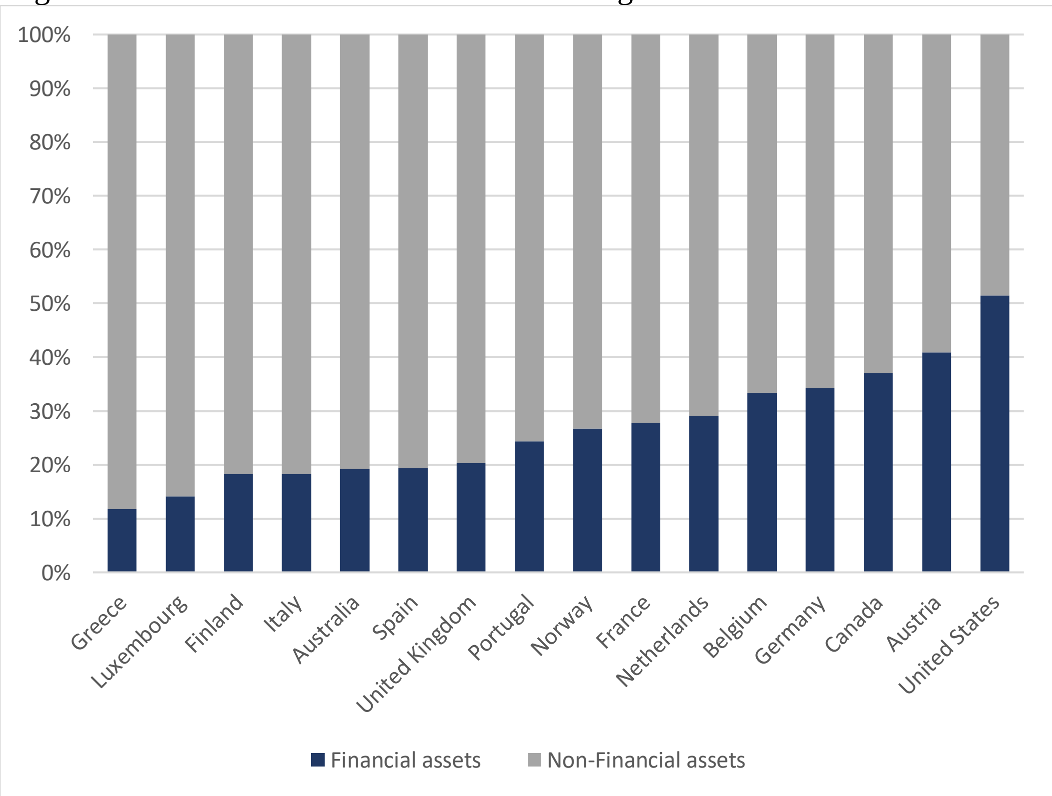
Country	Mean/Median	(Top 5% – Median)/Median	(Median – Lowest Quintile)/Median
Australia	1.6	9.5	1.0
Austria	3.6	34.7	1.1
Belgium	1.7	10.1	1.0
Canada	2.2	15.1	1.0
Finland	1.9	10.6	1.1
France	2.0	14.8	1.0
Germany	3.6	33.8	1.1
Greece	1.4	6.4	1.0
Italy	1.6	9.3	1.0
Luxembourg	1.8	13.8	1.0
Netherlands	5.0	43.9	1.8
Norway	1.9	12.7	1.5
Portugal	2.0	15.9	1.0
Spain	1.6	9.0	0.9
U.K.	1.8	11.1	1.0
U.S.	7.3	90.7	1.3
OECD18	2.5	20.4	1.1

Data source: OECD (2015). Year 2010 or latest available

Lastly, the third column of table 1.2 focuses on the lower tail of the distribution showing differences (expressed again as a share of median wealth) between median wealth and the lowest quintile of the wealth distribution. According to this ratio, Norway and Netherlands, among the 16 countries considered, are characterised by the highest level of wealth inequality in the lower tail of the distribution. Consider however, that cross-country differences in bottom-end wealth inequality are not so high. This means that high levels of inequality are mainly due to the higher concentration of wealth in the upper tail of the distribution. On the contrary, concentration of net wealth in the lower tail, where most of the households have no or very limited wealth, is likely to affect only partially overall inequality.

An important role in explaining differences in the degree of wealth inequality is played by financial assets which are mainly concentrated in the upper tail of the wealth distribution (OECD 2015). In this respect, Figure 1.3 reports cross-country differences in financial and real assets as a share of total gross wealth. The percentage of financial assets is very high in the United Stated where most of gross wealth is financial wealth. On the contrary, in all other countries considered the share of financial assets on gross wealth is lower than or equal to 40%. This percentage reaches its lowest values in Australia, Spain, Greece, Luxembourg.

Figure 1.3: Share of real and financial assets in gross wealth



Data source: OECD wealth distribution database. Year 2010 or latest available

1.3. Intergenerational transmission of economic advantage in the empirical literature

Income has been usually preferred over wealth by researchers, not only to measure current economic inequality, but also to evaluate to what extent economic inequality is persistent across generations. This is because data of wealth which cover two or more generations are rarely available. Moreover, income or earnings are usually the beast measure to consider if one wants to evaluate economic opportunities in the labour market as a function of parental economic background.

Intergenerational mobility has been usually defined as the “degree of fluidity” between the socio-economic status of parents and that of their children as adults (Blanden et al., 2007). Economists, have measured mobility across generations in terms of either income or earnings, although the intergenerational transmission related to other socio-economic outcomes (e.g. education, occupation) has also received great attention. Regardless of the measure of mobility in socio-economic status across generations, a strong association between parental and offspring’s outcomes entails a low degree of intergenerational mobility, which is arguably indicative of the fact that economic opportunities are not equally distributed between the individuals of a given society.

According to the classical “human capital view” based on two seminal works by Becker and Tomes (1979 and 1986), the intergenerational inequality transmission is mainly due to the role played by liquidity constraints: if capital markets are not perfect, investment in human capital of individuals coming from disadvantaged backgrounds are limited by the lack of economic resources. However, there could be other channels that may explain why individuals coming from better backgrounds are likely to get higher wages once in the labour market. For instance, economic power of parents may be easily exploited to help children finding the right job in terms of current and expected future income.

In any case, economic well-being is often correlated across generations not only because of the indirect association in economic opportunities in the labour market. Economic resources are also transmitted directly by means of donations and bequests which are not captured by evaluating permanent income flows. This is the reason why it is not simple to obtain measures of mobility able to summarise the degree of intergenerational correlation in permanent economic resources.

1.3.1. The intergenerational earnings or income elasticity: approaches and measurement issues

Empirically, many studies over the last 15/20 years try to evaluate to what extent economic advantages are transmitted from one generation to another (see Black & Devereux, 2010). The usual way to summarize the degree of intergenerational economic correlation is to use earnings or income as a measure of economic welfare of individuals and to estimate the following equation:

$$y_i^s = \alpha + \beta \; y_i^f + \varepsilon_i \tag{1}$$

where y_i^s and y_i^f are respectively the logarithm of permanent sons' and fathers' earnings and β is the intergenerational earnings elasticity (IGE)[1]. According to this measure of economic association between generations, a country is completely mobile when the estimated β equals 0 and the higher the earnings elasticity is, the lower the degree of economic mobility across generations will be.

The empirical framework subsumed by equation 1 might appear relatively simple at a first sight. However, several methodological issues arise when trying to estimate the β by means of OLS. For instance, deriving accurate estimates of the IGE has proved to be remarkably challenging since permanent incomes are generally unobservable. Usually, data limitations allow researchers to track individual income records only for a single or a few years. This source of bias has been reduced with by the increasing resort to large administrative dataset. Yet, richer data alone are not sufficient to overcome the challenges related to the measurement of permanent income.

Earlier studies on the intergenerational earnings mobility in the U.S. reported IGE coefficients around 0.2 (Becker and Tomes, 1986; Behrman and Taubman,

[1] For a review of the studies on intergenerational earnings mobility, see also Solon (1999), Corak (2006) and Blanden (2013).

1986; Sewell and Hauser, 1975), leading to the conclusion that the American society was characterized by a high degree of mobility across generations.

However, shortly after, subsequent works demonstrated that those estimates were substantially downward biased because of measurement errors in fathers' permanent earnings. Specifically, Solon (1992) and Zimmerman (1992) were the first ones to point out that the reliance on single-year measures of parental earnings and the use of homogenous sample, which generally present less income variation, would result in the underestimation of the IGE.

More formally, if permanent incomes of the first generation are measured with error, equation 1 becomes:

$$y_i^s = \alpha + \beta \ y_i^{f*} + \vartheta_i + \varepsilon_i \tag{2}$$

where y_i^{f*} is the unobservable permanent income of the first generations and ϑ_i is the measurement error that is assumed to be uncorrelated to y_i^{f*}. Hence, if $y_i^f = \ y_i^{f*} + \vartheta_i$, it is possible to compare the consistency of elasticities obtained by using permanent incomes of the first generation to that obtained by using yearly incomes:

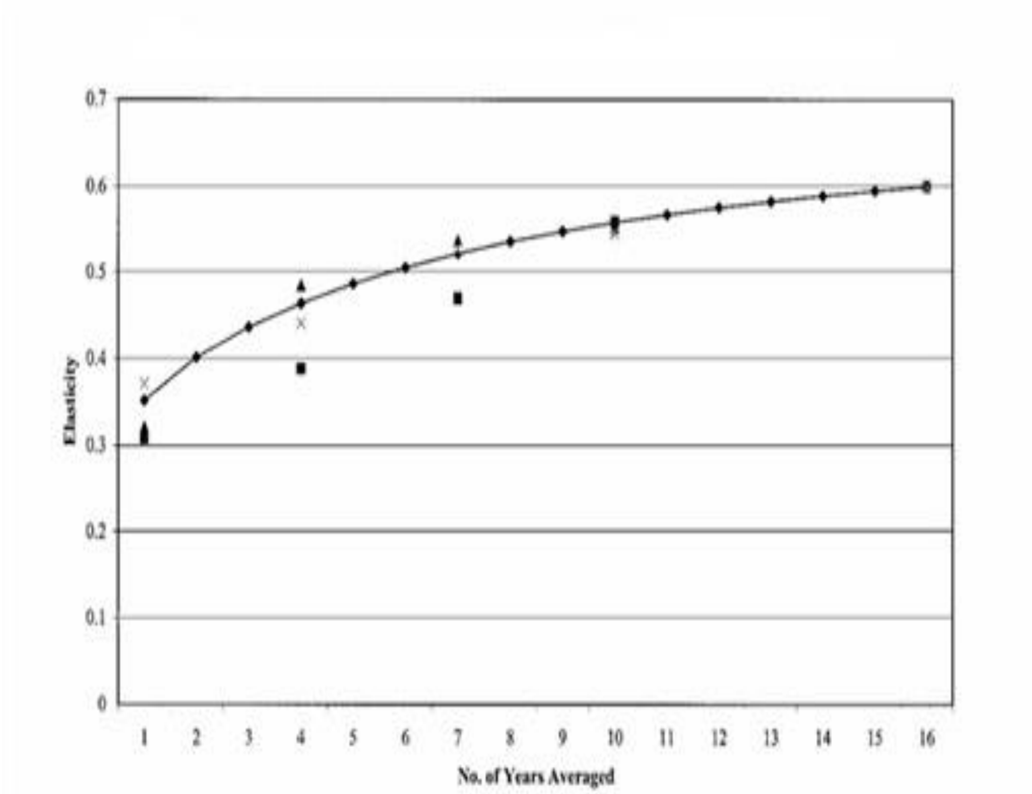
$$\hat{\beta}^* \xrightarrow{p} \frac{Cov\left(y_i^s, y_i^{f*}\right)}{var\left(y_i^{f*}\right)} > \hat{\beta} \xrightarrow{p} \frac{Cov\left(y_i^s, y_i^f\right)}{var\left(y_i^{f*}\right)+var(\vartheta_i)} \tag{3}$$

where $\hat{\beta}^*$ is the estimator obtained by using true lifetime incomes of fathers and $\hat{\beta}$ is the estimator obtained by using incomes affected by transitory shocks so that, by construction, $var\left(y_i^{f*}\right) < \ var\left(y_i^{f*}\right) + \ var(\vartheta_i)$.

As it is commonly assumed in the empirical literature, it is possible to reduce attenuation biases by averaging the regressor over time if the error component ϑ_i has zero-mean. Accordingly, studies based on larger and more representative datasets that use fathers' earnings averaged over more than one year (usually four or five) yielded estimates around 0.4.

However, Mazumder (2005a) points out that even using 5-years averaged incomes may lead to an underestimation of the IGE since transitory shocks are usually very important and persistent. For this reason, he evaluates the pattern of mobility as a function of the number of years fathers' earnings are averaged. Figure 1.4 shows that the estimated elasticities in the US is likely to be about 30 percent higher when fathers' earnings are averaged over 16 years than when they are averaged considering only 5 years. This means that permanent transitory shocks are likely to strongly affect estimates of the intergenerational economic mobility if permanent measures of economic status are not available.

Figure 1.4: IGE as a function of the number of years fathers' earnings are averaged



Source: Mazumder (2005a)

Another important source of bias is related to the selection of sons by age. More specifically, since measures of permanent income are not available, researchers must decide the optimal age at which earnings of the second generation should be measured in order to obtain estimates which are representative of correlations in lifetime resources. This is because estimated elasticities are usually affected by both left-hand side and right-hand side measurement errors as earnings-age profiles are steeper for adult children with higher expected permanent incomes.

According to an empirical study by Haider and Solon (2006) this lifecycle bias can be substantially reduced by choosing both generations around 40 years old. Their result has been confirmed by several subsequent empirical studies. For instance, Nybon & Stuhler (2016) find that different measures of intergenerational associations in earnings are more consistent if obtained by selecting both generations around midlife.

1.3.2. Lack of data which cover two generations: the two-sample two-stage least squares method

Direct information about fathers' earnings and/or income is usually limited in most of developed and less developed countries. For this reason, it would have been extremely hard to make comparisons in terms of economic mobility by considering only those countries for which an OLS estimates of intergenerational mobility is available.

A way to overcome this issue was first proposed by Björklund and Jäntti (1997) that make use of the two-sample instrumental variable methodology (TSIV), originally described by Angrist and Krueger (1992) and Arellano and Meghir (1992), to estimate intergenerational elasticities in Sweden and the United States. This approach uses two independent samples and some information about some socio-economic characteristics of fathers reported by their sons to predict earnings of the older generation. As time goes by, the two-sample two-stage least squares approach (TSTSLS) becomes gradually more used because computationally more convenient and asymptotically more efficient than the TSIV (Inoue and Solon, 2010)[2].

The TSTSLS estimator is obtained by using a sample of adult sons, who report some socio-economic characteristics of their actual fathers, and an independent sample of pseudo-fathers, in a two-stage approach. In the first stage the sample of pseudo-fathers is exploited by regressing the following equation:

$$Y_{i,t}^{pf} = \alpha + \theta_1 Z_i^{pf} + v_{i,t} \tag{4}$$

where $Y_{i,t}^{pf}$ are earnings of pseudo-fathers, Z_i^{pf} is a vector of their socio-economic characteristics, α is the intercept and $v_{i,t}$ is the usual disturbance. The estimated coefficient $\hat{\theta}_1$ is then used to predict missing fathers' earnings by merging the two samples according to child-reported characteristics of actual fathers. The intergenerational earnings (or income) elasticity β is thus estimated in the second stage:

$$y_{i,t}^{s} = \alpha + \beta \hat{y}_i^F + \epsilon_{i,t} \tag{5}$$

where $y_{i,t}^{O}$ is the logarithm of son's earnings and $\hat{y}_i^F = \hat{\theta}_1 Z_i^F$ is the prediction of the logarithm of fathers' earnings.

According to an empirical regularity (the mincer equation), the socio-economic characteristics which are usually taken to predict fathers' economic status are either fathers' education, occupational status, sector of activity, area of residence or a subset of these predictors[3]. The more these socio-economic characteristics perform well at predicting fathers' economic status, the less estimated elasticities will be

[2] For instance, this approach has been used to estimate intergenerational elasticities in many countries. See for instance estimates for Sweden and U.S. (Björklund and Jantti, 1997), France (Lefranc and Trannoy, 2005), Brazil (Ferreira and Veloso, 2006; Dunn 2007), Australia (Leigh, 2007a), Italy (Piraino, 2007; Mocetti, 2007), U.K. (Nicoletti and Ermish, 2007) and Spain (Cervini-Plà, 2015).

[3] See Jerrim et al. (2016) for a review of studies on intergenerational income mobility which use the TSTSLS approach.

biased compared to the ones obtained by regressing sons' earnings on actual fathers' earnings. More specifically, when one tries to impute fathers' economic status, he is likely to make some errors in measuring their income. This reduces estimated elasticities under the assumption of classical measurement error. Moreover, if the set of socio-economic characteristics is not able to capture other characteristics of individuals (soft skills, social networks, cultural factors, cognitive and non-cognitive abilities), which are positively correlated across generations, then the elasticity will be again downward biased. At the same time, since the elasticity converges in probability to the covariance between the income of the two generations over the variance of the income of the first, if the fraction of the variance predicted from the set of socio-economic characteristics exploited in the first stage is less than one, then the estimated elasticity may be also upward biased[4].

Even though the final effect of all potential sources of bias is not clear a-priori, TSTSLS estimates of earnings mobility are usually considered as an upper bound on the true intergenerational association (Blanden, 2013). Nevertheless, the higher the R^2 of the first stage regression is (i.e. the fraction of earnings of the first generation predicted from the set of available socio-economic characteristics), the lower the amount of all these biases is likely to be[5].

The consistency of the two-sample estimator relies on two additional points. Firstly, auxiliary variables used in the first stage should have the same distribution in both the sample of pseudo-parents and the sample of offspring even though the TSTSLS approach automatically corrects for differences (Inoue and Solon 2010)[6].

Secondly, if auxiliary variables used in the first stage have a positive influence on offspring's income only via parental income and not directly, then the estimated elasticity will approximate the causal effect of fathers' income on sons' income. This means that all previously described sources of bias would disappear in the case of exogenous instruments. Nonetheless, studies on mobility across generations are

[4] See Olivetti and Paserman (2015) for a more formal description of all potential sources of bias related to the imputation of the income of the first generation.

[5] As the fraction of the variance explained from the set of predictors in the first stage increases, the amount of measurement error becomes lower. Moreover, the upward bias due to the underestimation of the variance of the first generation automatically decreases.

not usually intended to estimate the causal effect of parental background on offspring's economic outcomes. For this reason, first stage auxiliary variables should not be considered as exogenous since they are likely to have a direct influence on the outcome variable in the second stage regression.

1.3.3. Cross-country comparison in the intergenerational earnings elasticity

Because of all measurement issues that may arise when one tries to estimate the IGE, a large empirical effort has been made in the last two decades to improve the consistency of estimates. Most of the empirical evidence is provided by using either the OLS estimator or the TSTSLS method and by considering two generations around 40 years old to minimise the amount of lifecycle bias. In any case, the attenuation bias due to measurement errors in the right-hand side of equation 1 is only partially mitigated by averaging fathers' earnings over a 4/5 years period.

Table 1.3 summarizes estimated earnings elasticities from different empirical studies on 12 developed countries which use either the OLS or the TSTSLS estimator to measure intergenerational mobility.

Table 1.3: Intergenerational earnings elasticity: cross-country comparison

Country	Source	Empirical approach	IGE
US	Various (Averaged)	OLS	0.52
Italy	Piraino (2007)	TSTSLS	0.44
Spain	Cervini-Plà (2015)	TSTSLS	0.42
France	Lefranc & Trannoy (2005)	TSTSLS	0.40
UK	Ermish & Nicoletti (2007)	TSTSLS	0.29
Australia	Leigh (2007)	TSTSLS	0.25
Germany	Vogel (2006)	OLS	0.24
Sweden	Björklund & Chadwick (2003)	OLS	0.24
Canada	Corak & Heisz (1999)	OLS	0.23
Finland	Pekkarinen et al. (2009)	OLS	0.23-30
Denmark	Hussain et al. (2008)	OLS	0.14

According to this measure of intergenerational association in economic opportunities in the labour market, the Unites States is reported to be the less mobile society with an estimated β of respectively 0.52. This means that a 10 percent variation in fathers' earnings is associated with a 5.2 percent in sons'. Conversely, the North countries are reported to be the most mobile, reporting estimated IGE ranging from 0.14 to 0.24. The extent of earnings mobility in other developed countries such as Germany, Australia and UK is not so far from that reported in Scandinavian countries. Lastly, France Spain and Italy resulted to be low mobility societies with estimated elasticities around 0.40.

1.4. Intergenerational wealth mobility across two or more generations

Estimates of economic mobility across generations are usually intended to capture correlations in lifetime resources. As described in previous sections, estimates which use earnings or income as a measure of economic status are likely to be downward biased because of both left-hand side and right-hand side measurement errors. Moreover, correlations in income do not consider all possible mediating channels related to the transmission of economic status across different generations. This is the reason why, it could be better to evaluate intergenerational mobility by considering wealth as a measure of permanent economic status of the two generations. In particular, at time T the amount of wealth owned by an individual may be expressed in the following form:

$$W_{i,T} = W_{i,T-1}(1 + r_{i,T}) + Y_{i,T}(1 - c_{i,T}) + \ Tr_{i,T} \tag{6}$$

where $W_{i,T-1}$ is the stock of net wealth held in the previous period, $r_{i,T}$ is the rate of return on investments, $Y_{i,T}$ is the amount of disposable income, $(1 - c_{c,T})$ is the propensity to save and $Tr_{i,T}$ is the difference between the amount of direct wealth transfers received from the previous generation and those given to the next.

Since current income is affected by transitory shocks it is possible to rewrite equation 6 this way:

$$W_{i,T} = W_{i,T-1}(1 + r_{i,T}) + (Y^{*}{}_{i,T} + \vartheta_{i,T})(1 - c_{i,T}) + Tr_{i,T} \qquad (7)$$

where $Y^{*}{}_{i,T}$ is the permanent component of disposable income and $\vartheta_{i,T}$ captures transitory shocks. Then, if we assume a rate of return to investment equal to zero for the sake of simplicity, it is possible to express $W_{i,T-1}$ as the sum of all incomes and donations received in the past and on preferences in terms of propensity to save:

$$W_{i,T-1} = \left\{\sum_{t=1}^{T-1}\left[\left(Y^{*}{}_{i,t} + \vartheta_{i,t}\right)(1 - c_{i,t})\right] + \sum_{t=1}^{T-1}(Tr_{i,t})\right\} \qquad (8)$$

If, as it is commonly assumed in the empirical literature, transitory shocks of income have zero-mean such that for T large enough $\sum_{t=1}^{T-1}\vartheta_{i,t} \cong 0$, it is possible to re-write equation 8 in the following form:

$$W_{i,T-1} = \sum_{t=1}^{T-1}\left[\left(Y^{*}{}_{i,t}\right)\left(1 - c_{i,t}\right)\right] + \sum_{t=1}^{T-1}\left(Tr_{i,t}\right) \qquad (9)$$

by assuming that yearly wealth is measured when individuals are old enough such that they have had enough time to accumulate wealth. Therefore, one period later, it is possible to write:

$$W_{i,T} = \sum_{t=1}^{T}\left[\left(Y^{*}{}_{i,t}\right)\left(1 - c_{i,t}\right)\right] + \sum_{t=1}^{T}\left(Tr_{i,t}\right) \qquad (10)$$

Equation 10 is very useful to get an idea of why wealth could be preferred over income as a measure of permanent economic status of the two generations when data which cover parents and children over their entire lifecycle are not available. Unlike current income $Y_{i,t}$, which is affected by transitory shocks, current wealth $W_{i,T}$ automatically incorporates a measure of cumulate economic status which depends on the sum of all incomes earned in the past. This means, that estimates of intergenerational wealth correlations obtained by regression wealth of children on that of parents could be, at least from a theoretical point of view, higher than estimates of income correlations which use measures of incomes that are not averaged over many years. However, this is only true if individuals are taken at median ages or older such that transitory shocks cannot cause attenuation biases.

In any case, intergenerational correlations in wealth are likely to be higher than correlations in income also because of intergenerational transfers. In particular, the mediating role of donations and bequests should be very important at the beginning of the adulthood, when parents make inter-vivos transfers, and later during the lifecycle because of inheritance. This means that permanent economic resources are likely to be better captured at median ages when the difference between transfers received from the previous generation and transfers given to the next reaches its minimal value and economic resources are representative of cumulate earnings (Boserup et al. (2016).

1.4.1. The intergenerational wealth elasticity (IWE)

Despite all the potential advantages related to the use of wealth as a measure of permanent economic resources, only a few empirical recent studies have analysed how economic advantage is transmitted across generations by using wealth instead of earnings or income as a measure of economic well-being. This is mainly due to the already recalled limited availability of good quality data on wealth and to the fact that earnings are broadly considered as a good measure of differences in consumption capacity and economic welfare. Unlike studies of intergenerational income mobility which usually estimate the correlation in earnings or income between fathers and sons, studies on wealth mobility estimate the correlation between parents and adult children.

As in the case of income, the first commonly used way to evaluate the degree of intergenerational wealth mobility is to estimate the following equation:

$$w_i^0 = \alpha + \gamma \ w_i^P + \ X_i^{O,P} \varepsilon_i \qquad (11)$$

where w_i^0 and w_i^P are the logarithm of offspring's and parental wealth, $X_i^{O,P}$ is a vector which includes age and age squared of both offspring and parents and γ is the intergenerational wealth elasticity. Using this approach, Charles and Hurst

(2003), obtain a wealth elasticity of 0.37 for the United States. This means that, in the Unites States, a 10 percent increase in parental net wealth seems to be associated with a 3.7% increase in offspring's. Other studies which use the same log transformation, find lower elasticities for Sweden (Adermon et al., 2015), Denmark (Boserup et al., 2013), France (Arrondel, 2009) and Norway (Fageren et al., 2015). These results summarised in table 1.4 seem to confirm that the United States is a country with a low degree of intergenerational economic mobility even considering wealth instead of earnings as a measure of economic status.

Table 1.4: Intergenerational wealth association: cross-country comparison

Country	Source	Parent's Age	Offspring's Age	Estimated Elasticity (LOG)	Estimated Elasticity (IHS)	Rank Slope
US	Charles and Hurst (2003)	52	37.5	0.37	/	/
US	Pfeffer and Killewald (2015)	43.4	44.6	0.41	/	0.37
Denmark	Boserup et al. (2013)	48.6	33.9	0.27	0.19	0.23
Denmark	Boserup et al. (2016)	47.9	47.2	0.24	0.22	0.27
Sweden	Adermon et al. (2015)	57-63	42-49	0.32	/	0.39
Sweden	Black et al. (2015)	63.9	43.8	/	0.27	0.35
Norway	Fageren et al. (2015)	62.7	36.1	0.2	/	0.18
France	Arrondel (2009)	58.9	33.8	0.22	/	/

Consider however, that most studies are forced to take offspring and parents at different ages, because of the lack of data which cover two generations during their entire lifecycle. This means that, even though wealth is less affected by lifecycle bias than earnings or income, using too young offspring may cause some problems if they have had no enough time to accumulate financial and real assets (Charles and Hurst, 2003; Conley and Glauber, 2008). Two exceptions are provided by

Boserup et al. (2016) that obtained an IWE of 0.27 for Denmark and Pfeffer and Killewald (2015) that reported an elasticity of 0.41 for the United States by selecting offspring and parents when they are in their 40s. The latter results seems to confirm the presence of a downward bias in previous estimated elasticities which use too young offspring since the elasticity reported by Pfeffer and Killewald (2015) is higher than the one obtained by Charles and Hurst (2003) selecting offspring in their 30s and parents in their early 50s

1.4.2. The hyperbolic inverse sine transformation

Unlike income, wealth may also assume negative values because of financial liabilities. This means that estimated elasticities obtained by using the classical log-log specification automatically excludes all zero and negative values (i.e. the lower tail of the wealth distribution). This may cause a selection bias in estimated elasticities if the degree of intergenerational wealth correlation is not stable across the wealth distribution (Charles and Hurst, 2003; Killewald, 2013; Hansen, 2014; Pfeffer and Killewald 2015, Adermon et al. 2015). This is the reason why an alternative available approach has been used to estimate intergenerational wealth elasticities on the full sample of households using the inverse hyperbolic sine transformation (IHS). This transformation assumes the following form:

$$\theta^1 \sin h^{-1}(\theta W) = \theta^1 \ln\left(\theta W + (\theta^2 W^2 + 1)^{1/2}\right) \quad (12)$$

where W is a measure of wealth and θ is a scaling parameter. The proportion of the IHS transformation which is linear depends on the parameter θ: as the parameter gets close to zero, the transformation becomes linear for a larger fraction of its domain (Pence 2006). In the case of studies on wealth mobility the parameter is usually assumed to be one in order to get a transformation which is very similar to the logarithm transformation. Thus, when the parameter is equal to one, the IHS transformation becomes:

$$w = \log(W + \sqrt{W^2 + 1}) \quad (13)$$

This means that the IHS transformation behaves as $log|W|$ everywhere but in the neighbourhood of zero when the scaling parameter is equal to one.

Even though this alternative transformation allows researchers to compute estimates of mobility that do not exclude the lower tail of the wealth distribution, only a small number of studies try to estimate the IWE by using the IHS transformation. For instance, Boserup et al. (2013) report an estimated elasticity for Denmark of 0.27 and of 0.19 using respectively the log and IHS transformation. Table 1.4 shows that also in the case of Sweden the IHS elasticity reported by Black et al. (2015) is lower than the log elasticity reported by Adermon et al. (2015) in a study on the same country.

1.4.3. Rank-Rank slopes

The most commonly used way to evaluate the degree of intergenerational wealth association, without excluding zero or negative values is to estimate rank-rank slopes instead of elasticities. Rank-rank slopes may be easily obtained by estimating the following equation:

$$rank(W_i^0) = \alpha + \delta\, rank(W_i^P) + \varepsilon_i \tag{14}$$

where offspring's and parental wealth W_i^0 and W_i^P are percentile ranked so that δ is the percentile variation in offspring's wealth associated to a 1 percentile variation in parental wealth. There are many reasons to prefer rank-rank slopes over elasticities. As it is well known in the empirical literature, elasticities capture both the re-ranking across generations and the difference in the amount of inequality. On the contrary, rank-rank slopes are not sensitive to differences in the marginal distribution across groups (Chetty et al., 2014; Jäntti and Jenkins, 2014). As a matter of fact, it is possible to express the relationship between the elasticity and the rank-rank slope in the following form:

$$\beta \cong \rho_r \frac{\sigma_o}{\sigma_p} \tag{15}$$

where ρ_r if the rank-rank slope and σ_o/σ_p is the ratio between the standard deviations of offspring's and parental wealth. This means that while the elasticity is informative about the rate of regression to the mean of wealth, rank estimators are informative about the positional correlation in wealth. Observe that, since they are not affected by any change in the earnings dispersion across generations, rank-rank slopes seem to be less affected by transitory shocks and measurement errors and therefore more robust to lifecycle bias and attenuation bias (Gregg et al. 2014; Mazumder, 2015).

Finally, rank-rank measures do not exclude individuals in the lower tail of the wealth distribution. This aspect is important if the degree of wealth correlation is not stable along the wealth distribution. In particular, the degree of wealth association across different generations may be overestimated (underestimated) if the intergenerational correlation is lower (higher) in the lower tail than in the rest of the wealth distribution.

According to this different measure of wealth persistence across generations, the Unites States is confirmed to be a low mobility country among those for which a rank-rank slope estimate is available (table 1.4, last column). In this case, however, the difference in the degree of wealth association between the United Stated and Sweden appears to be very low. This means that Sweden, which is characterised by high levels of wealth inequality due to financial liabilities, is also a country with a low degree of mobility across generations when considering wealth instead of earnings as a measure of economic status.

1.4.4. The pattern of wealth mobility over the lifecycle of child

The framework proposed in section 1.4 describes why wealth should be preferred over income to measure correlations in permanent economic status. However, that framework is not able to suggest at what point of the lifecycle one should measure the intergenerational wealth association in order to capture the economic correlation in lifetime resources. As discussed in section 1.3.1, the intergenerational income correlation is better captured by selecting both generations in their 40s. This is because the income growth rate is usually higher for sons coming from higher income households. This means that the income variance is low at early stages of individuals careers and increases later during the lifecycle.

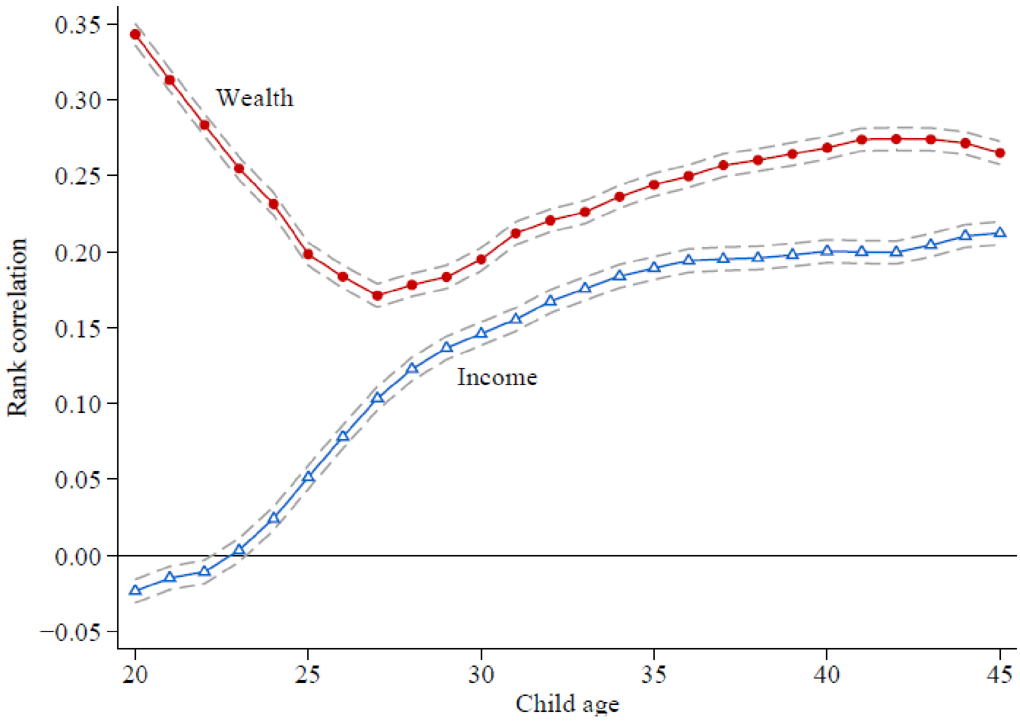
What about wealth? From a theoretical point of view, life-cycle accumulation models predict wealth to be hump shaped over an individual’s lifetime (Davies and Shorrocks, 2000). There is also some empirical evidence showing that wealth accumulation reaches its peak at retirement age, since assets are usually accumulated over the working age and decline after retirement age (see OECD, 2008). Thus, it is well acknowledged in the literature on wealth mobility that choosing too young offspring is likely to influence the consistency of estimated measures of intergenerational mobility. (Charles and Hurst, 2003; Conley and Glauber, 2008 Pfeffer and Killewald, 2015).

However, there is a lack of empirical evidence on the robustness of estimates of intergenerational mobility to the lifecycle bias. The only empirical study which attempts to assess the pattern of the intergenerational wealth correlation as a function of offspring’s age is the one by Boserup et al (2016). Contrary to expectations, they find a U-shaped pattern of the intergenerational wealth correlation as a function of children’s age, with higher intergenerational correlations if offspring are taken when they are very young or from their 40s.

They explain this pattern trough life-cycle patterns in transfers, earnings and consumption. More specifically, wealthy parents are likely to make a larger amount of inter-vivos transfers early in children’s life. Subsequently, their children have low current income, when investing in education, but higher expected lifetime income than other individuals their age. Thus, at this stage of their lifecycle they are likely to have a higher propensity to consume than the rest of the population (i.e. lower wealth accumulation at early stages of their careers). Then, after their parents died, they receive again direct transfers of wealth in the form of bequests. According to this simple explanation, the intergenerational wealth correlation should be very high considering children at the beginning of their adulthood; low at early stages of their careers; high again from their 40s; extremely high after they have received direct wealth transfers in the form of bequests.

This U-shaped pattern of wealth mobility as a function of children's age, which reflects the mediating role of different intergenerational channels at different points of the lifecycle, has been confirmed empirically by Boserup et al. (2016) in a study on mobility in Denmark. Using rank-rank measures of wealth mobility they find a rank correlation of 0.35 selecting children around 20 years old which decreases to 0.17 if children are selected around 27 years old. Their estimated rank correlation rises to 0.27 when children are taken in their 40s (figure 1.5).

Figure 1.5: Intergenerational rank correlation in wealth and income over the lifecycle of the child in Denmark



Source: Boserup et al. (2016)

On the contrary, the pattern of income mobility presented in figure 1.5 is very different and in line with previous studies which analyse how the intergenerational income correlation evolves over the lifecycle. In particular, the rank correlation in income is always lower than the rank correlation in wealth suggesting that using income as a measure of permanent economic status is likely to overestimate the degree of economic mobility across generations. Moreover, unlike wealth, income appears to be weakly correlated across generations when children are selected at the beginning of their adulthood. Subsequently, the rank correlation in income increases to 0.20 when the second generation is selected in their 40s.

The two patterns described by Boserup et al. (2016) suggest that it is better to select offspring around 40 years old even if wealth instead of income is used a measure of economic status of the two generations in order to get a proxy of the intergenerational correlation in lifetime resources.

1.4.5. Estimates of wealth and income mobility, are they comparable?

As described in previous sections, estimates of intergenerational mobility are limited by the lack of data which cover two generations for their entire lifecycle. This means, that estimates provided in the literature are likely to be only a good approximation of correlations in permanent economic status. In any case, researchers may choose between estimates of income or wealth mobility depending of the main goal of their analysis. For instance, if the main objective of a research is to evaluate the transmission from one generation to the next of economic opportunities in the labour market or consumption capacities, it is more appropriate to keep focusing on income or earnings mobility. On the contrary, if researchers want to consider all possible sources of intergenerational correlations and to use a measure which is more related to cumulate rather than current economic status of individuals it is better to estimate intergenerational correlations by focusing on wealth.

Obviously, the two measures of mobility are correlated because, all things being equal, the more income is correlated across generations, the higher the intergenerational correlation in the capacity of accumulate assets will be. However, if income measures of intergenerational correlations are affected by attenuation and lifecycle bias, economic mobility is likely to be overestimated. Moreover, it may be important to consider all direct intergenerational transfers which are likely to further decrease intergenerational economic mobility.

A simple way to evaluate if estimates of wealth mobility are more appropriate to capture economic correlations in lifetime resources is to compare estimated intergenerational rank correlations in wealth to estimated intergenerational correlations in income for all countries for which these two measures of mobility are available. Rank correlations are more appropriate than elasticities to make comparisons because the latter are influenced by changes in inequality across generations. This means that in those countries in which income inequality has increased more (less) than wealth inequality, IGE are likely to be automatically higher (lower) than IWE.

Ideally, one would consider rank measures of mobility estimated by selecting two generations in their 40s to minimise the amount of lifecycle bias. Unfortunately, rank correlations in wealth are often obtained by selecting younger offspring so that they are likely to be underestimated. This is the reason why, I restrict the comparison to three countries for which estimated rank correlations are obtained by selecting offspring aged 40 years old.

Table 1.5: Intergenerational rank correlations in wealth and income

Country	Rank-Rank slope (Wealth)	Rank-Rank Slope (Income)	Sources (Wealth/Income)
US	0.37	0.31-40	Pfeffer & Killewald (2015/ Mazumder (2015)
Denmark	0.27	0.20	Boserup et al. (2016)
Sweden	0.39	0.22	Adermon et al. (2015)/ Bratberg et al. (2017)

In all studies considered, rank correlations are estimated by choosing parents and adult children around 40 years old. Estimates of rank correlations in income for the US are obtained by averaging income of children over 1 to 15 years. In the other countries incomes are averaged over 3 to 5 years. Rank correlations in wealth are obtained by using a single year measure in the case of US or 2/3 years in the case of Denmark and Sweden.

Table 1.5 summarizes estimated rank correlations in wealth and income for countries for which both estimates are available. The two coefficients are obtained by considering either income or wealth of both parents as a measure of economic background and without excluding adult daughters from the second generation. Estimated rank correlations in wealth appear to be considerably higher than rank correlations in income in Sweden and in Denmark. This result may suggest that in Scandinavian countries the intergenerational correlation of economic resources is only partially captured by rank correlations in income. This means that in Denmark and Sweden parents are likely to transmit economic well-being to their children by means of inter-vivos transfers made at the beginning of children's adulthood. Alternatively, it may also be the case that estimates of income mobility are more affected by attenuation bias if they are not properly averaged over many years.

To evaluate this aspect, table 1.5 reports also estimated rank correlations in income and wealth for the US. Rank correlations in income appear to be considerably downward biased if parental and children's income are not averaged considering many years (Mazumder, 2015). In particular, the estimated rank correlation is 0.31, if parental income is not averaged, and 0.40 if it is averaged over 15 years. On the contrary, the estimates rank correlation in wealth is high and equal to 0.37 even considering a single-year measure of parental wealth.

According to evidence reported in table 1.5. it is still not completely clear if researchers should choose wealth or income when measuring intergenerational economic mobility. Rank correlations in wealth are likely to be higher than rank correlations in income when the latter is not properly averaged. In any case, higher intergenerational rank correlations in wealth may persist if other intergenerational channels related to bequests, donations or preferences are not negligible. However, further evidence is needed to obtain a clearer picture of the relationship between measures of intergenerational income mobility and estimates of wealth mobility. Therefore, estimates of income and wealth mobility for other countries are well accepted.

1.4.6. The multigenerational case

A further advantage of estimating intergenerational economic mobility by considering wealth instead of income is that wealth is likely to be transmitted more than income across multiple generations by means of direct multigenerational transfers. This the reason why some of the studies which estimate the degree of wealth association between parents and offspring, provide also evidence on multigenerational wealth associations[7]. For instance, using grandparent's wealth as a measure of economic background, Boserup et al. (2013), Pfeffer and Killewald (2015) and Adermon et al. (2015) report an estimated rank slope between 0.16 and 0.19 in their studies on Denmark, Unites States and Sweden (table 1.6). Moreover, the association between grandparents' and offspring's wealth is lower, but still statistically significant, in Denmark and the Unites States when also parental wealth is included as a further control (table 1.6, last column).

Table 1.6: Wealth Association across three generations: cross-country comparison

Country	Source	Grandparents' age	Offspring's age	Rank Slope	Rank Slope (including also parental wealth)
U.S.	Pfeffer and Killewald (2015)	61.6	37.0	0.19	0.10
Denmark	Boserup et al. (2013)	47.1	23.4	0.16	0.12
Sweden	Adermon et al. (2015)	48-55	42-49	0.17	Not significant

The latter results, while suggesting a strong persistence of wealth across generations, seem to confirm the dynastic component of wealth inequality. However, as in the two generations case, estimates of wealth mobility should be taken carefully since grandparents and offspring are often taken at different points of their lifecycle.

[7] Among all studies of economic mobility across generations, also Clark & Cummins (2014) and Barone & Mocetti (2016) provide estimate of multigenerational economic correlations. However, they are not included in table 1.6 for reasons of comparability. In particular, both studies consider generations that are several centuries apart. Moreover Barone & Mocetti (2016) obtain estimates of economic mobility by considering only a single Italian city (Florence).

1.5. Concluding Remarks

Measuring economic disparities by using net wealth rather than income is not an easy task. Data on all real and financial assets are rarely available and with many differences across countries. For instance, including pension assets or valuables other than vehicles in the computation may completely change international rankings. Moreover, the harmonization process is still not perfect and some cross-countries differences remain, starting with the number of years for which data are available or with differences in the degree of wealthy households over-sampling, used to mitigate the underestimation of wealth in the upper tail of the distribution.

Despite all measurement issues, at any point of time wealth is likely to capture differences in lifetime economic resources better than income because it is less affected by transitory shocks, strongly associated to cumulate earnings and directly transmitted from one generation to the next by means of donations or bequests. For all these characteristics, economic mobility across generations may be better measured by using wealth instead of income since suitable data which cover two generations over their entire lifecycle are usually not available.

Unfortunately, only few studies compare intergenerational correlations in income to intergenerational correlations in wealth by selecting two generations at median ages. Nevertheless, these studies show that economic mobility measured by correlations in income is likely to be overestimated if earnings of the two generations are not properly averaged over many years. Introducing wealth may, at least partially, reduce this kind of underestimation without requiring the use of very large panel which cover two generations over their entire lifecycle. However, further evidence is needed to confirm these results since estimates of mobility which use wealth as a measure of economic status are very recent and hardly comparable by country and age of the two generations.

Chapter 2: The Poor Stay Poor, the Rich Get Rich: Wealth Mobility Across Two Generations in Italy

Abstract

This work uses the two-sample two-stage least square (TSTSLS) method to assess the degree of wealth mobility across generations in Italy and highlight some of the mechanisms linking parental wealth to offspring's economic outcomes. Parental wealth is imputed by exploiting child-reported socio-economic characteristics of both parents since direct information about parental wealth is not available for Italy.

Using the Bank of Italy's survey on household income and wealth (SHIW) and two samples of offspring and pseudo-parents in their 40s, I find an intergenerational age-adjusted wealth elasticity (IWE) of 0.451 and a rank-rank slope of 0.349 which appear to be robust to the use of different predictors of parental economic status. These results suggest that Italy is a low mobility country also when wealth is taken as the measure of economic status.

As in the only previous study by Boserup et al. (2016) which analyses the pattern of wealth mobility over the lifecycle, this chapter shows a U-shaped pattern of the intergenerational wealth correlation as a function of the second generation's age with higher estimated correlations when children are taken at the beginning of their adulthood or in their 40s.

Geographical differences in the extent of intergenerational wealth mobility are analysed by estimating elasticities and rank-rank slopes in two different macro-areas of the country. Results suggest that the southern part of Italy is extremely less mobile than the northern part of the country.

Regarding the analysis of the mechanisms behind the intergenerational wealth correlation across two generations, this chapter suggests that income is the main intergenerational mediating factor if individuals are taken in their 40s. On the contrary, the correlation across generations of saving preferences and attitude to risk seems to explain only a small fraction of the IWE.

Introduction

Wealth, intended as the sum of all financial and real assets minus liabilities, is getting increasingly attention in the last few years for several empirical reasons. It can be considered as a better proxy of permanent economic resources than other more frequently used flow variables since it is strongly influenced by cumulative, rather than yearly, net earnings and thus it is less affected by transitory shocks (see Chapter 1). Moreover, unlike income or earnings, it may be directly transmitted from one generation to another through bequests or inter-vivos transfers.

The renewed interest on wealth has encouraged many studies on economic inequality. For instance, extreme concentration of wealth at the top of the distribution and economic inequality related to inheritance has been investigated by Piketty (2014) in his famous: "Capital in the 21st Century" which, while becoming a bestseller worldwide, has brought again attention on the topic of economic disparities and wealth accumulation.

Unfortunately, only few studies attempt to estimate wealth mobility across generations[8]. This is mainly due to the lack of suitable data on wealth which cover two generations during adulthood. Therefore, estimates of the intergenerational wealth association are only available for the Unites States (Charles and Hurst, 2003; Pfeffer and Killewald, 2015), France (Arrondel, 2008) or Scandinavian countries (Boserup et al., 2013; Fageren et al., 2015; Black et al., 2015; Adermon et al., 2015; Boserup et al., 2016). These empirical studies, while confirming that United States is a less mobile society than Denmark or Norway, highlight some of the mechanisms related to the transmission of wealth from one generation to the next.

This chapter contributes to the literature on wealth mobility in several ways. It provides a first estimate of the degree of wealth mobility across two generations in Italy which may be representative of the degree of wealth mobility in the Southern-European countries. Italy is an interesting case study since is characterized by higher levels of income inequality and intergenerational income immobility and lower levels of wealth inequality than other developed countries (D'Alessio, 2012;

[8] Two studies estimate the degree of wealth mobility in the very long run in England (Clarks and Cummins 2015), and in Florence (Barone e Mocetti, 2016) using rare surnames to track families.

Maestri et al, 2014; OECD, 2015). The lower degree of wealth inequality in Italy is mainly related to the high share of estate wealth on total net wealth which is usually less dispersed than financial wealth.

To measure intergenerational wealth mobility, I use both intergenerational wealth elasticities and rank-rank slopes. The latter is important to obtain proper estimates of mobility that do not exclude those with zero and negative wealth. Since direct information about parental economic status is not available, I estimate the IWE by exploiting the two-sample two-stage least squares method (TSTSLS). This approach, which has been already used in the empirical literature to estimate the degree of intergenerational earnings or income mobility, uses two independent samples and some socio-economic information about actual parents given by offspring to impute parental wealth ad obtain estimated intergenerational elasticities. The rank-rank slope is obtained by predicting parental wealth and imputing parental rank through the usage of information on socio-economic characteristics of actual parents given by offspring.

This chapter evaluates the robustness of estimated IWE and rank-rank slopes to the selection of different samples of offspring by age. Most of the evidence on the degree of wealth mobility is provided by elasticities computed by taking offspring and parents at different ages. This is due to the lack of data which cover two or more generations over their life-cycle. However, it is well acknowledged in the literature on wealth mobility that choosing too young offspring is likely to influence the consistency of estimated elasticities since they have had no enough time to accumulate wealth (Charles and Hurst, 2003; Conley and Glauber, 2008 Pfeffer and Killewald, 2015).

Nevertheless, since wealth is related to cumulative economic performances and intergenerational transfers that individuals may receive also when they are very young, estimates of wealth mobility are likely to be less affected by transitory shocks and affected in a different way by the lifecycle bias compared to estimates of income or earnings mobility. More specifically, wealthy parents are likely to make a larger amount of economic transfers to their children at the beginning of their adulthood. Subsequently, at early stages of their careers, children from wealthy households will have lower yearly incomes and propensity to save but higher expected permanent incomes and wealth accumulation than other young individuals This is the reason why the intergenerational wealth correlation is likely to be U-shaped over the lifecycle with lower estimated mobility when children are taken at the beginning of their adulthood or in their 40s (see Boserup, 2016).

The chapter evaluates also geographical differences in intergenerational wealth mobility. Since the sample of offspring is not as large as it is needed to obtain 20 different estimates of wealth mobility by region, I decided to compare intergenerational wealth mobility by considering only two different areas of Italy, the north/centre and the South/Islands.

Finally, I decompose the IWE into different factors which may explain why wealth is correlated across generations. In particular, there may be a positive intergenerational wealth association because of bequests and donations or if preferences, which may influence both the rate of return on savings and the propensity to save, and permanent income, which affects the amount of lifetime savings, are positively correlated across generations.

Results show an age-adjusted elasticity of 0.451, which is not that far from the value of 0.41 obtained by Pfeffer and Killewald (2015) in a study on the United States, and higher than estimated elasticities obtained for other countries. The estimated rank-rank slope of 0.349 is instead very close to estimates obtained for US and Sweden. These two different measures of mobility appear to be robust to different socio-economic characteristics used to predict parental wealth and less affected by the lifecycle bias if individuals of the second generation are taken when they are extremely young or in their 40s. This result seems to confirm previous evidence that show a U-shaped pattern of the intergenerational wealth correlation as a function of children's age.

Intergenerational wealth mobility appears to be extremely lower in the southern part of Italy than in the rest of the country with an estimated IWE of 0.621 and a rank-rank slope of 0.407. These results suggest a strong incidence of parental background on economic well-being for those living in the less developed regions of Italy even though spatial mobility across different areas of the country may partially explain estimated differences.

The division of the intergenerational association into different mediating mechanisms shows that permanent labour income of the second generation, among other mediating factors such as preferences and bequests or donations, is associated with most of the overall wealth elasticity across generations.

The chapter is organized as follows. Section 2.1 describes the conceptual framework behind the intergenerational transmission of wealth and the reasons why it may be useful to focus on wealth over income as a measure of parental background. Section 2.2 presents the empirical strategy used to estimate the degree of wealth mobility. Section 2.3. describes the data and the selection of offspring and parents into the final samples. Section 2.4 discusses the results obtained in terms of IWE and rank-rank slopes. Section 2.5 discusses the results regarding the mediating role of different intergenerational mechanisms. Section 2.6 concludes.

2.1. Conceptual Framework

As described in chapter 1, at any point of time t, the amount of net wealth of the generation 1, intended as the sum of all real and financial assets minus financial liabilities, can be described by the following expression:

$$W_{p,t}^{1} = W_{p,t-1}^{1}(1 + r_{p,t}^{1}) + Y_{p,t}^{1}(1 - c_{p,t}^{1}) + Tr_{p,t}^{1} \qquad (1)$$

where $W_{p,t-1}^{1}$ is the amount of net wealth owned by parents p at time $t-1$, $r_{p,t}^{1}$ is the rate of return of return on net assets, $Y_{p,t}^{1}$ is the amount of disposable income earned at time t, $c_{p,t}^{1}$ is the propensity to consume and $Tr_{p,t}^{1}$ is the difference between the amount of bequests or donations received from the previous generation and those given to the next. Similarly, one generation later, the amount of net wealth owned by an adult child c, at time t, is given by:

$$W_{c,t}^{2} = W_{c,t-1}^{2}(1 + r_{c,t}^{2}) + Y_{c,t}^{2}(1 - c_{c,t}^{2}) + Tr_{c,t}^{2} \qquad (2)$$

Therefore, in a two generations model, the amount of wealth owned by the first generation is positively correlated to that owned by the second for three main reasons. There may be a positive intergenerational wealth association as real or financial assets are directly transmitted from one generation to the next by means of donations or bequests. Moreover, preferences in terms of risk and attitudes toward future that influence both the rate of return on financial and real assets and the propensity to save, can be correlated across generations. Lastly, as it is well known from the literature on intergenerational income mobility, permanent disposable income, which affects the amount of lifetime savings, is positively correlated across generations through several channels. For instance, parents are likely to transmit some cognitive or non-cognitive abilities to their children that can be useful in the labour market. Moreover, in the presence of imperfect capital markets and liquidity constraint, wealthy parents are able to invest a greater amount of resources in their children human capital, boosting their economic outcomes in the labour market (Becker and Tomes, 1979, 1986). Finally, children growing up in higher income families may exploit their parents' social networks and economic power to obtain well paid occupation and higher wages than other children[9].

As in the case of income mobility, estimates of wealth mobility may be influenced by the age at which wealth of the two generations is measures since the importance of each single intergenerational channel may vary over the lifecycle. For instance, the component $Tr_{c,t}^2$ is likely to be very important at the beginning of the adulthood, when wealthy parents make inter-vivos transfers to their children, and later during the lifecycle when offspring receive direct transfers by means of bequests. On the contrary, estimates of wealth mobility may be less affected by attenuation bias since wealth measured at time t is likely to be less influenced by transitory shocks than current income (see chapter 1). For instance, if current incomes of employees are particularly low (high) with respect to his permanent income because of an economic crisis (boom) or because they are taken at early

[9] See, among others, Meade (1973), Bowles and Gintis (2002) and Franzini and Raitano (2009) for a detailed description of the channels of influence of parental background on children's economic outcomes.

(later) stages of their careers, then using yearly incomes will lead to biased estimates of intergenerational mobility.

In any case, there is a lack of empirical evidence on the robustness of estimates of intergenerational wealth mobility to the lifecycle bias. The only empirical study which attempts to assess the pattern of intergenerational wealth correlation as a function of offspring's age is that by Boserup et al (2016). They found a U-shaped pattern of intergenerational wealth correlation as a function of children's age, with higher intergenerational correlations if children are taken at the beginning of their adulthood or from their 40s and up. They explain this pattern trough lifecycle variations in transfers, earnings and consumption. More specifically, wealthy parents are likely to make a larger amount of transfers early in children's life. Subsequently, their children have low current income when investing in human capital, but higher expected permanent income than other individuals their age.

2.2. Methodology

2.2.1. Imputed intergenerational wealth elasticity

As it has been largely explained in Chapter 1, the TSTSLS method has been largely used to provide estimates of mobility when data on economic status which cover two generations are not available. Instead of estimating fathers' earnings and the intergenerational earnings elasticity as it is common in the empirical literature, this chapter uses the TSTSLS method to impute parental wealth and evaluate the degree of persistence of wealth across generations, together with its intergenerational transmission channels. Unlike the literature on intergenerational income mobility which usually estimate the correlation between fathers' and sons' economic status, the empirical literature on intergenerational wealth mobility, use wealth of both parents as a measure of economic status of the first generation and do not exclude women from the second generation.

The TSTSLS methodology implemented in this chapter uses a sample of adult children that report some retrospective information about parents and an independent sample of pseudo-parents to estimate the intergenerational wealth elasticity in a two-stage approach. In the first stage, the same set of socio-economic characteristics of parents reported by adult children is exploited in the sample of pseudo-parents to predict net wealth:

$$W_{i,t}^{pp} = \alpha + \theta \, Z_i^{pp} + \omega_{i,t} \tag{3}$$

where W_i^{pp} is the yearly wealth of pseudo-parents, Z_i^{pp} is a vector of socio-economic characteristics of pseudo-parents and $\omega_{i,t}$ is a disturbance.

In the second stage, the estimated coefficient $\hat{\theta}$ allow us to predict wealth of actual parents i.e. $\widehat{w}_i^P = \hat{\theta} \, Z_i^P$. The IWE is thus estimated this way:

$$w_{i,t}^O = \alpha + \beta \widehat{w}_i^P + \omega X_i + \epsilon_{i,t} \tag{4}$$

where $w_{i,t}^O$ is the logarithm of offspring's wealth, $\widehat{w}_i^P = \hat{\theta} \, Z_i^P$ is the imputed parental wealth and $X_{i,t}$ is a vector of control which include age and age squared of offspring to consider the influence of age on both the process of accumulation and the probability of receiving bequests from parents as individuals get older.

As it is common in the literature on wealth mobility, I want to use parental wealth as a measure of economic status of the first generation. Thus, I exploit several socio-economic characteristics of both parents which are likely to predict their permanent economic status. More specifically, I take educational attainments, work status and an age polynomial of both parents plus the region of residence of the family of origin as predictors in the first stage regression. All socio-economic characteristics taken to impute parental wealth are commonly used in the empirical literature on mobility for their capacity to predict lifetime socio-economic status of parents. Obviously, as when the TSTSLS method is used to predict income of the first generation, I am likely to make some errors in predicting wealth of the first generation if the set of auxiliary variables is not able to capture part of the variance related to any characteristic of individuals which is correlated across generations[10].

[10] Most of studies which use the TSTSLS to impute income of the first generation exploit either educational attainments or educational attainments and other socio-economic characteristics in the

In order to compare the probability limit of the imputed estimator to the one that I could have been obtained if data of actual wealth of parents were available, it is possible to exploit an approach similar to the one described by Olivetti & Paserman (2015) in their study on intergenerational mobility in the US. In particular, I can express offspring's wealth and parental wealth in the following forms:

$$w_i^O = \beta w_i^P + \varphi_i^P + \epsilon_i \tag{5}$$

$$w_i^P = \hat{\theta} Z_i^P + \omega_i \tag{6}$$

where, as in previous equations, w_i^O is offspring's wealth, w_i^P is net wealth of actual parents, Z_i^P is the vector of socio-economic characteristics used to predict parental wealth in the sample of pseudo-parents and $\widehat{w}_i^P = \hat{\theta} Z_i^P$ is the imputed wealth of parents.

The direct influence of all socio-economic characteristics used to predict parental wealth on offspring's wealth is captured by φ_i^P, and by construction ω_i is uncorrelated to $\widehat{w}_i^P$ and φ_i^P. Then, it is possible to decompose ϵ_i in a component which may be correlated to $\widehat{w}_i^P$ and one which is not, such that $\epsilon_i = c_i + u_i$. For instance, $\widehat{w}_i^P$ may be correlated to c_i if most skilled parents (i.e. the ones with a better combination of socio-economic characteristics) transmit their cognitive and non-cognitive abilities to their children which can be useful to obtain higher lifetime incomes and wealth accumulation later during the lifecycle.

Thus, the probability limit of the "actual" estimator (i.e. the one obtained if actual parental wealth were available) is:

$$\hat{\beta}_{actual} \xrightarrow{p} \frac{cov(w_i^O, w_i^P)}{var(w_i^P)} = \beta + \frac{cov(\varphi_i^P + c_i, \widehat{w}_i^P)}{var(\widehat{w}_i^P) + var(\omega_i)} + \frac{cov(u_i, \omega_i)}{var(\widehat{w}_i^P) + var(\omega_i)} \tag{7}$$

first stage regression. In the last few years, many studies on intergenerational mobility started using surnames (see Barone & Mocetti, or names to predict the socio-economic status of the older generation.

As expected, $\hat{\beta}_{actual}$ do not capture any causal effect of parental wealth on offspring's wealth (i.e. the β coefficient) because of unobservables which are correlated across generations[11].

On the contrary, the probability limit of the "imputed" estimator (i.e. the one obtained by implementing the TSTSLS method) is:

$$\hat{\beta}_{imputed} \xrightarrow{p} \frac{cov(w_i^O, \hat{w}_i^P)}{var(\hat{w}_i^P)} = \frac{var(\hat{w}_i^P)}{var(\hat{w}_i^P) + var(\omega_i)} \beta + \frac{cov(\varphi_i^P + c_i, \hat{w}_i^P)}{var(\hat{w}_i^P)} \quad (8)$$

Therefore, the "imputed" estimator may be different from the "actual" estimator because of different reasons. For instance, the first component of equation 8 captures the classical attenuation bias due to measurement errors in the imputation of parental wealth[12]. A second attenuation bias may occur if the set of socio-economic characteristics is not able to capture other characteristics of individuals (e.g. soft skills, social networks, cultural factors, cognitive and non-cognitive abilities), which are positively correlated across generations (i.e. the last term in equation 7 is not present in equation 8). Finally, the second term in equation 8 is larger than the second term in equation 7 if the variance of the imputed parental wealth is lower than the variance of the wealth of actual parents.

According to this framework, the "imputed" estimator may be either higher or lower than the "actual" estimator depending on the size of each different component of equation 8 compared to the corresponding term in equation 7. In any case, the difference between the "actual" estimator and the imputed "estimator" should become lower as the unexplained component of parental wealth decreases (i.e. the higher the fraction of the variance explained from the set of auxiliary variables exploited to predict parental wealth is, the lower the bias will be).

[11] Studies on mobility are usually not intended to obtain the causal effect of parental economic status on offspring's economic status. This the reason why I am comparing the "imputed" estimator to the "actual" estimator without requiring any exclusion restriction to hold.

[12] Observe however that the attenuation bias may be higher if adult children make some errors when reporting retrospective information of their parents. The consistency of the two-sample estimator relies on an additional point: auxiliary variables used in the first stage should have the same distribution in both the sample of pseudo-parents and the sample of offspring even though the TSTSLS approach automatically corrects for differences (Inoue and Solon 2010).

Usually the TSTSLS method it is assumed to perform well at estimating intergenerational income mobility. Therefore, I evaluate if auxiliary variables can do an equally good job at predicting parental wealth by comparing the R^2 of the first stage regression with those obtained by Mocetti (2007) and Piraino (2007) in their studies on income mobility in Italy. Moreover, as a further robustness check, I evaluate to what extent the estimated IWE changes as different predictors are taken to impute parental wealth in the first stage regression.

2.2.2. Imputed rank-rank slope

An important disadvantage of using elasticities to measure intergenerational wealth mobility is that they automatically exclude negative or zero wealth individuals because of the logarithm transformation. This may cause a selection problem if the intergenerational correlation is not stable across the wealth distribution (Boserup et al., 2013, Black et al., 2015; Adermon et al., 2015). For instance, excluding the lower tail of the wealth distribution will under (over)estimate the level of mobility if the actual level of intergenerational mobility is higher (lower) at the bottom of the distribution than in the remaining part of the distribution.

A way to overcome this kind of selection problem is to measure wealth mobility by using rank-rank slopes which, as described in chapter 1, are usually obtained by estimating the following equation:

$$p_o = \alpha + \gamma p_p + \varepsilon \tag{9}$$

where p_o is the percentile of offspring's wealth in their own distribution and p_p is the percentile of parental wealth. In this empirical framework, an estimated γ of 0.5 means that the expected difference in ranks between offspring would be about 5 percentiles if the difference in ranks among their parents was 10 percentiles. However, it is not possible to estimate rank-rank slopes by simply re-categorizing wealth of the two generations when data on wealth of actual parents are not available. For this reason, I use a different approach consisting in two different steps.

Firstly, I obtain a prediction of parental wealth by exploiting the sample of pseudo-parents and the same set of auxiliary variables used for obtaining TSTSLS estimates of the IWE. Secondly, predicted parental wealth is percentile ranked so that I can estimate the following equation:

$$p_o = \alpha + \gamma \hat{p}_p + \varepsilon \tag{10}$$

where p_o is the percentile of offspring's wealth in their own distribution and $\hat{p}_p$ is the imputed percentile of parental wealth. This approach, except for the set of auxiliary variables used in the first step, is very close to the ones used by Olivetti et al. (2016) and Barone and Mocetti (2016) to obtain intergenerational and multigenerational rank-rank measures of economic mobility[13].

Consider however, that from a statistical point of view, it is not easy to understand to what extent this imputed rank-rank slope can be compared to rank-rank slopes estimates obtained by percentile ranking wealth of actual parents. Obviously, when rank are imputed, I am likely to make some errors in placing all parents in the right percentile of their wealth distribution. For this reason, estimates obtained by using imputed rank are likely to be affected by attenuation bias. This kind of rank measurement errors cannot be intended as "classical" since both the dependent variable and the regressor in equation 10 are uniformly distributed. More specifically, the correlation between actual and imputed rank is, by definition, between the value of 0 and 1 such that, if parental rank is measured without error, then the correlation will be equal to one and the greater the error is the lower the correlation between actual and imputed rank will be. This means that this kind of measurement error is negatively correlated with actual rank of parents (Nybom and Stuhler, 2016).

[13] Olivetti et al. (2016) impute father's and grandfather's income rank, which is unobserved, using the average income of fathers of children with a given first name. Barone and Mocetti (2016) use surnames to track families over different generations and obtain imputed rank-rank slopes.

Nevertheless, the measurement error related to the imputation of ranks should be lower than the measurement error related to the imputation of continuous values since imputation errors decrease as the categories to be imputed become lower[14] (Jerrim et al., 2016). In any case, I will test the robustness of estimated rank-rank slopes to different sets of socio-economic characteristics considered to impute parental wealth.

2.3. Data and Sample Selection

2.3.1. Data source

As in previous studies on intergenerational economic mobility in Italy, I use data from the Bank of Italy Survey on Household Income and Wealth (SHIW), a representative survey of the Italian population which is available annually from 1977 to 1987 and every two years after 1987. It is usually considered as the best source of income distribution data in Italy and, starting from the wave of 1987, it also collects both real and financial wealth data at the household level. Another relevant aspect of the SHIW is that, starting from the wave of 1995, respondents, who are heads of the household, are asked to report some characteristics of their parents when the latter were approximately the same age as the former. Some of these retrospective characteristics such as educational attainments, employment status and age are taken in this chapter to predict parental wealth.

Net wealth is recorded on an annual basis and obtained as the sum of real and financial assets minus financial liabilities. All economic variables are deflated by the consumer price index. A detailed list of all real/financial assets and financial liabilities used to obtain household wealth showed in appendix B.

2.3.2. Sample Selection

Ideally, one would have used permanent, instead of current, measures of economic status for both generations to measure intergenerational economic

[14] Jerrim et al. (2016) show that the imputed intergenerational correlation is generally less biased than the imputed elasticity even when economic status of parents is not ranked. This is due to the fact that the variance of the percentile ranked actual-wealth is equal, by construction, to the variance of the percentile ranked imputed-wealth

mobility. Unfortunately, data which cover two generations over their entire lifecycle are usually not available. For this reason, it is well acknowledged in the literature on earnings or income mobility that obtaining estimated elasticities which are not affected by lifecycle measurement errors is a non-trivial exercise. In fact, despite the classical measurement error assumption, both left-hand and right-hand side errors may affect the consistency of the elasticity. Therefore, Haider and Solon (2006), suggest taking offspring around 40 years old to minimize measurement errors related to lifecycle when using current instead of permanent variables, even if age controls are included in the specification.

However, when moving to analyse the extent of wealth correlation across generations, it is not clear which is the optimal age to choose. Many life-cycle accumulation models predict wealth to be hump shaped over an individual's lifetime (Davies and Shorrocks, 2000). There is also some empirical evidence showing that wealth accumulation reaches its peak at retirement age, since assets are usually accumulated over the working age and decline after retirement age (see OECD, 2008; Finance and Network, 2013). Moreover, the probability of receiving direct transfers is high for young children coming from wealthy households and becomes higher as individuals get older because of bequests. With all this in mind, I try to select the two generations into sample by not considering too young individuals in the baseline model. However, I cannot select retired individuals since I would have needed information on their occupational status when they were employed. Unfortunately, this kind of information is not present in the dataset.

The sample of pseudo-parents is taken from the wave of 1989 which is the first one that contains information on both real and financial wealth at the household level and educational attainments of both employed and unemployed pseudo-parents. The baseline estimates are provided by including all households composed by an employed father[15] aged 40 to 54, a mother aged 35 to 54 and at least one child in the wave of 1989. On the contrary, the sample of offspring is taken from the waves of 2010 and 2012 which are the latest two which contain all background

[15] This kind of exclusion is a common procedure when using the TSTSLS method since unemployment of fathers is often transitory.

information about parents. I include all employed heads of the household aged 35 to 48 whose fathers were employed at the same age for a final sample of 1158 offspring and 2062 pseudo-parents[16]. Since financial wealth is measured in both samples at the household rather than at the personal level, I will estimate different specifications to evaluate the robustness of the results to this kind of potential source of bias.

2.4. Descriptive Statistics

Descriptive Statistics in table 2.1 show that offspring and pseudo-parents are taken on average in their 40s. This selection into sample is likely to prevent our estimates to be downward biased as offspring and pseudo-parents are not too young. Table 2.1 also presents summary statistics on wealth levels and dispersion in the two full samples which show that the wealth dispersion in Italy has increased over the last two decades. For instance, the ratio between the 90^{th} and the 10^{th} percentile (p90/p10) of the wealth distribution rose dramatically from 64 in the sample of pseudo-parents to 384 in the sample of offspring. Nearly all this variation is to be ascribed to an increase in the p50/p10 rather than in the p90/p50 ratio: while the former is about 6 times higher in the sample of offspring than in the sample of pseudo-parents, the latter remained basically stable during the period. Increasing inequality in the lower tail of the net wealth distribution is likely to be closely related to the growth of financial liabilities: over the last two decades, the share of households with zero or negative net wealth rose from 2.7 to 7.1 percentage points. Regarding wealth dispersion in the upper tail of the distribution, the p99/p90 ratio has increased from 2.59 to 3.91 across the two generations.

Table 2.2 shows descriptive statistics of the final sample used to estimate IWE after the logarithm transformation which excludes zero or negative wealth individuals. The extent of wealth dispersion in this subsample is obviously lower than the one showed in the full sample since less wealthy households are now

[16] I cannot select older offspring since I am able to measure their wealth only 21 years after pseudo-parents' wealth.

excluded. In this case, the p90/p10 ratio remains basically stable across the two generations.

Table 2.1: Two-Sample Descriptive Statistics (Full sample)

	Pseudo-Parents	Offspring	Sign of the Variation
Age (Mean)	45.61	41.49	
	(4.15)	(3.67)	
Percentiles of Net Wealth:			
p1	-3255.20	-9700.00	-
p5	1583.41	-486.04	-
p10	4715.08	1000.00	-
p25	18209.19	12812.92	-
p50	78875.77	96401.10	+
p75	164871.90	202983.80	+
p90	305527.70	384500.00	+
p95	440607.00	519971.50	+
p99	792127.90	1506128.00	+
Average Net wealth	127472.72	164302.01	+
	(172738.66)	(275969.20)	
Zero/Negative Wealth	2.7%	7.1%	+
Observations	2062	1158	

Author's elaboration based on the SHIW. Standard deviations in parenthesis. All economic variables are expressed at 2010 prices

On the contrary, a slight increase of the wealth dispersion across generations can be seen in the upper tail of the distribution. Finally, it is important to note that the average age of the two generations does not change moving from the full sample to the sub-sample of positive wealth households.

Table 2.2: Two-Sample Descriptive Statistics after the logarithmic transformation

	Pseudo-Parents	Offspring	Sign of the Variation
Age	45.60	41.49	
	(4.16)	(3.67)	
Percentiles of Net Wealth:			
p1	6.67	6.19	-
p5	8.05	7.60	-
p10	8.76	8.49	-
p25	10.03	10.10	+
p50	11.31	11.57	+
p75	12.04	12.26	+
p90	12.65	12.89	+
p95	13.00	13.18	+
p99	13.58	14.25	+
Log Net wealth	10.95	11.11	+
	(1.57)	(1.76)	
Observations	2007	1076	

Author's elaboration based on the SHIW. Standard deviations in parenthesis. All economic variables are expressed at 2010 prices

2.5. Estimated elasticities

This section reports estimates of the intergenerational wealth elasticity in Italy. I perform the TSTSLS method by exploiting a set of parental characteristics given by offspring in the surveys of 2010 and 2012, that can be used to predict their parents' wealth. More specifically, I use 5 education categories of both father and mother (none, elementary, lower secondary, upper secondary and university degree), 6 occupational qualifications of fathers (production worker, teacher or clerical worker, junior manager, manager, member of the arts or professions, other self-employee), 5 occupational qualifications of mothers[17] (not employed, production worker, teacher or clerical worker, manager or junior manager, self-employer/member of the arts), region of residence (Piemonte, Lombardia, Trentino-Alto Adige, Veneto, Friuli-Venezia, Liguria, Emilia-Romagna, Toscana,

[17] Excluding not employed mothers would have reduced significantly the sample dimension.

Umbria, Marche, Lazio, Molise, Abruzzo, Campania, Basilicata, Puglia Calabria, Sicilia, Sardegna) and a third grade polynomial for age of both parents. Since the region of residence is reported only for pseudo-parents, I use the offspring's region of birth as a proxy of the region of residence of actual parents[18].

Table 2.17 in the appendix reports the whole set of auxiliary variables used to predict parental wealth and some first stage post-estimation statistics. In particular, the R^2 of the first stage regression equal to 0.28 suggests that the set of auxiliary variables performs pretty well at predicting parental wealth. In fact, the estimated R^2 is not that far from the ones obtained by Piraino (2007) and Mocetti (2007) in their first-stage regressions implemented to predict fathers' income[19].

The usual way to obtain elasticities in the second stage, is to regress the logarithm of offspring's wealth on the logarithm of parental wealth, such as it is formalised in equation 4. This commonly used approach excludes all observations lower than or equal to zero. In this case, the TSTSLS age-adjusted intergenerational wealth elasticity estimate is 0.499 (table 2.3, column 1). This means that a 10 percent variation in parental wealth is associated with a 4.99 percent variation in offspring's.

Since data on financial net wealth of offspring are available only at the household level, I am overestimating the IWE if those adult children with a better economic background are more likely to marry wealthy partners boosting their overall household wealth. I try to reduce this potential source of bias by controlling for a proxy of the amount of personal saving capacity over household saving capacity. In particular, I control for the fraction of personal disposable income of the head over total household disposable income. The main assumption is that personal financial wealth and household financial wealth are more likely to be equal as the fraction of personal disposable income of the head over total household disposable income increases. This derive from the fact that the personal capacity of accumulate wealth is strongly correlated to personal lifetime income. Observe however, that

[18] The distribution of parental socio-economic characteristics in the two samples is reported in table 2.16 in the appendix A

[19] The R^2 of the first stage regression is 0.301 in the study of Mocetti (2007) and 0.322 in that of Piraino (2007).

this kind of control is not perfect. For instance, it may not work if at least a fraction of financial wealth at the household level is inherited by members other than the head of the household.

Table 2.3 (column 2) reports an estimated IWE of 0.451 when the fraction of personal disposable income of the head over total household disposable income is included in the specification. This result seems to confirm that some mechanisms related to assortative mating were likely to bias the estimated elasticity obtained without adding this control variable. A further way of controlling for this potential source of bias is to use personal estate wealth as a proxy of total personal net wealth, measured as the sum of all personal estate assets minus the total amount of mortgages. The IWE reported in the third column of table 2.3 seems to confirm that estimated elasticities seem to be robust to the use of household financial wealth instead of personal financial wealth.

Table 2.3: Estimated intergenerational wealth elasticities

	[1]	[2]	[3][a]
Parental net wealth	0.499***	0.451***	
	[0.061]	[0.061]	
Parental estate wealth			0.478***
			[0.074]
Pers. income share		Yes	
R-squared	0.078	0.124	0.062
Obs.	1076	1076	729

Author's elaboration based on the SHIW. Bootstrapped standard errors (reps 100) in parentheses. [a] Personal estate wealth is used as a dependent variable instead of total net wealth. All regressions include offspring's age and age squared as a control. * p<0.10, ** p<0.05, *** p<0.01

The main advantage of estimating the IWE by using a classical log-log specification is that it is possible to compare the obtained elasticity with most of previous estimates for other countries, which are based on the same transformation (table 2.4). More specifically, the degree of wealth mobility appears to be lower in

Italy than in France (Arrondel, 2008), Norway (Fageren et al., 2015), Denmark (Boserup et al., 2013), Sweden (Adermon et al., 2015; Black et al., 2015) and close to the values of 0.37 and 0.41 obtained for the United States by Charles and Hurst (2003) and Pfeffer and Killewald (2015). However, this kind of comparison should be taken carefully since the studies listed in table 2.4 use actual rather than imputed parental wealth.

Table 2.4: Intergenerational wealth mobility: cross-country comparison

Country	Source	Parent's Age	Offspring's Age	IWE	R2R
US	Charles and Hurst (2003)	52	37.5	0.37	/
US	Pfeffer and Killewald (2015)	43.4	44.6	0.41	0.37
Italy	Current	45.6	41.5	0.45	0.35
Denmark	Boserup et al. (2013)	48.6	33.9	0.27	0.23
Denmark	Boserup et al. (2016)	47.9	47.2	0.24	0.27
Sweden	Adermon et al. (2015)	57-63	42-49	0.32	0.39
Sweden	Black et al. (2015)	63.9	43.8	/	0.35
Norway	Fageren et al. (2015)	62.7	36.1	0.2	0.18
France	Arrondel (2009)	58.9	33.8	0.22	/

2.5.1. IWE: Robustness check

A usual way to test the robustness of estimated elasticities based on imputed values is to check how the elasticity changes as a single socio-economic predictor of parental wealth is excluded from the first stage regression[20]. Results presented in Appendix A (table 2.18) show that the estimated elasticity tends to be stable in all cases but when fathers' occupational qualification is excluded from the set of

[20] I perform the Sargan test to evaluate if the full set of instruments used in the first stage in uncorrelated with the error term of the second stage regression. Even though the test does not reject the null hypothesis, I can hardly assume that the set of auxiliary variables is exogenous.

predictors in the first stage regression. This result may suggest a direct correlation between this auxiliary variable and offspring's wealth. Nevertheless, excluding occupational qualification of the father reduces substantially the variance of predicted parental wealth: the first stage R^2 in this case is 0.167 (i.e. 0.11 lower than when all auxiliary variables are included in the first stage). Hence, imputed parental wealth seems to be less accurate when the occupational qualification of the father is not used as a predictor in the first stage regression.

Another way to test the robustness of the results is to evaluate how the elasticity changes as different measures of wealth of the two generations are used. Results presented in table 2.5 show that the estimated elasticity is extremely stable across different specifications either taking total net wealth (column 1) or estate/non-estate wealth (column 2/3) as a measure of economic status of both generations. Interestingly, the estimated elasticity remains stable even though the prediction ability of the set of auxiliary variables used in the first stage increases when non-estate wealth rather than total net wealth is taken as a measure of economic status. In particular, the R^2 of the first stage regression rises to 0.395 using non-estate wealth (table 2.17).

Table 2.5: IWE by different measures of wealth

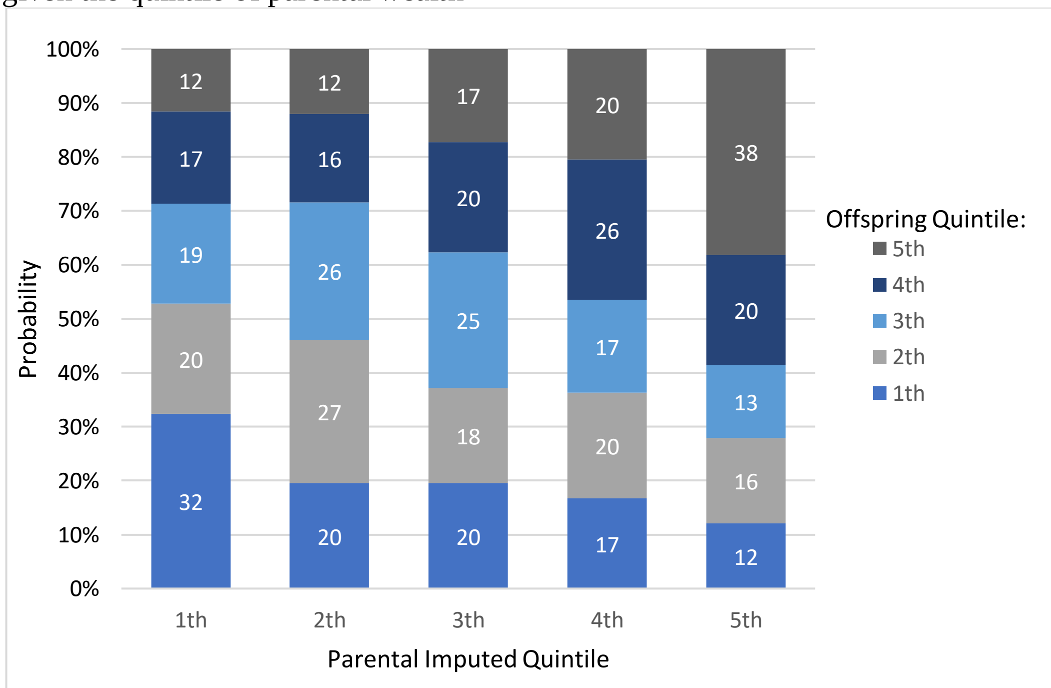
	[1]	[2][a]	[3][b]
Parental Net Wealth	0.451***		
	[0.061]		
Parental Estate Wealth		0.478***	
		[0.074]	
Parental Non-Estate Wealth			0.455***
			[0.049]
R-squared	0.124	0.064	0.170
First stage R-squared	0.278	0.240	0.395
Obs.	1076	729	1027

Author's elaboration based on the SHIW. Bootstrapped standard errors (reps 100) in parentheses. [a]Estate wealth is used as a dependent variable instead of total net wealth. [b]Financial wealth is used as a dependent variable instead of total net wealth. All regressions include, as further controls, offspring's age, age squared and the ratio between personal income and total household income. * p<0.10, ** p<0.05, *** p<0.01

2.6. Intergenerational transmission of wealth across the distribution

Although the elasticity is useful to summarize the degree of persistence of wealth across generations, it gives no information about the pattern of wealth transmission at different points of the distribution. A low level of mobility may be associated to the lack of opportunities of the poor as well as to the persistence of wealth at the top. There are many recent studies showing a higher intergenerational transmission of income and earnings at the top (e.g. Björklund et al. 2012) or stronger intergenerational correlations at higher positions in the parental wealth distribution (Charles and Hurst, 2003; Killewald, 2013; Hansen, 2014; Pfeffer and Killewald 2015, Adermon et al. 2015). As in many previous studies on economic mobility, I evaluate the pattern of mobility along the wealth distribution by computing the offspring's probability of ending up in a specific quintile of the wealth distribution given the quintile of their parents (figure 2.1).

Figure 2.1: Probability of ending in a specific quintile of the wealth distribution given the quintile of parental wealth



Author's elaboration based on the SHIW.

Results show that in Italy for each quintile of the wealth distribution, offspring are more likely to ends up in the same quintile as their parents (diagonal probabilities are all greater than 20 percent). In any case, the degree of persistence of wealth across generations is higher at the top and at the bottom of the distribution: 38 percent of offspring whose parents were collocated in the highest quintile of the distribution remains in the same quintile and about 60 percent in one of the highest two quintiles. Conversely, only about 12 percent of offspring from the best parental wealth background ends up in the worst wealth quintile.

The degree of persistence is also high at the bottom-end of the wealth distribution: about 52 percent of offspring coming from the lowest quintile of the parental wealth distribution ends up in one of the bottom two quintiles and only about 12 percent makes its way to the top.

2.7. Estimated Rank-Rank slope

As already specified, the disadvantage of using elasticities to measure intergenerational wealth mobility is that they automatically exclude negative or zero wealth individuals. This may cause a selection problem if the intergenerational correlation is not stable across the wealth distribution. This is the reason why, I estimate also rank-rank slopes with or without zero and negative wealth individuals[21].

Results are obtained by estimating equation 10 and are reported in Table 2.6. According to imputed rank-rank slopes, the degree of intergenerational wealth mobility seems to be slightly higher when negative or zero wealth households are not excluded from the analysis. This difference seems to confirm results presented in figure 2.1 which suggested that the degree of intergenerational mobility is not stable across the wealth distribution, with lower mobility at the top and the bottom of the distribution. In any case, the selection bias due to the exclusion of the lower tail of the wealth distribution doesn't appear to be huge since the fraction of

[21] Within a birth cohort, ranks are calculated as $((i - 0.5)/N) \cdot 100$, where i denotes individuals sorted by wealth and $i = 1, 2, ..., N$. A small random number is added to the wealth of each individual to ensure that all individuals may be ranked.

indebted households in Italy is not high compared to other countries such as Sweden (Davies, 2009).

As already said in previous sections, when one tries to impute parental rank he is likely to make some errors so that estimated rank-rank slopes may be downward biased because of non-classical measurement error. This is the reason why one should be cautious in comparing the rank-rank slopes obtained in this chapter to the ones obtained in previous studies for other countries which exploit actual instead of imputed rank of the first generation.

Table 2.6: Rank slopes by including/excluding zero or negative wealth individuals

	[Full Sample]	[Excl. zero/negative wealth households]
Parental Rank	0.349***	0.312***
	[0.029]	[0.029]
R-squared	0.122	0.096
Obs.	1158	1076

Author's elaboration based on the SHIW. Bootstrapped standard errors (reps 100) in parentheses. Both offspring's wealth and parental wealth are percentile ranked by offspring and parents birth cohort. * p<0.10, ** p<0.05, *** p<0.01

In any case, although measurement errors related to the imputation of the economic status of the first generations is likely to be lower for rank based measures, I evaluate the robustness of the estimated rank-rank slope to the set of auxiliary variables used to predict parental wealth and impute parental rank. Therefore, different estimates of the rank-rank slope are obtained by excluding a single predictor of parental wealth at a time from the first stage regression. Results reported in table 2.19 in appendix A show that the estimated rank-rank slope is extremely robust to the exclusion of each single predictor at a time in the first stage regression. More specifically, its value is comprised between 0.322 and 0.350 using different sets of auxiliary variables. This result seems to suggest that rank-rank slopes are even more robust to the selection of different socio-economic predictors than elasticities.

2.8. The pattern of intergenerational wealth mobility over the lifecycle

Estimates of the intergenerational economic mobility, are usually sensitive to the age at which the economic status of the two generations is observed (Grawe, 2006, Haider and Solon, 2006, Nybom and Stuhler, 2016) In particular, estimates of income mobility are assumed to be downward biased if economic status is measured at early stages of the second generation's career. Thus, Haider and Solon (2006) suggest offspring should be around 40 years old to minimize measurement errors related to lifecycle when using current instead of permanent variables, even if age controls are included in the specification.

In the case of intergenerational wealth mobility, there is a lack of evidence regarding the optimal age at which wealth of the two generations should be measured. For instance, most of studies listed in table 2.4 do not observe the two generations of parents and offspring in the same age. This is the reason why estimates of intergenerational wealth mobility obtained in the literature could be downward biased if too young offspring have had no enough time to accumulate the same amount of wealth as its parents.

The only empirical study which tries to assess the pattern of intergenerational wealth correlation as a function of offspring's age is that by Boserup et al (2016). Contrary to expectations, they find a U-shaped pattern of intergenerational wealth correlation as a function of child age in Denmark, with higher intergenerational correlations obtained if offspring are taken when they are very young or from their 40s and up. They explain the pattern of intergenerational wealth mobility over the life-cycle through life-cycle patterns in transfers, earnings and consumption. More specifically, wealthy parents are likely to make a larger amount of transfers early in offspring's life. Subsequently their children have low current income when investing in human capital, but high permanent income (see chapter 1)

To test this theoretical assumption, I re-estimate the intergenerational wealth elasticity and rank-rank slope by using three different samples of offspring by age. In a first estimate, I consider a sample of offspring aged 22 to 34 whose wealth is measured in the waves of 2000 and 2002 and 2004. Then, I raise the age at which offspring's wealth is measured by considering individuals aged 27 to 37 in the waves of 2004, 2006 and 2008[22]. I thus compare these two obtained elasticities and rank-rank slopes to baseline estimates obtained in all the rest of the chapter by considering adult children aged 35 to 48 whose wealth is measured in the waves of 2010 and 2012.

Results reported in table 2.7 and 2.8 seem to confirm results provided by Boserup et al. (2016) with higher intergenerational correlations obtained when the second generation is very young or around 40s. In particular, the estimated IWE is 0.474 when adult children are 22 to 34, 0.409 when they are 27 to 37 and 0.451 when they are 35 to 48.

Table 2.7: IWE by different age of offspring

	[22-34]	[27-37]	[35-48]
Log Parental Wealth	0.474***	0.409***	0.451***
	[0.07]	[0.07]	[0.06]
R-squared	0.173	0.129	0.120
Obs.	728	657	1116

Author's elaboration based on the SHIW. Bootstrapped standard errors (reps 100) in parentheses. All regressions include, offspring's age, age squared and the ratio between personal income and total household income as a control. Wealth of the youngest generation is measured in the waves of 2000, 2002 and 2004. Wealth of the medium generation is measured in the waves of 2004, 2006 and 2008. Wealth of the oldest generation is measured in the waves of 2010 and 2012. * p<0.10, ** p<0.05, *** p<0.01

A similar pattern of mobility is obtained looking at the estimated rank-rank correlation which is 0.383 for the youngest sample, 0.289 when children are 27 to 37 and 0.349 when the second generation is around 40 years old. Thus, unlike the case of intergenerational income or earnings mobility, the pattern of wealth mobility over the lifecycle is confirmed to be U-shaped. More specifically, estimates seem to be downward biased only if wealth of the second generation is measured when adult children are at early stages of their careers but not too young.

[22] These two different samples of offspring by age are selected such that the distribution of the socio-economic characteristics taken to predict parental wealth in the first stage is similar in the sample of offspring and of pseudo-parents.

Unfortunately, it is not possible to evaluate the pattern of intergenerational wealth correlation by using older offspring because of data limitations. However, intergenerational correlations are likely to be higher if individuals of the second generation are selected after their parents die because of the role of inheritances. In any case, if the main goal of an empirical analysis is to estimate the degree of lifetime intergenerational wealth correlation, it seems to be better to select both parents and offspring around 40 years old as suggested by Boserup et al. (2016)

Table 2.8: Rank-Rank slope by different age of offspring

	[22-34]	[27-37]	[35-48]
Parental Rank	0.383***	0.289***	0.349***
	[0.034]	[0.036]	[0.029]
R-squared	0.146	0.083	0.118
Obs.	771	693	1201

Author's elaboration based on the SHIW. Bootstrapped standard errors (reps 100) in parentheses. Both offspring’s wealth and parental wealth are percentile ranked by offspring and parents birth cohort. Wealth of the youngest generation is measured in the waves of 2000, 2002 and 2004. Wealth of the medium generation is measured in the waves of 2004, 2006 and 2008. Wealth of the oldest generation is measured in the waves of 2010 and 2012. * p<0.10, ** p<0.05, *** p<0.01

2.9. Geographical differences in intergenerational wealth mobility

In this section, I evaluate to what extent intergenerational wealth mobility changes between different areas of Italy. Ideally, I should estimate regional differences in intergenerational elasticities and rank-rank slopes to obtain a detailed picture of geographical differences in wealth mobility. Unfortunately, the sample of offspring is not as large as it is needed to obtain 20 different estimates of wealth mobility by region. This is the reason why I decided to compare intergenerational wealth mobility by considering only two different areas in Italy, north/centre and south/islands. These two areas are commonly assumed to be very different in terms of social and economic structure and levels of familism which is likely to strongly influence offspring’s economic opportunities in the labour market and the amount of savings for inheritance purposes.

Results reported in table 2.9 show large differences in intergenerational wealth elasticities by offspring' area of residence with higher estimated mobility in the northern/central area of the country than in the southern. More specifically, the IWE is twice as high in the southern part of Italy as in the northern/central part of the country. This means that a 10 percent variation of parental wealth is correlated to a 3.16 percent variation in offspring's wealth considering the North/Centre of Italy and to 6.21 percentage variation considering the South/Islands

Table 2.9: Estimated IWE by offspring's area of residence

	[North/Centre]	[South/Islands]	Difference
Parental Net Wealth	0.316***	0.621***	0.306**
	[0.071]	[0.119]	[0.133]
R-squared	0.03	0.152	
Obs.	738	338	

Author's elaboration based on the SHIW. Bootstrapped standard errors (reps 100) in parentheses. All regressions include offspring's age and age squared as a control. * p<0.10, ** p<0.05, *** p<0.01

The lower degree of intergenerational wealth mobility in the southern part of Italy is also confirmed from results presented in table 2.10. In this case, I evaluate geographical differences in wealth mobility using estimated rank-rank slopes that are usually considered to be particularly appropriate to compare different areas. This is because, as stated by Mazudmer (2005b), an estimated elasticity in a specific area or region would be informative about the rate of regression to the mean of wealth in that area. On the contrary, rank estimators can use ranks that are fixed to the national distribution.

Results presented in table 2.10 show that the rank-rank slope is about 0.15 points higher in the South/Islands than in the North/Centre of Italy. However, these estimated geographical differences in the extent of wealth mobility across generations do not consider spatial mobility as a possible source of bias. In particular, many individuals who reside in the northern Italy (i.e. the most developed area of the country) were born in less developed regions and moved to the north for educational reasons or to get well paid jobs. Therefore, I re-estimate rank-rank slopes by including a dummy for spatial mobility which assumes the value of one if adult children reside in a different area with respect to the one where they were born. Results showed in table 2.20 in Appendix A are very close to the ones obtained without controlling for spatial mobility. In any case, this is only an imperfect way of controlling for geographical mobility since individuals may move many times during their adulthood for both educational and occupational reasons.

Table 2.10: Estimated Rank-Rank slope by offspring's area of residence

	[North/Centre]	[South/Islands]
Parental Net Wealth	0.289***	0.407***
	[0.037]	[0.048]
R-squared	0.082	0.162
Obs.	777	381

Author's elaboration based on the SHIW. Bootstrapped standard errors (reps 100) in parentheses. Both offspring's wealth and parental wealth are percentile ranked by offspring and parents birth cohort. * p<0.10, ** p<0.05, *** p<0.01

2.10. The mediation role of different intergenerational channels

As discussed in section 2.2, there are mainly three different factors that may explain why wealth is positively associated across generations. First, bequests or inter-vivos transfers may directly increase wealth if they are received from the previous generation. Indirectly, wealth may be correlated across generations through income and/or educational attainments since wealthy parents may have higher cognitive or non-cognitive abilities that can be transmitted to their children or greater opportunities of investment in their children's human capital (Becker and Tomes 1979 and 1986). The latter two channels may dramatically increase economic outcomes of offspring once they enter the labour market and thus the rate of lifetime wealth accumulation. Lastly, preferences such as risk propensity or attitudes toward future may as well be transmitted from parents to offspring influencing their saving propensity or the rate of return of investments.

The usual way to decompose the intergenerational wealth elasticity into different mediating factors is to re-estimate the equation 4 (i.e. the baseline elasticity obtained without controlling for any mediating variable) with some additional controls included in the vector $V_{i,t}^{O}$[23]:

$$w_{i,t}^{O} = \alpha + \beta_2 \widehat{w}_i^{P} + \sigma V_{i,t}^{O} + \omega X_{i,t} + \epsilon_{i,t} \qquad [11]$$

The main assumption is that if a mediating variable is positively correlated with both parental and offspring's wealth, then the estimated elasticity will fall once this control is included in the regression. Therefore, the difference between the coefficients $\hat{\beta}$ obtained by estimating equation 4 and the estimator $\hat{\beta}_2$ can be interpreted as the fraction of the elasticity associated to a single mediating factor.

Observe however, that this is true only if a mediating variable included in the vector V_i^{O} is not correlated with the error term. Conversely, if the mediating variable is positively (negatively) correlated with other unobservable factors that influence offspring's wealth, the coefficient $\hat{\beta}_2$ is upward (downward) biased and the channel of influence is overestimated (underestimated). Moreover, since I am using imputed wealth for the first generation, the correlation between parental wealth and a single mediating factor may be underestimated if the set of socio-economic characteristics used to predict parental wealth are not able to completely capture some characteristics of individuals which are correlated to wealth of both generations. For instance, if an unobservable (for instance propensity to save) which is positively correlated to wealth of the two generations and to a single mediating factor included in the vector $V_{i,t}^{O}$ (for instance savings) is not totally captured by auxiliary variables used to impute parental wealth (i.e. the imputed parental wealth is less correlated to the vector $V_{i,t}^{O}$ in equation 11 than actual parental wealth), then I am likely to underestimate the mediating role of that intergenerational channel. On the contrary, the role of a single mediating factors may be also underestimated if yearly measures

[23] Most of the studies which decompose the IWE into different components use this kind of approach.

included in the vector $V_{i,t}^{O}$ are not able to capture permanent differences in economic performances in the labour market or if saving preferences and attitude toward risk change over the lifecycle.

With all this in mind, I try to analyse the mediating factors behind the intergenerational wealth correlation. The mediating role of abilities and human capital accumulation is captured indirectly by evaluating the difference between the elasticity obtained by estimating equation 4 (i.e. the baseline elasticity obtained without controlling for any mediating variable) and that obtained when labour income and three categories of expected future income (e.g. higher future real income, lower future real income, or no expected variations) are included as controls.

Educational attainments may also have a direct influence on offspring's wealth accumulation, since more educated individuals may be able to obtain higher returns on their investment or may have higher saving rates than the rest of the population. Thus, the direct influence of human capital on offspring's wealth is evaluated by adding a three categories educational dummy as a further control[24].

Regarding the mediating role of the intergenerational correlation in the rate of return on investments and savings, I control for annual savings, three categories of financial risk propensity and the amount of overall income that offspring would save against unexpected events, such as increased uncertainty over future earnings or unexpected expenses (for instance, for health problems or other emergencies). These variables should, at least partially, capture intergenerational wealth correlations trough saving propensity and the return on investments.

Lastly, to test the mediating role of bequests and inter-vivos transfers, I can use two different approaches. Firstly, I can consider the residual wealth elasticity as an upper bound of the fraction of the elasticity related to direct intergenerational transfers. However, in this case, the unexplained elasticity may also capture the influence of other unobservable factors such as altruism, financial literacy, transitory shocks or additional parental characteristics. Alternatively, I can analyse

[24] Results are quite similar if more than 3 categories of educational level are included in the regression

the mediating role of inheritance by considering only estate wealth which can be divided in directly accumulated wealth and inherited wealth so that I can obtain estimates of IWE either including or excluding inherited estate wealth as a further control.

Descriptive statistics for all covariates taken from the waves of 2010 and 2012 and included in the equation 11 are reported in table 2.11.

Table 2.11: Second stage covariates: descriptive statistics.

Income	23270.010 (15750.981)
Saving	7520.804 (14908.786)
Precautionary Saving	51698.880 (114528.884)
Expected future real income.	
Lower than current	*0.632*
No expected variations	*0.117*
Higher than current	*0.249*
Educational Level:	
Less than Upper Secondary	*0.400*
Upper Secondary	*0.576*
University Degree	*0.024*
Risk Propensity:	
High	*0.174*
Medium	*0.361*
Low	*0.465*

Author's elaboration based on the SHIW. Mean values, standard deviations in parenthesis. All economic variables are deflated by using the consumer price index.

Unsurprisingly, most of sample offspring in the sample have a medium level of education (upper secondary) and a low level of financial risk propensity. For instance, the share of total households which prefer investments that offer very high returns, but with a higher risk of losing part of the capital, is less than 20 percent. Regarding saving preferences, the amount of annual savings is on average about 32% of personal annual income and the amount of cumulate resources that offspring would save against unexpected events such as increased uncertainty over future earnings or unexpected expenses is about 7 times the amount of annual savings. Table 2.12 reports the elasticity obtained by estimating the equation 4 (column 1) and lower estimates obtained controlling for income and expected future income (column 2); income, three categories of expected future income and educational attainments (column 3); offspring's preferences (column 4); all available mediating variables (column 5).

Table 2.12: IWE, mediating variables

	[1]	[2]	[3]	[4]	[5]
Log Net Wealth	0.451***	0.254***	0.201***	0.367***	0.203***
	[0.060]	[0.059]	[0.059]	[0.061]	[0.057]
Income		0.738***	0.677***		0.671***
		[0.076]	[0.071]		[0.082]
Precautionary				0.196***	0.107*
				[0.066]	[0.059]
Savings				0.330***	-0.034
				[0.065]	[0.059]
Expected future income		Yes	Yes		Yes
Education			Yes		Yes
Risk Propensity				Yes	Yes
R-squared	0.124	0.249	0.263	0.176	0.268
Obs.	1076	1076	1076	1076	1076

Author's elaboration based on the SHIW. Bootstrapped standard errors (reps 100) in parentheses. Monetary controls are standardized. All regressions include, offspring's age, age squared and the ratio between personal income and total household income as further controls. * p<0.10, ** p<0.05, *** p<0.01

As previously noted, the baseline estimated elasticity is 0.451. The reduction associated to the inclusion of annual income and expected future income is large since the estimated elasticity falls to 0.254. However, this reduction may be downward biased as annual economic measures are likely to be affected by measurement errors. In any case, the result is consistent with the evidence provided by Charles and Hurst (2003) for the United States that report a 52 percent reduction of the elasticity when actual income of both fathers and offspring are included in the regress. Conversely, studies on Scandinavian countries which find higher levels of wealth mobility across generations, report also a minor role of labour income as a mediating factor (Boserup et al, 2013). The influence of parental background on economic opportunities of offspring in the labour market may thus account for most of cross-country differences in the degree of intergenerational wealth mobility.

Table 2.13: Mediating Variables

Mediating Variable	Fraction of the elasticity explained
Preferences	18.6%
Income	43.7%
Income + Education	55.4%
All Together	55.4%
Unexplained Elasticity	44.6%

Author's elaboration based on the SHIW.

The direct association between human capital and wealth is described by including educational attainments beside labour income as a further control in equation 11. Controlling for both variables increases the difference between the coefficients $\hat{\beta}_1$ and $\hat{\beta}_2$ of an additional 11 percent. Therefore, educational attainments may be correlated to offspring's saving rates and returns on investment by capturing, for instance, differences among individuals in financial literacy.

Controlling for the amount of overall savings, precautionary savings and risk propensity reduces the estimated IWE to 0.367. This means, that about 19 percent of the overall estimated elasticity may be correlated to the intergenerational transmission of preferences (table 2.13) which may influence saving propensity and attitudes to risk of both generations.

Lastly, when all mediating variables are considered together, I obtain a residual wealth elasticity of 0.203, which is not significantly different from the one obtained controlling only for labour income and education. This seems to exclude the presence of a direct association between offspring's and parental wealth through savings and attitudes to risk.

2.10.1. Intergenerational wealth mobility and inherited estate wealth

In previous section, I could not directly test the role of bequests and inter-vivos transfers by estimating equation 11, since the waves of 2010 and 2012 provide no information about the amount of direct total wealth transfers received from parents during lifetime. Nevertheless, I can use the unexplained elasticity as an upper bound of the mediating role of bequests and inter vivos transfers. In this case, by making the strong assumption that the residual elasticity captures no additional unobservable influences, bequests and donations in the model seem to reduce the IWE by about 45%.

Alternatively, I can estimate the mediating role of bequests and donations by exploiting information on personal inherited estate wealth. Also in this case, I take all heads of the households aged 35 to 48 with positive estate wealth such that I can re-estimate equation 11 by substituting total net wealth with estate wealth for both generations. Thus, I re-estimate equation 11 with or without including inherited estate wealth as further control in the vector $V_{i,t}^{O}$ to assess the fraction of elasticity which is correlated to direct intergenerational transfers.

Table 2.14 reports the estimated elasticity of offspring's wealth with or without controlling for savings, risk propensity, labour income, educational attainments and inherited estate wealth of the second generation. The estimate of the influence of parental estate wealth on offspring's through donations or inheritance is lower than the one obtained using the unexplained elasticity as a proxy of the role of direct intergenerational transfers. In particular, inheritance and bequest seem to explain about 30% of the overall IWE. However, when all other control variables are included (column 2), the mediating role of inheritance seems to be even lower and equal to about 17% of the baseline estimated IWE.

Table 2.14: Intergenerational Estate Wealth Elasticity: Mediating Variables

	[1]	[2]	[3]	[4]
Parental Estate wealth	0.478***	0.343***	0.260***	0.182**
	[0.070]	[0.063]	[0.077]	[0.071]
Inherited estate wealth		0.304***		0.270***
		[0.026]		[0.031]
Income			0.244***	0.180***
			[0.037]	[0.039]
Precautionary			0.053	0.026
			[0.034]	[0.029]
Savings			-0.017	0.002
			[0.035]	[0.033]
Expected future income			Yes	Yes
Education			Yes	Yes
Risk Propensity			Yes	Yes
R-squared	0.064	0.237	0.169	0.299
Obs.	729	729	729	729

Author's elaboration based on the SHIW. Bootstrapped standard errors (reps 100) in parentheses. Monetary controls are standardized All regressions include offspring's age and age squared as controls. * p<0.10, ** p<0.05, *** p<0.01

The latter result seems to confirm that the unexplained elasticity should be considered as an upward biased estimate of the fraction of intergenerational wealth elasticity associated to the mediating role of bequests and donations. Consider however, that usually only a small fraction of offspring in their 40s have already received at least one direct transfer from their parents. For instance, considering a sample of offspring aged 35 to 48 with positive levels of estate wealth, only 37 percent of individuals have inherited some estate wealth (table 2.15). Moreover, inherited wealth is more dispersed on average, than total net wealth. This means that even though the elasticity of wealth with respect to direct intergenerational transfers is not so high, receiving or not a bequest or a donation is likely to be associated to the probability of ending up in one of the top quintiles of the wealth distribution.

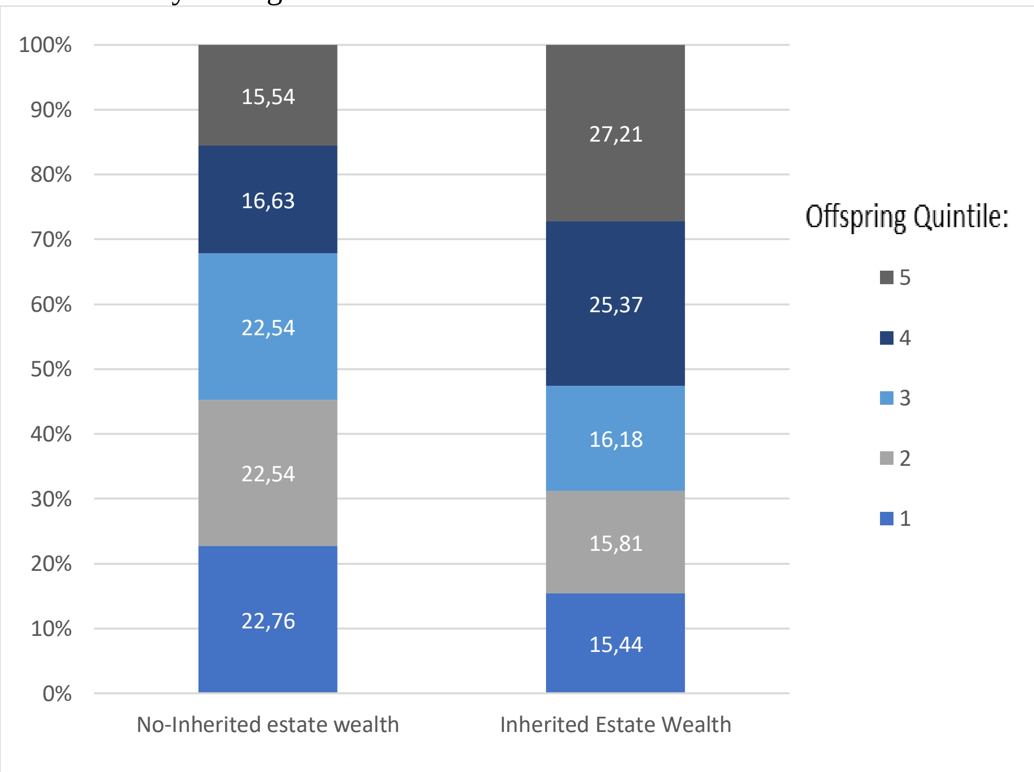
Table 2.15: Estate wealth: Descriptive Statistics

Estate Wealth	220329.12 [232118.24]
Inherited Estate Wealth	204441.44 [202503.84]
Percentage of individuals with positive inherited wealth	37.3%

Author's elaboration based on the SHIW

For instance, figure 2.2 shows that about 27 percent of individuals that received at least one estate wealth direct transfer from parents ends up in the top quintile of the estate wealth distribution (more than 50 percent in the top two quintiles) and only about 15 percent in the lower. Conversely, reaching the highest quintile of the wealth distribution without receiving donations or inheritances is far more difficult: only about 15.5 percent of individuals who do not receive any direct intergenerational transfers are likely to reach the highest quintile of the wealth distribution. Observe however that, within the sample, many individuals are likely to have at least one parent still in life. This means that they have not received yet the overall amount of intergenerational transfers since they are aged around 40 years old. Unfortunately, it is not possible to control for the number of parents in life since the SHIW does not provide this kind of information.

Figure 2.2: Probability of ending in a specific quintile of the estate wealth distribution by having received or not some inherited estate wealth.



Author's elaboration based on the SHIW

2.11. Concluding remarks

This chapter provided a first estimate of the intergenerational wealth elasticity and rank-rank slope in Italy using data from the Bank of Italy's Survey on Household Income and Wealth (SHIW). To overcome the lack of information on parental wealth, the two-sample two-stage least squares methodology has been used by selecting a sample of offspring that report some socio-economic information about their actual parents and an independent sample of pseudo-parents in their 40s

The resulted intergenerational wealth elasticity of 0.451 and rank-rank slope of 0.349 revealed that Italy, as well as the United States and Sweden, is a country with a lower degree of wealth mobility across generations than other Scandinavian countries or France. Moreover, the degree of wealth mobility in Italy appeared to be particularly low at the top and at the bottom of the wealth distribution and in the southern part of the country where estimated elasticity resulted to be 0.621.

To test the pattern of the intergenerational wealth correlation over the children's lifecycle, the intergenerational wealth elasticity and the rank-rank slope are re-estimated by using three different samples of offspring by age. Results confirmed previous evidence that showed a U-shaped pattern of the wealth correlation as a function of offspring's age with higher intergenerational wealth correlations if offspring are taken when they are at the beginning of their adulthood or in their 40s. This is the reason why, unlike estimates of mobility which use income or earnings as a measure of economic status, estimates obtained by selecting young offspring seems not to be downward biased. However, further evidence is needed to assess the degree of intergenerational wealth mobility if offspring are selected when they are retired.

The decomposition of the intergenerational association into different mediating mechanisms showed that permanent labour income of the second generation, among other mediating factors such as preferences and bequests or inter-vivos transfers, seems to be associated with most of the overall wealth association across generations. More specifically, while the intergenerational wealth elasticity became 43.7 percent lower when labour income of offspring is included as a control, a smaller fraction of the wealth association seemed to be related to direct intergenerational transfers such as bequests or donations. This evidence suggest that parental background is likely to be strongly associated to economic opportunities of children once they enter the labour market.

Appendix A

Table 2.16: Two sample descriptive statistics

	Pseudo-Parents	Parents described by Offspring
Father's age	46.825	48.018
	(4.230)	(3.837)
Mother's age	43.435	44.666
	(4.811)	(4.175)
Father's educational level:		
None	0.017	0.051
Elementary	0.308	0.407
Lower secondary	0.314	0.309
Upper secondary	0.281	0.185
University degree	0.080	0.048
Mother's educational level:		
None	0.024	0.059
Elementary	0.368	0.463
Lower secondary	0.313	0.301
Upper secondary	0.229	0.149
University degree	0.066	0.028
Father's qualification:		
Production worker	0.357	0.466
Teacher or clerical worker	0.263	0.190
Junior manager	0.099	0.052
Manager	0.035	0.021
Self-Employed	0.201	0.218
Mother's qualification:		
Not employed	0.588	0.527
Production worker	0.129	0.195
Teacher or clerical worker	0.173	0.140
Manager or junior manager	0.021	0.019
Self-Employed/member of the arts	0.090	0.120
Region of residence:		
Piemonte	0.102	0.097
Lombardia	0.195	0.118
Trentino-Alto Adige	0.018	0.076
Veneto	0.063	0.074
Friuli-Venezia	0.024	0.016
Liguria	0.034	0.038
Emilia-Romagna	0.057	0.063
Toscana	0.062	0.057
Umbria	0.012	0.016
Marche	0.016	0.024
Lazio	0.115	0.104
Abruzzo	0.015	0.017
Molise	0.004	0.009
Campania	0.065	0.079
Puglia	0.076	0.073

Basilicata	0.019	0.030
Calabria	0.031	0.040
Sicilia	0.067	0.042
Sardegna	0.025	0.030

Author's elaboration based on the SHIW.

Table 2.17: First Stage Auxiliary variables and Post-Estimation Statistics

	Net Wealth (Log)	Net Wealth
Father's education (5 Cat.)	Yes	Yes
Mother's education (5 Cat.)	Yes	Yes
Father's qualification (6 Cat.)	Yes	Yes
Mother's qualification (5 Cat.)	Yes	Yes
Region of Residence (19 Cat.)	Yes	Yes
Father's age polynomial	Yes	Yes
Mother's age polynomial	Yes	Yes
R-squared	0.278	0.252
F-statistic	18.02	16.56
Obs.	2007	2062

Author's elaboration based on the SHIW

Table 2.18: IWE using different sets of auxiliary variables in the first stage

	IWE	First-stage R^2
All aux. variables	0.451*** [0.062]	0.278
Excluding fathers' educational level	0.472*** [0.064]	0.257
Excluding mothers' educational level	0.476*** [0.062]	0.254
Excluding fathers' occupational status	0.561*** [0.075]	0.167
Excluding mothers' occupational status	0.514*** [0.066]	0.237
Excluding region of residence of parents	0.518*** [0.069]	0.211
Excluding fathers' age polynomial	0.470*** [0.063]	0.256

Excluding mothers' age polynomial	0.477***	0.259
	[0.065]	
Obs.	1076	

Author's elaboration based on the SHIW. Bootstrapped standard errors (reps 100) in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table 2.19: Rank to rank slopes using different sets of auxiliary variables in the first stage

	R2R	First-stage R^2
All aux. variables	0.349***	0.252
	[0.030]	
Excluding fathers' educational level	0.350***	0.231
	[0.028]	
Excluding mothers' educational level	0.332***	0.226
	[0.030]	
Excluding fathers' occupational status	0.322***	0.159
	[0.027]	
Excluding mothers' occupational status	0.340***	0.212
	[0.029]	
Excluding region of residence of parents	0.334***	0.209
	[0.027]	
Excluding fathers' age polynomial	0.345***	0.230
	[0.028]	
Excluding mothers' age polynomial	0.349***	0.233
	[0.028]	
Obs.	1158	

Author's elaboration based on the SHIW. Bootstrapped standard errors (reps 100) in parentheses. Both offspring's wealth and parental wealth is percentile ranked within offspring's age. * p<0.10, ** p<0.05, *** p<0.01

Table 2.20: Estimated Rank-Rank slope by offspring's area of residence. Robustness check

	[North/Centre]	[South/Islands]
Parental Net Wealth	0.285***	0.404***
	[0.036]	[0.047]
Area of birth≠Area of residence	-3.74	4.63
	[2.54]	[7.42]
R-squared	0.084	0.163
Obs.	777	381

Author's elaboration based on the SHIW. Bootstrapped standard errors (reps 100) in parentheses. Both offspring's wealth and parental wealth are percentile ranked by offspring and parents birth cohort. * p<0.10, ** p<0.05, *** p<0.01

Appendix B

Table 2.21: Components of net wealth

Variable	Description
Real Assets:	
AR1	Real Estate: housing, land other buildings
AR2	Businesses
AR3	Valuables
Financial Assets:	
AF1	Deposits, CDs, repos, postal saving certificates
AF2	Government Securities
AF3	Other Securities: bonds, mutual funds, equity, shares in private limited companies and partnerships, foreign securities, loans to cooperatives
AF4	Credit due from other households
Financial Liabilities:	
PF1	Liabilities to banks and financial companies[25]
PF3	Liabilities to other households

Source: Bank of Italy's SHIW.

[25] Short term debts, overdraft on credit cards and current accounts and trade of business debts are not included

Chapter 3: Intergenerational Earnings Inequality in Italy: New Evidences and Main Mechanisms[26]

Abstract

This chapter provides new and detailed estimates of intergenerational earnings inequality in Italy and sheds light on mechanisms behind the association of gross and net earnings between fathers and sons.

Being not available panel data following subsequent generations in Italy, we make use of a recently built dataset that merges information provided by IT-SILC 2005 (i.e., the Italian component of EU-SILC 2005) with detailed information about the whole working life of those interviewed in IT-SILC recorded in the administrative archives managed by the Italian National Social Security Institute (INPS). This dataset allows us to rely on the two-sample two-stage least squares method (TSTSLS) to predict father earnings and, then, compute point in time intergenerational elasticities (IGE) and imputed rank-rank slopes. Furthermore, the characteristics of the dataset allow us to extend point in time estimates considering, for both sons and "pseudo-fathers", average earnings in a 5-year period and observing sons at various ages, thus assessing the robustness of our estimates to attenuation and life cycle biases.

Confirming previous evidence (Mocetti 2007; Piraino 2007), we find that Italy is characterized by a relatively high earnings inequality in cross country comparison – the size of the estimated β is usually over 0.40 – and the size of the intergenerational association increases when older sons and multi-annual averages are considered.

We also investigate mechanisms behind this association both: i) including a set of possible mediating factors of the parental influence (e.g., sons' education, occupation, labour market experience) among the control variables when regressing sons' earnings on fathers' earnings and ii) following the sequential decomposition approach suggested by Blanden et al. (2007). Results show that a limited share of the intergenerational association is attributable to sons' educational and occupational attainment, while the largest part of the association is mediated by sons' employability along the career, i.e., by their effective experience since the entry in the labour market.

[26] This chapter is part of a research project with Michele Raitano (Sapienza University of Rome) and Teresa Barbieri (Ph.D candidate in Economics and Social Sciences at Sapienza University of Rome).

Introduction

In the last few decades, a growing body of international literature has focused on intergenerational transmission of social and economic advantages (and disadvantages). Economists have focused their attention on measuring the degree of income persistence across two generations and, more specifically, on the estimation of the intergenerational elasticity coefficient β that captures how much of the income difference between two parents still is preserved between their children (see Blanden, 2013). Due to constraints that effect women participation in the labour market, literature on intergenerational mobility usually focuses on the association between fathers and sons' earnings.

Even if reliable estimates of the intergenerational earnings elasticity (IGE) are available only for few nations, a generally accepted ranking has emerged from cross-country empirical studies on economic mobility as concerns developed countries (Solon, 2002; Corak, 2013; D'Addio, 2007; Bjorklund & Jantti, 2009; Blanden, 2013): Nordic European countries emerge as the most mobile, while the US, the UK and Southern European countries are reported to be the most unequal. According to the few available estimates (Mocetti, 2007, Piraino, 2007), Italy belongs to the low-mobility group.

Actually, due to the unavailability of datasets jointly recording information on children and parents' earnings or income, Italy has received a limited attention in the intergenerational mobility literature. Nonetheless, the IGE in Italy has been estimated in recent years by means of the two-sample two-stage least squares (TSTSLS) method, which allows researchers to overcome the lack of data regarding actual fathers' incomes (Mocetti 2007; Piraino, 2007). More specifically, when long panel data recording income information for both generations of parents and children observed at middle ages are not available, the TSTSLS empirical approach exploits two independent samples of sons and pseudo-fathers and some sons-reported retrospective information about fathers to obtain a prediction of fathers' earnings in the first stage and the IGE in the second. Mocetti (2007) and Piraino (2007), followed this approach by using various cross-sections of the Bank of Italy's Survey of Household Income and Wealth (SHIW), computed point in time measures (i.e. concerning a single year) of intergenerational net earnings elasticity. They obtained estimated values amounting, respectively, to 0.50 and 0.44.

An alternative measure of mobility, i.e. the rank-rank slope, has recently proved to be more robust across samples and specifications (Dahl & Delaire 2008; Chetty et al. 2014) and with respect to both life-cycle and attenuation bias (Gregg et al. 2014) than the IGE[27]. However, to the best of our knowledge, no studies have estimated rank-rank slopes for Italy so far.

Therefore, the aim of this chapter is to provide new estimates of the earnings mobility in Italy by means of a proper dataset, that, compared to the SHIW, allows us to observe sons' and pseudo-fathers' earnings for more than one-year. To this aim, we use the AD-SILC dataset, that has been developed merging information provided in IT-SILC (2005) – where a retrospective section on parental characteristics is recorded – with information on the whole working history since the entry in the labour market of all individuals interviewed in IT-SILC provided by the administrative archives managed by the Italian National Social Security Institute (INPS). Thus, we can exploit the longitudinal nature of these data to apply the TSTSLS procedure, computing multi-year earnings values for both generations. INPS data record earnings gross of taxes and contribution paid by the worker. This means that we can compute indexes of intergenerational inequality of gross earnings, thus computing the size of income persistence produced by the labour market, before the redistributive effect of taxes and transfers. In order to compare our results with those provided by Mocetti (2007) and Piraino (2007), who focused on net earnings, we also reconstructed net earnings for both generations to re-estimate the intergenerational elasticity.

However, the aim of this chapter does not limit to compute summary measures of intergenerational inequality (as the IGE or the rank-rank slope). Indeed, we also

[27] More specifically, intergenerational elasticity capture both the re-ranking across generations and the differences in the amount of inequality within each generation (due to changes in income distribution across generations). Thus, the IGE is very sensitive to changes in inequality and it may not capture changes in positional income mobility only, but also the evolution of cross-sectional earnings inequality (Lefranc, 2011). This may be problematic when we want to compare the degree of intergenerational mobility across countries with different level of cross-sectional inequality.

aim at assessing which are the main mechanisms behind the correlation between parents' and children' earnings. In particular, we aim at analysing whether the bulk of intergenerational inequality is explained by educational and occupational attainments of children coming from different backgrounds or a significant association between parents' and children' earnings emerges also controlling for these children's outcomes.

To this end, we first compare our baseline results adding in our estimates of the link between fathers' and sons' earnings further variables that can mediate the relationship between fathers' circumstances and sons' earnings (e.g. sons' educational attainments, contractual arrangement and experience in the labour market).

Moreover, we apply a sequential decomposition approach (Blanden et al. 2007; Hirvonen, 2010; Buchner at al., 2012; Macmillan, 2013; Blanden et al, 2014) to disentangle the share of the IGE explained by various children's characteristics that might be affected by parental circumstances. According to the Becker and Tomes theoretical framework (1979 and 1986), when capitals markets are not perfect and public investment in education does not fully compensate for them, investment in children human capital by parents coming from disadvantaged background are limited, since parents face liquidity constraints. Literature on intergenerational mobility based on this theoretical framework recognizes education as the main transmission mechanism of persistence across generations: children coming from a more disadvantaged background receive a lower level of investments education and, consequently, later in life they will have less job opportunity and lower earnings.

However, this "human capital view" has been challenged by some scholars that recognize the importance of a "direct" effect of family background on earnings, not mediated by "formal" educational attainments. (e.g., Breen & Goldthorpe, 2001; Goldthorpe & Jackson, 2008; Franzini & Raitano, 2009; Franzini et al, 2013; Hudson and Sessions 2011, Raitano & Vona, 2015).

The decomposition approach, as mentioned, measures to which extent the IGE is explained by sons' characteristics (e.g. education or occupation). The explained part is measured accounting for both the relationship between parent's earnings and children's characteristics and the return to those characteristics in the labour market. Thus, the intergenerational elasticity can be decomposed in two parts: the indirect effect of parental background acting through children's endowment of different characteristics and a residual direct effect not explained by these characteristics.

The reminder of this chapter is structured as follows. Section 3.1 presents the main findings of the empirical literature on intergenerational mobility, focusing on the differences between the empirical approaches that have been proposed to tackle with the issue of intergenerational inequality when information of parents' earnings are not available. Section 3.2 describes the dataset and the sample selection used to run our estimates. Section 3.3 describes the methodology and the empirical strategy that we follow in this chapter. Section 3.4 presents results of the TSTSLS estimates of the IGE comparing results obtained observing parents and children for different time spans. Section 3.5 presents results of the estimates of imputed rank-rank slopes comparing again results obtained observing parents and children for different time spans. Section 3.6 shows how IGE and rank-rank slopes change when we add some children outcomes among the control variables. Section 3.7 shows results of the decomposition of the IGE for Italy into different mediating variables that may account for the transmission of earnings between parents and children. Section 3.8 concludes, summarizing our main results.

3.1. Intergenerational earnings mobility: OLS estimates

Over the last two decades, economists have broadly analysed to what extent economic advantages are transmitted from one generation to the next[28]. The ideal way to evaluate the degree of intergenerational economic mobility is to use permanent earnings (or permanent incomes, when also information on labour incomes are not available) as a measure of economic welfare of individuals and to estimate the following equation:

[28] For a review of the studies on intergenerational earnings mobility, see Solon (1999), Black and Deveroux (2010) and Blanden (2013).

$$y_i^s = \alpha + \beta \; y_i^f + \varepsilon_i \tag{1}$$

where y_i^s and y_i^f are respectively the logarithm of permanent sons' and fathers' earnings and β is the IGE[29]. According to this measure of economic association between generations, a country is completely mobile when the estimated β equals 0, while the higher the earnings elasticity is, the lower the degree of economic mobility across generations will be.

Unfortunately, several methodological issues arise when trying to estimate equation 1. Firstly, also the few datasets covering two generations usually report short-term rather than permanent measures of earnings. This implies that, under classical measurement errors assumptions, estimated elasticities obtained using yearly instead of permanent fathers' earnings are likely to be downward biased due to the so-called attenuation bias (Solon, 1992; Zimmerman, 1992). A usual way to reduce this kind of bias is to average fathers' earnings over a period as large as possible. The greater the number of years available when averaging fathers' earnings is, the closer to the true β the estimated IGE will be (Mazumder, 2005a).

Secondly, the lack of permanent measures of earnings might cause the so-called lifecycle bias if too young children are considered. More specifically, estimated elasticities are influenced by the amount of earnings dispersion which tends to become higher as individuals get older, since earnings profiles are steeper for those with higher long-run earnings. Therefore, Haider and Solon (2006) suggest choosing both parents and children at median age to minimise the lifecycle bias when permanent measures of earnings are not available.

Table 3.1 summarizes estimated earnings elasticities from different empirical studies on 8 developed countries which use a 4/5 year-time average of parental earnings on the right-hand side of equation 1. Reported elasticities identify the Unites States as the less mobile society among those considered, with an estimated

[29] Usually the IGE is computed by considering only fathers and sons in order not to have a selection bias due to the lower women participation in the labour market.

β of 0.54. Conversely, Denmark is reported to be the most mobile country with an estimated earnings elasticity of 0.14.

Table 3.1: Intergenerational earnings elasticity: OLS estimates (4/5yrs averaged fathers'earnings)

Country	Source	Earnings Elasticty
U.S.	Zimmerman (1992)	0.54
Norway	Nilsen et al. (2012)	0.27 (on average)
Germany	Vogel (2008)	0.25
Sweden	Björklund & Chadwick (2003)	0.24
Canada	Corak & Heisz (1999)	0.23
Finland	Pekkarinen et al. (2009)	0.23-0.30
Denmark	Hussain et al. (2008)	0.14

As described in chapter 1, information about parents' earnings and/or income are usually absent in many developed countries and in most of less developed countries. For this reason, it is extremely hard to rank countries in terms of economic mobility by considering only those for which an OLS estimate on effective fathers' and sons' incomes is available. A way to overcome this issue was first proposed by Björklund and Jäntti (1997) that make use of the two-sample instrumental variable methodology (TSIV), originally described by Angrist and Krueger (1992) and Arellano and Meghir (1992), to estimate intergenerational elasticities in Sweden and the United States. This approach exploits two independent samples and some information about some socio-economic characteristics of actual parents (usually of the father) reported by their children (usually the sons) to predict earnings of the older generation.

As time goes by, the TSTSLS method becomes gradually more used because computationally more convenient and asymptotically more efficient than the TSIV (Inoue and Solon, 2010). As described in the previous chapters, the TSTSLS method is implemented by exploiting a sample of adult sons, who report some socio-economic characteristics of their actual fathers, and an independent sample of individuals, different from the actual fathers observed during the childhood of the adult sons, to obtain intergenerational elasticities in a two-stage approach.

Consider however, that the number of retrospective variables available to impute fathers' earnings are likely to influence the estimated IGE. In particular, as $0 \leq R^2 \leq 1$, the variance of imputed fathers' earnings is less than or equal to the variance of actual fathers' earnings and $\hat{\beta}_{TSTSLS} = \beta_{TRUE}$ when, in the first stage regression, the $R^2 = 1$. This means that the higher the number of good auxiliary variables is, the higher the explained variance of pseudo-fathers' earnings will be and the lower the bias of the TSTSLS estimator is expected to be. This is mainly due to the fact that the estimated elasticity converges in probability to the following expression:

$$\beta \cong \rho_{sf} \frac{sd_s}{sd_f} \tag{2}$$

where ρ_{sf} is the correlation between sons' and fathers' earnings and sd_s and sd_f are the two standard deviations.

3.2. Data and sample selection

Our estimates of intergenerational earnings mobility are obtained by relying on AD-SILC, a very rich panel dataset built merging the 2005 wave of the Italian sample of the Survey on Income and Living Condition (IT-SILC) conducted by Istat (the National Italian Statistical Institute) with information collected from administrative archives managed by the Italian Social Security Institute (INPS) that cover individual earnings histories from the moment they enter the labour market up to the end of 2013. The administrative archives provide records of every job relationship that individuals experienced during the year such as the duration (measured in weeks), the fund where the worker pays contributions (allowing us to distinguish private and public employees and the various groups of self-employed), gross earnings (including personal income taxes and pension contributions paid by the worker). Furthermore, we can distinguish weeks spent working from weeks spent receiving maternity, sickness and CIG allowances or unemployment benefits. The panel structure of our data allows us to exactly measure the time of entry in the labour market and the effective labour market experience since the entry. Note that administrative archives record information on all types of workers in Italy, thus they are free from attrition; furthermore, earnings measured in administrative archives are less affected by measurement errors than survey data.

As in most of studies on intergenerational mobility we analyse the relationship between parents and children focusing on fathers and sons. In order to carry out our empirical strategy, the IT-SILC 2005 survey contains a specific section about intergenerational mobility and thus, information about fathers' characteristics when sons were aged around 14, e.g. father's educational attainments, occupations and activity status. The 2005 wave of IT-SILC has then been merged with the INPS archives in order to obtain retrospective information on fathers through the IT-SILC and sons' earnings from the administrative archives.

We select two subsamples of sons and pseudo-fathers according to the following rules. We consider sons born in the period 1970-1974 and follow these individuals since they are aged 35 up to age 39. Thus, according to their birth year, sons are followed in the period 2005-2013 and earnings since age 35 to age 39 are averaged. Pseudo-fathers are selected among those individuals observed in the period 1980-1988 and aged between 40 and 44 in INPS archives (and their earnings over the period are also averaged): thus we consider pseud-fathers born in the period 1940-1944. The two generations are thus observed at middle ages according to the selection rules proposed by Haider and Solon (2006) to minimize the amount of lifecycle bias.

Our main variable of interest, annual gross earnings, includes both employment and self-employment labour income and is considered in real terms (it has been deflated according to the 2012 Consumer Price Index). Thus, considering gross incomes, we are able to first evaluate the extent of intergenerational mobility in the labour market before the effect of taxes and transfers tooks place. Then, in order to compare our results to previous estimates of the IGE for Italy (Piraino, 2007;

Mocetti, 2007), we reconstruct net earnings and estimate intergenerational mobility measures after the redistributive intervention on earnings exerted by the State through social contributions and income taxes[30].

Descriptive statistics presented in table 3.2 show that the two final samples count 1445 sons and 2742 pseudo-fathers. Gross earnings are slightly more dispersed in the sample of sons than in the sample of pseudo-fathers. As expected, income taxation reduces earnings dispersion in both generations.

Table 3.2: Two-Sample Descriptive Statistics

	Sons	Pseudo-Fathers
Age (Mean)	38.80	41.97
	(0.69)	(0.44)
Log Gross Earnings (Mean)	10.00	9.90
	(0.66)	(0.49)
Log Net Earnings (Mean)	9.65	9.63
	(0.59)	(0.46)
Observations	1445	2742

Author's elaboration based on the AD_SILC dataset.
Standard deviations in parenthesis. All economic variables are deflated by using the 2012 consumer price index

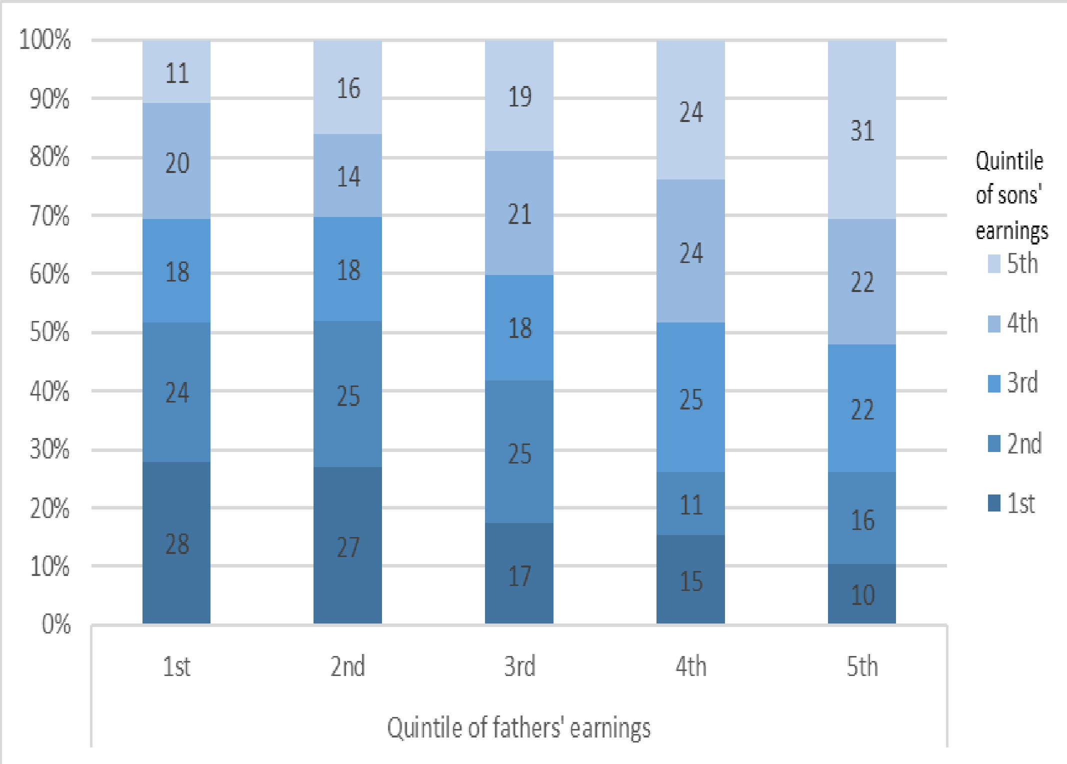
A first way to describe the extent of intergenerational mobility in Italy is to present sons' probabilities of ending up in a specific quintile of the earnings distribution given the quintile of their fathers' (figure 3.1). This kind of descriptive analysis may be also useful to evaluate the pattern of mobility along the distribution, as previous

[30] We first subtract employee and self-employed mandatory social contributions and then apply to all individuals tax rules (i.e. tax rates and related deductions).

literature reports higher levels of intergenerational economic correlation at the top of the earnings' distribution (see Björklund et al. 2010).

Figure 3.1 shows that for most gross earnings quintiles, sons are more likely to ends up in the same quintile as their fathers (diagonal probabilities are all greater than 20 percent expect the third quintile[31]).

Figure 3.1: Probability of ending up in a specific quintile of the gross earnings distribution given the quantile of their fathers'



Author's elaboration based on the AD_SILC dataset.

The degree of persistence of earnings across generations is particularly high at the top and at the bottom of the distribution: 31 percent of sons whose pseudo-fathers were collocated in the highest quintile of the distribution remains in the same

[31] We do not report also mobility matrix for net earnings since results are the same, as taxation does not re-rank individuals.

quintile and more than 50 percent in one of the highest two quintiles. Conversely, only about 10 percent of sons from the best economic background end up in the worst quintile. The degree of persistence is also high at the bottom-end of the earnings distribution: about 52 percent of sons coming from the lowest quintile of the fathers' earnings distribution remains in one the bottom two quintiles.

3.3. Empirical strategy

As in previous studies on intergenerational economic mobility in Italy, we exploit the TSTSLS method to obtain measures of intergenerational associations for both gross and net annual earnings. We perform the method by exploiting a set of fathers' socio-economic characteristics reported by sons that can be used to predict their fathers' earnings. More formally, in the first stage we estimate the following equation by exploiting the sample of pseudo-fathers:

$$Y_{i,t}^{pf} = \alpha + \theta_1 Z_i^{pf} + v_{i,t} \tag{3}$$

where $Y_{i,t}^{pf}$ is is the logarithm of pseudo-fathers' earnings, Z_i^{pf} is the vector of socio-economic characteristics of pseudo-fathers and $v_{i,t}$ is the usual disturbance. The set of auxiliary variables contained in Z_i^{pf} includes 4 educational categories (primary or lower, lower secondary, upper secondary and tertiary degree), 27 occupational categories (according to the 2 digits ISCO-88 classification), 20 dummies on the region of residence[32] and a dummy for self-employment.

Then, we obtain the IGE in the second stage, by regressing the logarithm of sons' earnings on that of pseudo-fathers':

$$y_{i,t}^{S} = \alpha + \beta \hat{y}_i^F + \mu B_i^s + \epsilon_{i,t} \tag{4}$$

[32] We link sons' region of birth to parents' region of residence to avoid biases related to a possible mobility across regions of children during their adult age.

where $y_{i,t}^{S}$ is the logarithm of sons' earnings, $\hat{y}_i^F = \hat{\theta}_1 Z_i^F$ is the prediction of the logarithm of fathers', B_i^s is year of birth of the son and β is the IGE.

Even though we are exploiting an instrumental variable approach based on two independent samples, we do not aim to identify the causal effect of fathers' earnings on sons' earnings. Our goal is to merely predict the former in the best possible way. This is the reason why we do not require the set of auxiliary variables - used to predict fathers' earnings in the first stage - to satisfy any exclusion restriction. However, we are not able to obtain a perfect prediction of fathers' lifetime earnings by using the set of socio-economic characteristics at our disposal. This is why a TSTSLS estimator could be affected by three different kind of potential biases compared to the OLS estimator obtained by using fathers' earnings averaged over a multi-year period (see chapter 2 for a more formal description).

Firstly, an attenuation bias deriving from the fact that we are using an imputed value instead of an actual value as a regressor. We are thus introducing measurement error.

Secondly, if socio-economic characteristics of fathers are positively correlated with the error term in equation 4 (if auxiliary variables are not exogenous), we are introducing an upward bias in our estimates as the predicted variance of the earnings of the first generation is lower than actual variance.

A further source of potential bias can derive from the fact that there could be other unobservables included in $v_{i,t}$ (e.g. soft skills, social networks, cultural factors, cognitive and non-cognitive abilities) not totally captured by the set of auxiliary variables used in the first stage. In this case, estimates of earnings mobility could be upward biased (downward biased) if these unobservables are negatively (positively) correlated across generations[33].

Generally speaking, the R^2 of the first stage regression may be considered as a good measure of the fraction of the variance of pseudo-fathers' earnings predicted from auxiliary variables. Unfortunately, empirical works that use the TSTSLS approach are often not able to use permanent or, at least, time-averaged earnings as

[33] See Olivetti and Paserman (2015) for a more detailed and formalised discussion of the different potential sources of bias deriving from imputing fathers' earnings.

a dependent variable in the first stage. This means that, in the first-stage regression, the estimated R^2 is influenced by different factors. More formally, at any point of time, earnings of pseudo-father i may be expressed according to the following expression:

$$Y_{i,t}^{pf} = Y_i^{pf} + \varphi_{i,t} + \omega_t \tag{5}$$

where $Y_{i,t}^{pf}$ and Y_i^{pf} are respectively yearly and averaged pseudo-fathers' earnings, $\varphi_{i,t}$ are transitory individual shocks (or measurement errors) and ω_t are aggregate transitory shocks. This means that, by definition:

$$\sigma^2\left(Y_{i,t}^{pf}\right) > \sigma^2\left(Y_i^{pf}\right) \tag{6}$$

$$R^2\left(Y_{i,t}^{pf}\right) < R^2\left(Y_i^{pf}\right) \tag{7}$$

where $\sigma^2\left(Y_{i,t}^{f}\right)$ and $\sigma^2\left(Y_i^{f}\right)$ are the two variances and $R^2\left(Y_{i,t}^{f}\right)$ and $R^2\left(Y_i^{f}\right)$ are the proportion of the two variances that is predictable from the set of auxiliary variables in the first stage. According to this framework, it is plausible to say that R^2 in the first stage depends on three factors: 1. The number of auxiliary variables exploited to predict earnings (and their predictive power); 2. The number of years on which pseudo-fathers' earnings are averaged; 3. The amount of transitory shocks occurred to individuals over the period of analysis[34].

In this chapter, we try to partially reduce some of these sources of biases with respect to previous evidence for Italy. To do that we exploit a set of auxiliary variables which allow us to explain about 40% of the variance of pseudo-fathers' earnings (about 10% higher than those obtained in the first stage by Piraino, 2007 and Mocetti, 2007). This means that we are partially reducing unexplained variance

[34] For a more detailed discussion of the downward bias derived from using yearly instead of averaged earnings for the first generation, see Jerrim et al. (2016)

due to unobservables included in $v_{i,t}$. Our result derives also from the fact that we are able to reduce measurement error due to transitory shocks by averaging earnings of pseudo-fathers over a 5-year period, in order to get a better prediction of lifetime earnings.

3.4. Estimated intergenerational earnings elasticities

Estimated IGE for gross earnings is presented in table 3.3. The first column reports an estimated IGE of 0.496, obtained when earnings of both pseudo-fathers and sons are observed in a 5-year period. Such a result means that a 10 percent variation in fathers' earnings is associated with a 4.96 percent variation in son's earnings. This estimated IGE is slightly higher than that of 0.44 reported by Piraino (2007) and close to that of 0.50 reported by Mocetti (2007) using net instead of gross incomes.

However, when we use a single year measure for both the two generations – observing fathers and sons, respectively, in 1985 and 2009 only – the estimated IGE becomes lower than the ones obtained by Piraino (2007) and Mocetti (2007) which used point in time estimates. The lower value obtained in this paper compared to previous evidence is probably related to a reduction in the unexplained variance of pseudo-fathers' earnings. On the contrary, the use of time-averages increases our estimated elasticity. This means that, although the two generations are taken at middle ages as suggested by Haider and Solon (2006), using a single year measure of earnings may cause a downward bias in estimated IGE due to both left-hand and right-hand side measurement errors. These results are consistent with previous evidence which show that both TSTSLS and OLS estimates of intergenerational earnings elasticities are likely to be downward biased using point in time measures of fathers' earnings, even when commonly used selection rules for both generations are exploited (Gregg et al. 2014, Jerrim et al., 2016).

The last column of table 3.3 shows that the IGE increases when zero earnings observations are not excluded from the analysis, i.e. when individuals that are not present in INPS archives in a year in the observed period are considered in the estimates considering a zero-earning value for that year. This suggests that sons of poorer fathers are likely to have more unstable careers (i.e. to spend a year without earnings) than workers coming from a better background.

Table 3.3: Association between son's and father's gross earnings. Prime age sons[a]. OLS estimates in the second stage[b]

	Observation span of fathers' and sons' earnings				
	5 years-5 years	5 years-1 year	1 year-5 years	1 year-1 year	5 years-5 years Imputing zeros[c]
Father's earnings	0.496***	0.441***	0.402***	0.382***	0.623***
s.e.	[0.056]	[0.056]	[0.054]	[0.054]	[0.081]
Obs	1445	1365	1445	1365	1481
R^2	0.059	0.048	0.043	0.040	0.044
R^2 first stage	0.409	0.409	0.404	0.404	0.409

[a] when observed in a 5 year period, fathers and sons are considered, respectively, when aged 40-44 in the period 1980-1988 and 35-39 in the period 2005-2013. When observed in a single year, fathers and sons are considered, respectively, in 1985 and 2009. [b] TSTSLS are carried out: in the first stage father's earnings are imputed regressing log annual gross earnings on dummies on education, occupation, self-employment, region of work; in the second stage sons' log annual gross earnings are regressed on predicted fathers' log earnings, also controlling for sons' year of birth. [c] 5-year average of sons' earnings in age class 35-39 are computed assigning a zero value to sons who do not report earnings in administrative archives in a certain year. *** p<0.01, ** p<0.05, * p<0.10. Source: elaborations on AD-SILC dataset

The presence of the life cycle bias is confirmed when we replace the sons' generation by considering a sample of younger sons aged 25-29 born from 1970 1974 (Table 3.4). In this case, the estimated IGE obtained by measuring over a 5-year period falls to 0.270 (0.365 when also zero earnings observations are included in the analysis).

Some sensitivity tests are performed to evaluate the robustness of our estimated elasticity. First, we check whether the estimated IGE changes if we exclude a single predictor from the first stage regression[35]. More specifically, the TSTSLS estimate should be considered upward (downward) biased if auxiliary variables used in the first stage have positive (negative) direct effect on sons' earnings. Results presented

[35] We perform the Sargan test to evaluate if the full set of instruments used in the first stage in uncorrelated with the error term of the second stage regression. The test rejects the null hypothesis, which means that at least one instrument is not exogenous.

in table A.1 in the appendix show that the estimated elasticity tends to be extremely stable if either educational or occupational categories are excluded from the set of auxiliary variables exploited as predictors in the first stage. On the contrary it becomes higher (lower) if we exclude the dummy for self-employment (region of residence).

Table 3.4: Association between son's and father's earnings. Young sons[a]. OLS estimates in the second stage[b]

	Observation span of fathers' and sons' earnings				
	5 years-5 years	5 years-1 year	1 year-5 years	1 year-1 year	5 years-5 years Imputing zeros[c]
Father's earnings	0.270***	0.225***	0.235***	0.237***	0.365***
s.e.	[0.058]	[0.079]	[0.057]	[0.076]	[0.097]
Obs	1395	1147	1395	1147	1410
R^2	0.016	0.020	0.013	0.022	0.018
R^2 first stage	0.409	0.409	0.404	0.404	0.409

[a] When observed in a 5 year period, fathers and sons are considered, respectively, when aged 40-44 in the period 1980-1988 and 25-29 in the period 1995-2003. When observed in a single year, fathers and sons are considered, respectively, in 1985 and 1999. [b] TSTSLS are carried out: in the first stage father's earnings are imputed regressing log annual gross earnings on dummies on education, occupation, self-employment, region of work; in the second stage sons' log annual gross earnings are regressed on predicted fathers' log earnings, also controlling for sons' year of birth. [c] 5-year average of sons' earnings in age class 25-29 are computed assigning a zero value to sons who do not report earnings in administrative archives in a certain year. *** p<0.01, ** p<0.05, * p<0.10. Source: elaborations on AD-SILC dataset

As mentioned, previous estimates for Italy (Piraino, 2007; Mocetti, 2007) are computed on net earnings. In order to better compare our estimates, we derive also measures of net earnings for both generations. In table 3.5 we present the IGE computed on net earnings. The estimated IGE of 0.428 is obtained when earnings of both sons and pseudo-fathers are observed over a 5-year period. This estimated IGE is lower than the one previously obtained when using gross earnings. It is possible to notice that, with respect to our previous estimates, the R^2 for the first stage equation – thus, the explained variance of pseudo-fathers' earnings – increases: the same auxiliary variables seem to better predict net earnings than gross earnings. Moreover, the income taxation system has reduced more earnings dispersion in the sons' generation than in the first generation.

When comparing our estimates using net earnings, we can see that estimated IGE now is lower compared to those reported by both Mocetti (2007) and Piraino (2007), even if we use earnings of both pseudo-fathers and sons observed in a 5-year period. Moreover, when we use a 1-year measure of net earnings for both generations, we obtain an even lower estimated IGE with respect to previous estimates for Italy (Mocetti, 2007; Piraino, 2007) which use point in time measures. As in the case of the estimated IGE obtained using gross earnings, the use of time-averages increases our estimated IGE.

Table 3.5: Association between son's and father's net earnings. Prime age sons[c]. OLS estimates in the second stage[b]

	Observation span of fathers' and sons' earnings				
	5 years-5 years	5 years-1 year	1 year-5 years	1 year-1 year	5 years-5 years Imputing zeros[c]
Father's earnings	0.428***	0.383***	0.350***	0.333***	0.540***
s.e.	[0.048]	[0.048]	[0.049]	[0.046]	[0.073]
Obs	1445	1365	1445	1365	1481
R^2	0.056	0.047	0.042	0.040	0.038
R^2 first stage	0.463	0.463	0.472	0.472	0.463

[a] when observed in a 5 year period, fathers and sons are considered, respectively, when aged 40-44 in the period 1980-1988 and 35-39 in the period 2005-2013. When observed in a single year, fathers and sons are considered, respectively, in 1985 and 2009. [b] TSTSLS are carried out: in the first stage father's earnings are imputed regressing log annual net earnings on dummies on education, occupation, self-employment, region of work; in the second stage sons' log annual net earnings are regressed on predicted fathers' log earnings, also controlling for sons' year of birth. [c] 5-year average of sons' earnings in age class 35-39 are computed assigning a zero value to sons who do not report earnings in administrative archives in a certain year. *** p<0.01, ** p<0.05, * p<0.10. Source: elaborations on AD-SILC dataset.

In any case, comparing estimates of intergenerational elasticity coefficient is not a trivial exercise, because differences in estimates must be interpreted considering many factors such as the measure of earnings or income used, the sample selection and the applied methodology. For example, when the TSTSLS method is applied, the set of auxiliary variables used in the first stage to predict fathers' earnings vary across different studies, depending on the availability of retrospective socio-economic information about fathers reported by sons. In the best-case scenario, a large number of socio-economic characteristics of the father such as his education, occupational qualification, sector of activity, geographic area and age (or year of birth) are all exploited as predictors; in the worst, estimates are obtained by using only one retrospective variable such as in the case of Brazil (see for example Dunn, 2007).

Some results from empirical studies estimating earnings elasticities for different countries using either the TSIV of the TSTSLS method are presented in table 3.6.

Table 3.6: Intergenerational earnings elasticity for developed and less developed countries: TSTSLS or TSIV estimates

Country	Source	Earnings Elasticity
Ecuador	Grawe (2004)	1.13
Brazil	Dunn (2007)	0.69
Chile	Nunez and Miranda (2011)	0.66
South Africa	Piraino (2015)	0.62-0.68
China	Gong et al. (2012)	0.63*
Peru	Grawe (2001)	0.60
Brazil	Ferreira & Veloso (2006)	0.58
U.S.	Björklund and Jäntii (1997)	0.52
Italy	Mocetti (2007)	0.50
Pakistan	Grawe (2001)	0.46
Italy	Piraino (2007)	0.44
Nepal	Grawe (2001)	0.44
Spain	Cervini-Plà (2015)	0.42
France	Lefranc & Trannoy (2005)	0.40
South Korea	Ueda (2013)	0.35
Japan	Ueda (2013)	0.35
U.K.	Bidisha et al. (2013)	0.33
Germany	Cavaglià (2015)	0.30

U.K.	Nicoletti and Ermish (2007)	0.29
Sweden	Björklund and Jäntii (1997)	0.28
Australia	Leigh (2007A)	0.20-0.30
Taiwan	Kan et al. (2015)	0.18*

* Income elasticity is reported since an estimate of the earnings elasticity is not available for the country.

Unlike OLS estimates of earnings mobility, which are only available for a small number of developed countries, elasticities obtained by means of either the TSTSLS or TSIV approach are provided for many developed and less developed countries. The latter are reported to be less mobile societies as estimated earnings elasticities are basically greater than 0.60. On the contrary, Taiwan, Sweden and Australia, among those considered, are countries with high levels of intergenerational mobility with estimates IGE below the value of 0.30. If we consider our estimates of the IGE of 0.43, when we use net earnings or 0.50 when we use gross earnings, we can consider Italy as a medium-mobility country, when compared to both developed and less developed countries, and a low-mobility country when restricting the analysis to the subsample of developed countries. For instance, IGE estimates in other developed countries such as Germany, UK, Sweden, Australia and Japan are below the value of 0.40. It is interesting to compare our estimates with the elasticity of another Mediterranean country, Spain (Cervini, 2015), obtained using TSTSLS method and gross earnings. According to her results, the IGE for Spain is of 0.42, lower than our estimated IGE of 0.50 obtained using gross earnings and very close to the one obtained when using net earnings (0.43).

3.5. Estimated rank-rank slopes

Since the size of the intergenerational elasticity coefficient depends on the income dispersion in the two generations, we also estimate an alternative measure of intergenerational mobility: the rank-rank slope, a measure of the association between fathers' relative position in their respective earnings distributions (Dahl & DeLeire, 2008). From a statistical point of view, rank-rank slopes are usually intended to be more robust across samples and specifications (Chetty et al. 2014; Gregg et al. 2014).

The intergenerational elasticity coefficient converges in probability to the correlation coefficient of log earnings times the ratio between the standard deviation in sons' generation and that in fathers' generation. Hence, given the connection between the intergenerational elasticity coefficient and the correlation coefficient and given that the correlation coefficient and the rank-rank slope are both scale-invariant measures of relative mobility, we can easily see how the rank-rank slope is closely related to the intergenerational elasticity coefficient, but has the advantage to be "independent" from inequality within generations. In other words, the intergenerational elasticity coefficient may be affected by a change in inequality across the two generations, whereas the rank-rank slope is not.

If our aim is to provide estimates of intergenerational mobility for Italy that can be compared with those of other countries, estimating rank to rank slopes may be a more suitable strategy. Since the level of inequality is not the same across countries, the rank-rank slope may provide a better picture of differences in intergenerational mobility.

Rank-rank slopes are also more robust with respect to both the two key measurement issues, namely life-cycle and attenuation bias (Gregg et al. 2014). Life-cycle bias is mainly driven by mismeasurement of earnings gaps between individuals rather than positional inaccuracy along the earnings distribution. When using rank to rank slope we have also to deal with an attenuation bias smaller in magnitude since measurement errors and transitory shocks cause scale mismeasurement rather than positional inaccuracy in the earnings distribution.

Rank-rank slopes are usually obtained by estimating the following equation:

$$p_s = \alpha + \gamma p_f + \varepsilon \qquad (8)$$

where p_c is the percentile of sons' earnings in their own distribution and p_f is the percentile of fathers'. In this framework, an estimated γ of 0.5 means that the expected difference in ranks between sons would be about 5 percentiles if the difference in ranks among their fathers was 10 percentiles. However, we are not able to estimate rank-rank slopes by simply re-categorizing earnings of the two generations since data on actual fathers' earnings are not available. For this reason, we exploit a different approach consisting in two different steps. Firstly, we obtain a prediction of fathers' earnings by exploiting the sample of pseudo-fathers and the same set of auxiliary variables used for obtaining TSTSLS estimates of the IGE. Secondly, predicted fathers' earnings are percentile ranked so that we can estimate in the last step the following equation:

$$p_s = \alpha + \gamma \hat{p}_f + \varepsilon \tag{9}$$

where p_c is the percentile of sons' earnings in their own distribution and $\hat{p}_f$ is the imputed percentile of fathers' earnings. This approach, apart for the set of auxiliary variables exploited in the first step, is very close to that used by Olivetti and al. (2016) to obtain intergenerational and multigenerational imputed rank-rank slopes for the US[36].

From a statistical point of view, it is not easy to understand to what extent our imputed rank-rank slope can be compared to rank-rank slopes obtained by percentile ranking actual fathers' earnings. Obviously, when we impute the percentile of the father from a predicted variable we are likely to make some errors in placing all fathers in the right percentile of their earnings distribution. For this reason, our estimates are likely to be affected by attenuation bias. However, this kind of positional measurement errors cannot be intended as "classical" (see Nybom and Stuhler, 2016) since both our dependent variable and the regressor in equation 8 and 9 are uniformly distributed. This means that all statistical properties based on the assumption of normally distributed variables do not hold in our case. This is why we should exercise caution in comparing our imputed rank-rank slope to estimates obtained in previous studies for other countries.

[36] As in a previous article by Olivetti and Paserman (2015) they impute father's income, which is unobserved, using the average income of fathers of children with a given first name.

Table 3.7 presents our findings and shows, in the case of multi-year averages for both generations, an estimated value of 0.254 which, interestingly is characterized by a lower reduction, compared to the IGE in table 3.5, when different yearly values of annual earnings are considered. Moreover, in table 3.8 we report imputed rank to rank slopes for net earnings. Since income taxation should affect earnings dispersion but not the position on the ladder of the income distribution, estimates of imputed rank to rank slopes do not change. These findings further confirm the robustness of the rank-rank slope.

Table 3.7: Association between son's and father's gross earnings. Prime age sons[a]. Rank to rank estimates[b]

	Observation span of fathers' and sons' earnings				
	5 years-5 years	5 years-1 year	1 year-5 years	1 year-1 year	5 years-5 years Imputing zeros[c]
Father's earnings	0.254***	0.237***	0.228***	0.217***	0.249***
s.e.	[0.025]	[0.026]	[0.026]	[0.027]	[0.025]
Obs	1445	1365	1445	1365	1481
R^2	0.071	0.062	0.058	0.053	0.071
R^2 first stage	0.409	0.409	0.404	0.404	0.409

[a] When observed in a 5 year period, fathers and sons are considered, respectively, when aged 40-44 in the period 1980-1988 and 35-39 in the period 2005-2013. When observed in a single year, fathers and sons are considered, respectively, in 1985 and 2009. [b] TSTSLS are carried out: in the first stage percentiles of father's earnings are imputed regressing log annual gross earnings on dummies on education, occupation, self-employment, region of work; in the second stage percentiles of sons' log annual gross earnings are regressed on predicted percentiles of fathers' log earnings, also controlling for sons' year of birth. [c] 5-year average of sons' earnings in age class 35-39 are computed assigning a zero value to sons who do not report earnings in administrative archives in a certain year. *** p<0.01, ** p<0.05, * p<0.10. Source: elaborations on AD-SILC dataset

However, it is not easy to compare our estimate to those obtained for other countries as this alternative measure of intergenerational association has a shorter history with respect to IGE and moreover, to the best of our knowledge, there is no evidence of rank-rank estimates obtained by computing fathers percentiles according to parental earnings obtained through an imputation procedure.

To the best of our knowledge Dahl & Delaire (2008) were pioneers in the usage of rank to rank: for the USA, they estimate a rank-rank slope of 0.289 taking 34 years old sons and averaging fathers' earnings from age 20 to 55 also including years of zero earnings. Still for the USA, Chetty et al. (2014) estimate a rank-rank slope of 0.34 whereas Mazumder (2015) estimate a rank-rank coefficient of 0.40 when using 15 years of fathers' earnings (0.31 if using a single year of father's earnings). Bratberg et al. (2017) in a recent work on cross country measures of intergenerational mobility display rank-rank estimate for several countries: 0.383 for the US, 0.257 for Germany, 0.233 for Norway and 0.215 for Sweden. For the UK, we have rank-rank estimates from Gregg et al. (2014): 0.34 for sons aged 42 and parental income measured when sons were 16.

Table 3.8: Association between son's and father's earnings percentiles. Young sons[a]. Rank to rank estimates[b]

	Observation span of fathers' and sons' earnings				
	5 years-5 years	5 years-1 year	1 year-5 years	1 year-1 year	5 years-5 years Imputing zeros[c]
Father's earnings	0.181***	0.182***	0.169***	0.177***	0.148***
s.e.	[0.0265]	[0.0282]	[0.0268]	[0.0298]	[0.0283]
Obs	1395	1147	1395	1147	1410
R^2	0.038	0.058	0.034	0.056	0.042
R^2 first stage	0.409	0.409	0.404	0.404	0.409

a When observed in a 5 year period, fathers and sons are considered, respectively, when aged 40-44 in the period 1980-1988 and 25-29 in the period 2005-2013. When observed in a single year, fathers and sons are considered, respectively, in 1985 and 1999. **b** TSTSLS are carried out: in the first stage percentiles of father's earnings are imputed regressing log annual gross earnings on dummies on education, occupation, self-employment, region of work; in the second stage percentiles of sons' log annual gross earnings are regressed on predicted percentiles of fathers' log earnings, also controlling for sons' year of birth. **c** 5-year average of sons' earnings in age class 25-29 are computed assigning a zero value to sons who do not report earnings in administrative archives in a certain year. *** p<0.01, ** p<0.05, * p<0.10. Source: elaborations on AD-SILC dataset.

It is quite striking how these results differ from those related to cross-country rankings based on the IGE. Even if rank-rank slope estimates are available only for few countries, and thus we cannot insert our results in a widely accepted cross-country ranking based on the rank-to rank slope, now distances between countries are reduced and Italy results to be not very distant from Nordic countries, with a level of mobility very close to the one reported for Germany.

As in the case of estimated IGE, also rank to rank estimates appear to be affected by the life cycle bias. Indeed, when we consider sons aged 25-29 instead than 35-39 (table 3.8), the estimated rank to rank coefficient falls to 0.181 when earnings of both generations are measured over a 5-year period.

3.6. Intergenerational mechanisms

A classical way to examine intergenerational mechanisms behind the intergenerational transmission of earnings is to re-estimate the equation 4 with some additional controls included in the vector $X_{i,t}^{s}$ (see Raitano and Vona 2015):

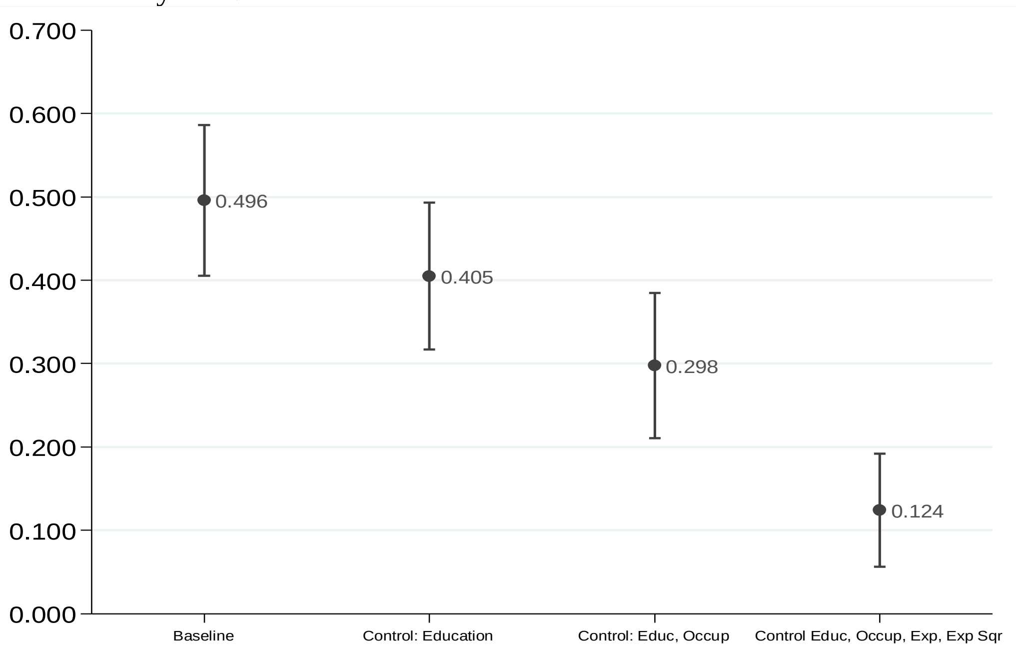
$$y_{i,t}^{S} = \alpha + \beta_2 \hat{y}_i^F + \delta X_{i,t}^{s} + \theta B_i^s + \epsilon_{i,t} \tag{10}$$

where $y_{i,t}^{S}$ is the logarithm of sons' earnings (a time average is used for sons with two or more observations), $\hat{y}_i^F = \hat{\theta}_1 Z_i^F$ is the prediction of the logarithm of fathers', $X_{i,t}^{s}$ is the vector of control variables, B_i^s is year of birth of son and β_2 is the new estimated IGE.

Among all possible channels of influence, we consider 8 categories of sons' educational level, 27 categories of occupations (according to 2 digits ISCO), the working status (private employee, public employee, self-employed, professional or parasubordinate worker) and work experience measured as the number of working weeks since they entry into activity. We consider three different models, where 5-year average earnings for both generations are considered: in the first only son's educational attainment is included in the vector $X_{i,t}^{s}$; the second one includes both sons' educational levels, occupational qualification and working status; the last adds experience and thus considers all mediating variables.

The assumption is that if a mediating variable is positively correlated with both fathers' and sons' earnings, the estimated elasticity will fall once this control is included in the regression. Therefore, the difference between $\hat{\beta}$ obtained by estimating equation 4 (our baseline) and $\hat{\beta}_2$ can be interpret as the fraction of the elasticity associated to a single mediating factor. However, this is true only if this mediating variable included in the vector $X_{i,t}^s$ is not correlated with the error term. Conversely, if the mediating variable is positively (negatively) correlated with other unobservable factors that influence sons' earnings, the coefficient $\hat{\beta}_2$ is upward (downward) biased and the channel of influence is overestimated (underestimated).

Figure 3.2: T2TSLS estimated coefficient of the association between son's and father's earnings, including sons' outcomes among the covariates[a]. Fathers and sons observed for 5 years[b].

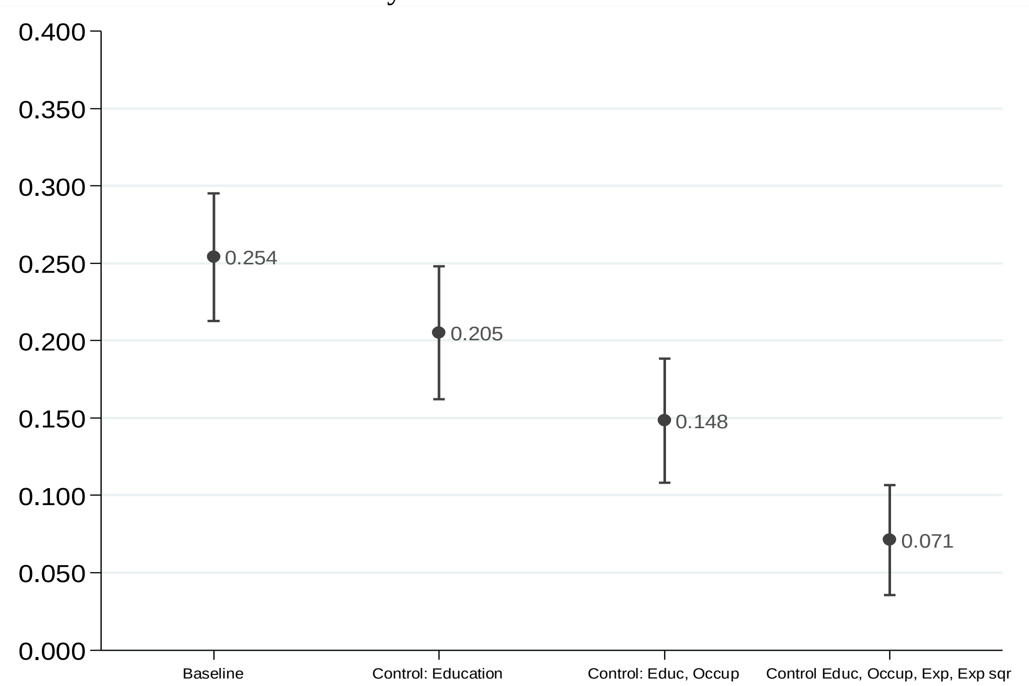


[a] Dummies on sons' year of birth are included among covariates in all estimated models. b Fathers and sons are observed, respectively, when aged 40-44 in the period 1980-1988 and 35-39 in the period 2005-2013. 90% confidence intervals. Source: elaborations on AD-SILC dataset

Estimated elasticities obtained by means of equation 10 are presented in figure 3.2 together with their 90% confidence intervals. Estimates suggest that including all three control variables together is the only result statistically different from the baseline estimate (when no sons' characteristics are controlled for).

On the contrary, the estimated IGE obtained by including either sons' educational levels or educational levels and occupation and work status are not statistically different from the baseline. These results provide some evidence that higher income of fathers' may influence their sons' economic outcomes in ways other than through the mere investment human capital. More specifically, sons from lower income families may obtain less stable occupations which negatively affects their experience and may reduce their gross annual earnings, as shown in the "full model"

Figure 3.3: Rank to rank estimated coefficient of the association between son's and father's earnings percentiles, including sons' outcomes among the covariates[a]. Fathers and sons observed for 5 years[b].



[a] Dummies on sons' year of birth are included among covariates in all estimated models. [b] Fathers and sons are observed, respectively, when aged 40-44 in the period 1980-1988 and 35-39 in the period 2005-2013. 90% confidence intervals. Source: elaborations on AD-SILC dataset.

Results obtained by estimating equation 10 are confirmed when we examine the relative importance of the three mechanisms by means of rank-rank estimates, carried out starting from predicted incomes obtained by the two-stage procedure (Figure 3.3). As in the case of elasticity, we compare our baseline rank-rank slopes estimate with those obtained using different set of controls: first we add to our baseline model dummies on education, then both dummies on education and work status and, in the last model, dummies for education, work status, and effective experience. Education, again, seems to capture only a small fraction of the intergenerational earnings persistence. In the next section, we will deepen these results by means of a decomposition analysis.

3.7. Decomposition approach

A further detailed way to examine the role of mechanisms driving the intergenerational correlation of earnings is to exploit the sequential decomposition approach suggested by Blanden, Gregg and Macmillan (2007) and further developeded in Blanden et al. (2014).

Following Blanden et al. (2014) we decompose the IGE into two parts: the first one is how much of the father-son earnings relationship is accounted for by transmission factors – that is, some sons' outcomes, e.g. education or occupation, that are affected by parental characteristics and then influence sons' earnings –, whereas the second one is the unexplained persistence in earnings that is not transmitted through the considered mediating variables. The part of the intergenerational persistence explained by the pathway factors is the product of two measures: the relationship between fathers' earnings and the pathway factor and its monetary return in the labour market.

Among all possible transmission mechanism, this section focuses on two mediating variables: educational attainments and occupational qualification. The first step of the decomposition method consists in estimating the univariate relationship between sons' educational attainments and the prediction of logarithm of fathers' earnings:

$$Educ_i^s = \alpha_{ed} + \lambda_{ed}\hat{y}_f + e_{1i} \tag{11}$$

Then, to combine the estimated association with the return of educational attainments in the labour market, the logarithm of sons' earnings is regressed on sons' educational attainments. We control for the prediction of the logarithm of fathers' earnings, thus estimating the effect of education on sons' earnings independent of that estimated in equation 11:

$$lnY_i^{son} = \omega_1 + \rho_{ed} Educ_i^{son} + \gamma_{inc}\hat{y}_f + \nu_{1i} \tag{12}$$

It follows that the IGE estimated in equation 4 (i.e. our baseline) can be decomposed into two different parts:

$$\beta = \lambda_{ed}\rho_{ed} + \gamma_{inc} \tag{13}$$

where $\lambda_{ed}\rho_{ed}$ is the indirect effect of fathers' earnings on sons' through the educational channel and γ_{inc} is the unexplained persistence in earnings that is not transmitted through education.

Then, we account for occupational attainments only by estimating in equation 14 the association between occupational status and father's earnings and in equation 15 its monetary pay-off in the labour market:

$$Occ_i^s = \alpha_{occ} + \lambda_{occ}\hat{y}_f + e_{1i} \tag{14}$$

$$y_i^{son} = \omega_2 + \rho_{occ} Occ_i^{son} + \gamma_{inc}\hat{y}_f + \nu_{2i} \tag{15}$$

In this case, the decomposition becomes:

$$\beta = \lambda_{occ}\rho_{occ} + \gamma_{inc} \tag{16}$$

Moreover, we want to consider the interaction between educational attainments and occupational choices. Therefore, once we have estimated the relationship of each variables with fathers' earnings, we estimate an equation where we consider together the return to education and occupation in the labour market. In the next equation 17, we obtain the monetary pay-off of each variable, conditional on the others.

$$y_i^s = \omega_1 + \rho_{ed} Ed_i^s + \rho_{occ} Occ_i^s + \gamma_{inc} \hat{y}_f + \nu_{3i} \tag{17}$$

Now β can be decomposed as follows:

$$\beta = \lambda_{ed}\gamma_{ed} + \lambda_{occ}\gamma_{occ} + \gamma_{inc} \tag{18}$$

where we can distinguish the component of beta accounted for by educational attainments and the part of beta accounted for by occupational outcomes. Thus, $\lambda_{ed}\gamma_{ed} - \lambda_{ed}\rho_{ed}$ gives the extent to which the influence of education is transmitted through occupation.

According to Hirvonen (2010), in order to obtain consistent estimates for the coefficients of the two mediating variables, error terms of equation 11 and equation 14 must be uncorrelated with the error term in the return equation 17. However, this assumption is likely to be violated since both educational attainments and occupational status could be related to other variables, such as cognitive and non-cognitive skills, education quality and other hardly observables factors as, for example, social networks and family ties. Unfortunately, our dataset does not provide information on education quality (e.g. marks or field of study), on cognitive and non-cognitive skills and social network (e.g. channels used to find job) to control for other sons' characteristics.

Moreover, consider that our decomposition approach cannot be directly compared to that proposed by Blanden et al. (2007) and Blanden et al. (2014) as we are using imputed instead of actual fathers' earnings. In fact, estimated λ_{ed} and γ_{inc} may be biased due to unobservables included in the error terms of equation 11 and 12, that are not captured by the set of auxiliary variables used to predict fathers' earnings. More specifically, there could be some variables (e. g. soft skills, social networks, cultural factors, cognitive and non-cognitive abilities) that are positively correlated to earnings of the two generations (i.e. they are in the error term of our equation 12) and to educational attainments of offspring. Therefore, we are likely to be underestimating (overestimating) the mediating role of education if imputed earnings are less (more) correlated to the mediating variable than actual earnings (i.e. imputed earnings are less correlated to unobservables in equation 12 which are correlated to educational attainments)

With all this in mind, we proceed to decompose intergenerational mobility into different channels. Educational attainments of sons included in the decomposition analysis are provided by the 2005 wave of the IT-SILC survey. More specifically, educational levels are coded according to the five main International Standard Classification of Education levels (ISCED). Here we rely on a four-modal distribution of education: "tertiary graduates", "high-school graduates", "middle school graduates" and "elementary". However, when we estimate the univariate relationship between fathers' earnings and sons' education, exclusive dummies would lead to ambiguity in the interpretation of the coefficient for the middle category. Thus, following Blanden et al. (2014) we redefine our dummy on education as equal to one for all those who are at the relevant education level or above: "tertiary graduates", "at least high-school" and "at least middle school". In this case the coefficient must be interpreted as the incremental effect of that education level compared to the next lower level of education.

Regarding occupational status, it was originally classified according to ISCO codes: the lowest ISCO code indicates the highest occupational quality. We convert ISCO categories in a four-modal distribution of occupation: "higher managerial and professional" (corporate managers, professionals, legislators), "lower managerial and professional" (associate professionals, managers of small enterprises), "intermediate" (clerks and service workers), "bottom occupation" (assemblers, agricultural, crafts, elementary occupations). As with education, we then redefine our variables equal to one for all those who are at the relevant occupational level or above[37].

[37] We use less categories for both mediating variables than we did in the previous sections for computational reasons

The decomposition analysis is carried out on IGE estimates run on 5-year earnings averages for both generations (see section 3.4). Results are summarized in Table 3.9. The overall IGE can be decomposed into the relationship between father's earnings and the mediating variables (λ) multiplied by the return to those variables in the labor market (γ), plus the unexplained persistence in earnings that is not transmitted by those factors. Column (i) considers only education as mediating variable, column (ii) only occupation and column (iii) consider the interaction between the two variables.

Table 3.9: Decomposition: share of β explained by mediating variables.

factor	(i)	(ii)	(iii)
college degree	0.022		0.011
at least highschool	0.047		0.035
at least middle school	0.018		0.018
Total educational outcomes	0.087		0.064
higher manangerial or professionals		0.004	0.001
at least lower managerial or professional		0.021	0.017
at least intermediate		0.026	0.017
total occupational outcomes		0.051	0.035
total accounted for (λ*γ)	0.087	0.051	0.099
not accounted for	0.409	0.445	0.397
total	0.496	0.496	0.496
% through ed.outcomes	17.61%		12.91%
% through occupational outcomes		10.34%	7.08%
% of total	17.61%	10.34%	19.99%

Author's elaboration based on the AD_SILC dataset.

Following Blanden (2014) we add to the full decomposition, model (iii), the two variables in the order in which they occur in the aging process. The sum of the explained and unexplained component of β is 0.496, that is the total association between fathers' earnings and sons'. In model (i) we first include only education that explains 17.6% of the intergenerational persistence, whereas around 82% can be accounted as the direct effect of father's earnings. In model (ii) we include only occupations that accounts for almost 10.3% of the intergenerational elasticity coefficient. When in model (iii), our complete decomposition, we include both education and occupation, the magnitude of the indirect effect implies that around 20% of total effect is mediate by education and occupation. The share of persistence accounted for by the former decreases from 17.6% to 12.9%. Thus, the two mechanisms are clearly correlated and occupation takes over some of the explanatory power of education. This means that parental background exerts its effect on education, education effects sorting into occupation and occupation influences earnings. When we move from model (i) to model (iii) we notice that the proportion of the intergenerational elasticity coefficients explained increase only by 2.4 percentage points thus occupation contributes directly only marginally in explaining intergenerational persistence.

In table 3.10 we report the estimates that are behind the decomposition presented in table 3.9. The first column reports the λ coefficient estimated in the set of regression of the relationship between the mediating variables and father's earnings. The second pair of columns presents the γ coefficients from the single regression of log sons' earnings on the set of included pathway variables. Columns from two to four display the γ coefficient from the regression of sons' earnings on the mediating factors: equation (i) regress sons' earnings on education, equation (ii) on occupation and equation (iii) on both educational and occupational levels.

Table 3.10: Detailed decomposition results

	association with father's earnings (λ)	return in the labour market (γ)		
		(i)	(ii)	(iii)
Education:				
college	0.217	0.1024		0.0501
	[0.0331]	[0.0520]		[0.0586]
at least high school	0.2752	0.1704		0.1262
	[0.0376]	[0.0382]		[0.0383]
at least middle school	0.065	0.2803		0.2836
	[0.0161]	[0.1119]		[0.1071]
Occupation:				
high managerial and professional	0.0964		0.0421	0.0155
	[0.0277]		[0.0685]	[0.0750]
at least low managerial and professional	0.1955		0.1094	0.0869
	[0.0414]		[0.0541]	[0.0536]
at least intermediate	0.2392		0.108	0.0695
	[0.0420]		[0.0476]	[0.0476]

Author's elaboration based on the AD_SILC dataset.

3.8. Concluding remarks

This chapter provides new evidence on the degree of earnings correlation across generations in Italy, which is usually considered as a low mobility country (Piraino, 2007; Mocetti, 2007). New results are provided by relying on the AD-SILC, a very rich panel dataset built merging the 2005 wave of the Italian sample of the Survey on Income and Living Condition (IT-SILC) conducted by ISTAT (the National Italian Statistical Institute) with information collected from administrative archives managed by the Italian Social Security Institute (INPS) that cover individual earnings histories from the moment they enter the labour market to the end of 2013. The advantages of exploiting this dataset are twofold. Firstly, unlike previous estimates of the intergenerational earnings elasticity (IGE) for Italy obtained by using net earnings, we are able to examine the extent of intergenerational mobility in the labour market which is not mediated by the redistributive effect of taxes and, once reconstructed net earnings, we can compare the two measures. Secondly, we can rely on a large panel dimension which permits to obtain a measure of earnings which is less affected by lifecycle and attenuation biases.

As in previous studies on intergenerational economic mobility in Italy, we exploited the two-sample two-stage least squares (TSTSLS) method to obtain different measures of intergenerational earnings associations. Nonetheless, unlike previous studies for Italy, we exploited the large panel dimension of the dataset to measure earnings over a 5–year period both in the first and second stage of the TSTSLS approach. Moreover, our auxiliary variables have a higher number of categories, thus allowing us to obtain a higher predictive power in the first stage.

Results showed an IGE of 0.496 for gross earnings and an IGE of 0.428 for net earnings. Both the two measures of mobility become lower if estimates are obtained by using point in time measures of earnings of the two generations or if earnings of sons are taken when they are at early stages of their careers.

We also provided estimates of rank-rank slopes for Italy that proved to be more robust across different specifications, samples and measures of earnings. Since this measure remove the "within generation" inequality component, it is particularly suited for cross-country comparisons. However, rank-rank slope measures are available only for few countries. Therefore, it is not easy to make international rankings based on this measure of intergenerational economic mobility. In any case, according to our estimated rank-rank slopes, conversely on what we find for the IGE, Italy is not so distant from Nordic European countries and very closed to the level of mobility of Germany. Therefore, it is highly desirable for future research to provide, besides the IGE, also measures based on the rank to rank slope.

Education is usually recognized as the most prominent mechanism affecting the intergenerational transmission of income from parents to children. We presented additional estimates including as regressors children characteristics affected by parental circumstances – e.g. education, occupation – to assess whether a residual influence of parental background still emerges when these characteristics are controlled for.

Furthermore, we also applied the decomposition method proposed by Blanden et al. (2014) in order to compare the role played by education and occupation as transmission mechanisms of intergenerational inequality. We found that, when considered together, education and occupation account for around 20% of father-son earnings relationship: education contributes to 12.9% of the earnings persistence, while occupation account for around 7.1%.

Thanks to the sequential decomposition we assessed that the proportion of β accounted for by education becomes smaller when occupational attainments, that occur later in life with respect to the educational ones, are included. Therefore, part of the effect of education is absorbed by occupational choices. Considering education alone, as the only transmission mechanism, may overstate its explanatory power of the persistence of socio-economic outcomes (Hirvonen, 2010). Even when we considered both education and occupation, it is highly likely that the part of the intergenerational elasticity coefficient ascribed to education, still conceals some of the explanatory power that should be ascribed to other mechanisms (e.g. soft and hard skills). Therefore, it is likely that we are overestimating the effect of the education and these results should be interpreted as an upper bound. The role of education in Italy, compared to that found by Blanden at al. (2014) for the UK and the US is very limited and it is even more limited if our results should be interpreted as an upper bound.

D'Addio (2007) suggests that in many country – among which we find both USA and UK - high skill premia are associated with low levels of intergenerational mobility. However, this picture does not fit for Italy, where we can find the coexistence of low labor market rewards for education and a high level of intergenerational persistence. Recent literature posits that in Italy is possible to detect a decrease in the earnings differential between educated and less-educated workers (Lovaglio & Verzillo 2016; Naticchioni et al. 2010). In particular, most recent cohorts of high-skilled workers are suffering much heavier earnings penalty with respect to unskilled workers (Naticchioni et al. 2016). Thus, low wage premia for highly qualified workers may disincentive family in investing in their children education. This is probably the reason why education accounts for a limited part of the intergenerational resemblance of earnings, that is more likely to be driven by other mechanisms such as the importance of family connections and social ties in finding highly rewarded jobs (Raitano & Vona, 2015)

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Appendix

Tab. A1: Association between son's and father's earnings. Prime age sons. Fathers and sons observed for 5 years[a]. OLS estimates in the second stage dropping one coefficient at a time in the first stage[b]

	Regressors dropped in the first stage			
	Education dummies	Occupation dummies	Dummy on self-employment	Dummies on region of work
Father's earnings	0.489***	0.466***	0.640***	0.370***
s.e.	[0.055]	[0.057]	[0.064]	[0.057]
Obs	1445	1445	1445	1445
R^2	0.055	0.052	0.069	0.031
R^2 first stage	0.380	0.351	0.282	0.374

[a] When observed in a 5-year period, fathers and sons are considered, respectively, when aged 40-44 in the period 1980-1988 and 35-39 in the period 2005-2013. When observed in a single year, fathers and sons are considered, respectively, in 1985 and 2009. [b] TSTSLS are carried out: in the first stage father's earnings are imputed regressing log annual gross earnings on dummies on education, occupation, self-employment, region of work; in the second stage sons' log annual gross earnings are regressed on predicted fathers' log earnings, also controlling for sons' year of birth. *** p<0.01, ** p<0.05, * p<0.10. Source: elaborations on AD-SILC dataset.

Tab. A2: Association between son's and father's earnings. Prime age sons. Fathers and sons observed for 5 years[a]. Rank to rank estimates dropping one coefficient at a time in the first stage[b]

	Regressors dropped in the first stage			
	Education dummies	Occupation dummies	Dummy on self-employment	Dummies on region of work
Father's earnings	0.244***	0.237***	0.262***	0.187***
s.e.	[0.025]	[0.026]	[0.026]	[0.026]
Obs	1445	1445	1445	1445
R^2	0.066	0.063	0.075	0.042
R^2 first stage	0.380	0.351	0.282	0.374

[a] When observed in a 5-year period, fathers and sons are considered, respectively, when aged 40-44 in the period 1980-1988 and 35-39 in the period 2005-2013. When observed in a single year, fathers and sons are considered, respectively, in 1985 and 2009. [b] TSTSLS are carried out: in the first stage father's earnings are imputed regressing log annual gross earnings on dummies on education, occupation, self-employment, region of work; in the second stage sons' log annual gross earnings are regressed on predicted fathers' log earnings, also controlling for sons' year of birth. *** p<0.01, ** p<0.05, * p<0.10. Source: elaborations on AD-SILC dataset

General Conclusions

Measuring economic disparities by using net wealth rather than income is not an easy task. Data on all real and financial assets are rarely available and with many differences across countries. For instance, including pension assets or valuables other than vehicles in the computation of net wealth may completely change international rankings. Moreover, the harmonization process is still not perfect and some cross-countries differences remain, starting with the number of years for which data are available or with differences in the degree of wealthy households over-sampling, used to mitigate the underestimation of wealth in the upper tail of the distribution.

Despite all measurement issues, at any point of time wealth is likely to capture differences in lifetime economic resources better than income because it is less affected by transitory shocks, strongly associated to cumulate earnings and directly transmitted from one generation to the next by means of donations or bequests. For all these characteristics, economic mobility across generations may be better measured by using wealth instead of income since suitable data which cover two generations over their entire lifecycle are usually not available.

Unfortunately, only few studies compare intergenerational correlations in income to intergenerational correlations in wealth by selecting two generations at median ages. Nevertheless, these studies show that economic mobility measured by correlations in income is likely to be overestimated if earnings of the two generations are not properly averaged over many years. Introducing wealth may, at least partially, reduce this kind of underestimation without requiring the use of very large panel which cover two generations over their entire lifecycle. However, further evidence is needed to confirm these results since estimates of mobility which use wealth as a measure of economic status are very recent and hardly comparable by country and age of the two generations.

The second chapter of the thesis provided a first estimate of the intergenerational wealth elasticity and rank-rank slope in Italy using data from the Bank of Italy's Survey on Household Income and Wealth. To overcome the lack of information about parental wealth, the two-sample two-stage least squares methodology has been implemented by selecting a sample of offspring, that report some socio-economic information about their actual parents, and an independent sample of pseudo-parents in their 40s

The resulted intergenerational wealth elasticity of 0.451 and rank-rank slope of 0.349 revealed that Italy, as well as the United States and Sweden, is a country with a lower degree of wealth mobility across generations than other Scandinavian countries or France. Moreover, the degree of wealth mobility in Italy appeared to be particularly low at the top and at the bottom of the wealth distribution and in the southern part of the country where estimated elasticity resulted to be 0.621.

To test the pattern of the intergenerational wealth correlation over the children's lifecycle, I re-estimated the intergenerational wealth elasticity and the rank-rank slope by using three different samples of offspring by age. Results confirmed previous evidence showing a U-shaped pattern of the wealth correlation as a function of offspring's age with higher intergenerational wealth correlations when offspring are taken when they are at the beginning of their adulthood or in their 40s. However, further evidence is needed to assess the degree of intergenerational wealth mobility by selecting older offspring.

The decomposition of the intergenerational association into different mediating mechanisms showed that labour income of the second generation, among other mediating factors such as preferences and bequests or inter-vivos transfers, seems to be associated with most of the overall wealth association across generations. More specifically, while the intergenerational wealth elasticity became 43.7 percent lower when labour income of offspring is included as a control, a smaller fraction of the wealth association seemed to be related to intergenerational correlations in saving propensity or returns on investments.

The last chapter, which is part of a research work with Michele Raitano and Teresa Barbieri, provides new evidence on the degree of earnings correlation across generations in Italy. New results are obtained by relying on the AD-SILC, a very rich panel dataset built merging the 2005 wave of the Italian sample of the Survey on Income and Living Condition (IT-SILC) conducted by ISTAT (the National

Italian Statistical Institute) with information collected from administrative archives managed by the Italian Social Security Institute (INPS) that cover individual earnings histories from the moment they enter the labour market to the end of 2013.

As in previous studies on intergenerational economic mobility in Italy, we exploited the two-sample two-stage least squares (TSTSLS) method to obtain different measures of intergenerational earnings associations. Nonetheless, unlike previous studies for Italy, we exploited the large panel dimension of the dataset to measure earnings over a 5–year period both in the first and second stage of the TSTSLS approach. Moreover, our auxiliary variables have a higher number of categories, thus allowing us to obtain a higher predictive power in the first stage.

Results showed an IGE of 0.496 for gross earnings and an IGE of 0.428 for net earnings. The two measures both become lower if estimates are obtained by using point in time measures of earnings of the two generations or young sons.

We also provided estimates of rank-rank slopes for Italy that proved to be more robust across different specifications, samples and measures of earnings. According to our results, conversely on what we find for the IGE, Italy is not so distant from Nordic European countries and very closed to the level of mobility of Germany. Therefore, it is highly desirable for future research to provide, besides the IGE, also measures of mobility based on the rank-rank slope.

Finally, we presented additional estimates including as regressors children characteristics affected by parental circumstances – e.g. education, occupation – to assess whether a residual influence of parental background still emerges when these characteristics are controlled for. Additionally, we also applied the decomposition method proposed by Blanden et al. (2014) in order to compare the role played by education and occupation as transmission mechanisms of intergenerational inequality. We found that, when considered together, education and occupation account for only around 20% of father-son earnings relationship: education contributes to 12.9% of the earnings persistence, while occupation account for around 7.1%.