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ORIGINAL RESEARCH

Using Survey Data to Estimate Intergenerational Mobility in Income and Education in Portugal

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Abstract
Previous studies about intergenerational mobility for the Portuguese economy find that education and income persistence is very high in comparison with other developed economies. We construct relative, absolute, global and local measures of mobility for Portugal, comparing them with existing evidence for this and other countries. These are the intergenerational income elasticity (computed using the two-sample two-stage least squares method), income correlation, rank-rank slope, bottom to top income level probability, the share of individuals earning more than their fathers and also the intergenerational education correlation, the low to high education level probability, and the share of individuals with a higher education level than their fathers. We consider the 1968–1988 cohorts and the 1995 and 2019 waves of the European Community Household Panel and the European Union Statistics on Income and Living Conditions, respectively. Overall, based on the point estimates, women seem to present more mobility in income. Upward income mobility is verified at the bottom while persistence exists at the top. Women present a greater absolute educational mobility. More than 80% of individuals have a higher education than their fathers and full upward education mobility exists for children of low-educated fathers. Mobility in education is higher for the offspring of medium–high-income fathers. Individuals with a high education level, in the medium–high income level or with occupations requiring a higher education level show higher mobility.

Keywords Intergenerational mobility in income and education · Relative and absolute intergenerational mobility indicators · Global and local intergenerational mobility measures · Two sample two stage least squares · Ordered probit · Mincer equations

JEL Classification E24 · C26 · I24 · J62 · O15

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1 Introduction

The lack of intergenerational mobility prevents an efficient allocation of resources. When children of more educated parents are more likely to obtain more education and higher-paying jobs regardless of their innate abilities, the role of individual talent is suppressed. This pattern, highlighted in the works of Marrero and Rodriguez (2013) and Van de Gaer et al. (2001), reveals a vicious cycle between intergenerational persistence and inequality: high inequality promotes an unequal distribution of parental investments and opportunities, which then harms mobility in the next generation, perpetuating further inequality. Moreover, low mobility shapes individuals' perceptions regarding fairness and aspirations in a negative way (Ray, 2006; Ross, 2019; Weintraub et al., 2015), with a lower tolerance for inequality and policies to fight it, thereby discouraging growth and social stability.

Despite the positive changes that were made in Portugal through the years, the findings of several studies for the Portuguese economy made by international and national organizations, stress some persistence regarding income and education mobility.

On one hand, the educational level of the Portuguese population has been improving steadily since the Carnation Revolution (25th of April 1974) when a democratic regime was instituted. In the decades that followed, a strong consolidation of the social and economic development was verified, with the expansion of the welfare state being its main pilar. The State's increased spending and intervention in the economy was reflected in higher investment in infrastructure, technological modernization, and education, as well as in the expansion of social policies to overcome poverty and unemployment. A comparison between the 1981 and 2021 CENSUS of the population shows that the illiterate population with 15 years or more, decreased from 37 to 6%, while the same population with a higher education degree increased from 2 to 20%. Most of the population with 15 or more years has at least the basic or secondary education completed. Compulsory education has also increased: individuals are now required to stay in school until they are 18 years old. Regarding income, the National Statistics Office (INE) reports that around 70% of household income is derived from labour. The Gini index in the last 30 years has been between 32 and 38%, showing persistence.

On the other hand, studies seem to support the view that low educational attainment is likely to perpetuate, and a high education persistence should exist from one generation to another (Bank of Portugal, 2022; Clements, 1999; OECD, 2019). Besides, according to the OECD (2018), a five-generation time window is needed for someone who belongs to the 10% poorest population to reach the median income.

We aim to answer the general research question: "What is the current state of intergenerational mobility in income and education in Portugal?" This is followed by other three minor questions: (i) "Are there gender differentials in mobility?" (ii) "How does the Portuguese mobility compare to other countries?"; and (iii) "Are there differences in mobility when considering different individual characteristics?" Therefore, our goal is to summarize the different aspects of intergenerational mobility to allow for a more general overview of the phenomenon. To reach this goal, we construct measures of intergenerational mobility in income and education for Portugal using the 1968–1988 cohorts of the European Community Household Panel (ECHP) and the 1995 and 2019 waves of the European Union Statistics on Income and Living Conditions (EU-SILC).

To the best of our knowledge, we are the first to compute global and local measures of absolute and relative intergenerational income mobility for Portugal. These are the intergenerational income elasticity (IGE), the intergenerational correlation coefficient, the

rank-rank slope, the share of individuals earning more than their fathers, and the probability that a child born with a low-income father has of reaching the top income level in his or her generation (we define it as the bottom to top income level probability), complemented by an ordered logit transition matrix. Additionally, we compute global and local intergenerational educational mobility measures in relative and absolute terms to complement income mobility measures. We calculate the intergenerational education correlation and the probability that a child born with a low-educated father has of reaching the highest education level (denoted by low to high education level probability), also complemented by an ordered logit transition matrix. Also, the share of individuals with more education than their fathers is computed. Each measure is computed for both genders separately as well as together. Furthermore, we analyse different subsamples to uncover which characteristics of fathers and children may be related to more or less mobility, including their education levels, occupation categories, income levels, and status in employment.

This paper is organized as follows. In Sect. 2, the state of the art on intergenerational mobility in Portugal is revised. Section 3 details the methodology. In Sect. 4, we describe the data and sample construction. Section 5 provides a discussion of the results. Section 6 concludes.

2 Literature Review

In this section, we present the state of the art regarding intergenerational mobility studies, with a particular focus on Portugal. We also identify the shortcomings in existing works and define our contribution to the literature.

The recent availability of proper databases made the empirical study of intergenerational mobility in income and education possible. However, deep single-country research is mainly focused on the USA and Canada (e.g., Chetty et al., 2014, 2016, 2017, 2020a, 2020b, 2020c; Chetty & Hendren, 2018a, 2018b, Hilger, 2016; Latif, 2017, 2018; Fletcher & Han, 2019). For the European Continent, existing work is still focused on Scandinavian countries, the UK, Germany and Austria (as Björklund & Jäntti, 1997; Dearden & Reed, 1997; Blanden et al., 2004; Bauer & Riphahn, 2006; Nicoletti & Ermisch, 2008; Heidrich, 2017; Neidhöfer and Stockhausen, 2018; Brandén, 2019; Eriksen & Munk, 2020; Kyzyma & Groh-Samberg, 2020) while for Southern European countries the Italian and Spanish cases were addressed in the works of (Acciari et al., 2022; Cervini-Plá, 2015; Mocetti, 2007; Piraino, 2007).

Studies on education mobility in Portugal are scarce. For income, which should have a close relationship with human capital formation, they are almost non-existent. Carneiro (2008) uses transition matrices to show that educational persistence is strong in Portugal: more than 90% of children who do not complete high school, with fathers who did not complete primary education is verified, while almost no children complete less than high school if their fathers have a university degree. Evidence shows that parental generational differences in educational attainment create differences in opportunities for their children and these differences in educational attainment differ from generation to generation.

Pereira (2010) studies the transmission of higher educational attainment in Portugal through the use of probabilistic regression with data for individuals aged between 18 and 64 years old. The author concludes that parents' education strongly matters for children's higher educational attainment. The likelihood of reaching a higher education degree is greater for individuals born into families with higher education (about eight times higher

in comparison with offspring of parents with 9 or fewer years of education), meaning that low education levels are likely to perpetuate over time. Men generally perform more poorly than women, meaning that they have overall lower mobility: they show a mean increase in the probability of higher education degree attainment around 10%.

Bago d'Uva and Fernandes (2017) use multinomial probabilistic models and linear regression analysis to study the educational mobility of individuals born from 1940 to 1985. Mobility presented by the 1940 cohort is low: more than 80% of children with low educated fathers didn't reach tertiary education and 75% of individuals attain the same level as fathers considering tertiary education. Upward mobility is generally lower in Portugal when compared to the European Union. In this country, individuals born in the 1970s present higher upward mobility than the ones born in the 1940s (40.6% versus 15.4%, respectively). The increase in mobility was more pronounced for Portugal when compared to the European Union, with the gap between the two being shrinking from the 1970s on, being around 5.8% points. The difference in upward mobility between Portugal and the European Union for the youngest cohort is mainly due to men (33.4% for Portugal and 42.8% for the EU), while the share of girls reaching a higher education level than their parents is close to the European average (47.9% for Portugal and 49.8% for the EU).

Six works identified include Portugal along with other countries. Comi (2004) uses data on current income for the 1994–1998 period considering 12 European countries. Portugal, Ireland, and the Mediterranean countries are the most relatively persistent in income and education. Relative persistence in income measured by the earnings elasticity is stronger for the pair father-son when compared to the pair father-daughter (0.20 compared to 0.15, respectively). The same occurs for the eigenvalues of transitional educational matrices (around 0.30 for men and 0.17 for women). Another study reporting that Portugal is the least mobile country of those belonging to the OECD is Causa and Johansson (2010), who computed wages' persistence (as a proxy of income) as the difference between wage premium and wage penalty, around 70% points when corrected for distributional differences. Schneebaum et al. (2014) consider 20 European countries and find that for the intergenerational correlation in education, Portugal presents the highest mobility considering the pair father-sons, equal to 0.24, while for the pair father-daughters, being equal to 0.26, it is surpassed by France, the Nordic and Anglo-Saxon countries, Greece, Czech Republic, and Poland. In Nybom's (2018) analysis of intergenerational persistence in education from a linear regression on educational outcomes and individuals born around 1980, there is cross-country heterogeneity in high-income countries, with Portugal standing amongst the most persistent, along with Hungary and Uruguay. Evidence from the OECD (2018) shows that, through the use of earnings elasticities, men present higher mobility than women. The Portuguese men's persistence (income elasticity of 0.4) is above countries such as Canada and below the USA, Italy, France and Brazil. Regarding women, more mobility is verified in the country in comparison with the UK and Australia, while lower than Spain. The OECD (2018) also computes the regression coefficient between the average of parents and child's years of education, finding that persistence verified in Portugal (coefficient around 65%) is below Indonesia and India. For the intergenerational correlation, around 50%, mobility is higher than in Spain, Belgium, Chile, Slovenia, Indonesia and India. Additionally, when considering the share of sons in the top quartile of earnings when the father is at the bottom, Portugal is the country presenting the highest mobility, after Chile and Denmark, with approximately 20% of individuals. The Global Database on Intergenerational Mobility (GDIM, 2018), constructed by Narayan et al. (2018), also presents mobility estimates for Portugal, for both income and education. These are given by the intergenerational coefficient of the regressions between child and parental income or education, respectively.

It is found that mobility in income is equal to 0.28, regardless of considering all children, sons or daughters, moms and dads. For education, is around 0.6–0.7. The authors consider that income mobility is lower than what is expected for the level of education mobility, for the 1960 and 1970 cohorts, as it occurs with Ethiopia, the former Yugoslav Republic of Macedonia, Nepal, and Romania. For the intergenerational correlation in education, the values range between 0.44–0.46, while the probability a child from the bottom half of the distribution ends up in the highest quartile is around 10–25%. Summing up, there is mixed evidence for Portugal, though most papers appear to confirm International Organizations' concerns about the high persistent level in the country.

Our work is the most comprehensive when analysing mobility across generations, given the limitations that may be found in existing literature which we briefly describe. Firstly, most of the works do not analyse income and education simultaneously, which we consider of extreme relevance, since previous theoretical research, using models, has shown that education should determine income mobility. For example, in Becker and Tomes (1979)'s work, the income of children is part of the parental utility, which is maximized with an optimal investment in children's both non-human and human capital. The authors show, that, among others, the inheritability of endowments and the likelihood parents have to invest in their children are responsible for the equilibrium levels towards which mobility in income tends to. Solon (2004) transforms the previous model to rationalize the log-linear regression for intergenerational income mobility and also shows that an effective investment in human capital and progressive public investment on human capital contribute to the patterns shown by the income elasticity's steady-state value. Additionally, if education is important for income mobility, some connection may also be expected between both education and income mobility, as shown in the theory developed by Becker et al. (2018), in which the children's human capital production function is increased by the parents' human capital. They show that, when parental human capital and investments in children have complementarities in the production of children's human capital, richer parents will invest more in their children's human capital, in comparison with poor parents: this is translated in economic status persistence across generations. Though a relationship is expected, it can be broken due to, for example, a labour market where education is not easy to monetize or other characteristics that individuals can't control. Therefore, it is important to study both these dimensions in simultaneous, to make an integrated analysis, that will enable to properly address policy implications given the patterns observed.

Furthermore, the use of mobility measured in both absolute and relative terms is also of interest in this context. Absolute mobility provides the extent to which individuals are better off than their parents. According to Deutscher and Mazumder (2023), absolute upward mobility captures broad rising levels of education and economic growth. This means that upward mobility will result with no ambiguity in a welfare improvement, considering the Pareto Principle. Absolute mobility measures such as the share of individuals earning more than their father (or with a higher education level) and the bottom to top income (education) level probability provide different information about absolute mobility. While the first measure indicates the proportion of children that are better off (in terms of education and income) than their parents, hence providing a current measure; the second measure gives us a more dynamic perspective, by estimating the probability of a children whose parents are in the bottom quintile of the parental (or educational) distribution to reach the top quintile (when adults).

On the other hand, relative mobility regards the extent to which the relative position of children is connected to the relative position of parents in their respective generations. Deutscher and Mazumder (2023), state that changes in relative mobility may capture a

variety of income movements, with different directions. To capture this wide range of possibilities regarding the outcome of relative mobility measures we use the intergenerational income elasticity, the intergenerational income (education) correlation and the rank-rank slope. The elasticity provides information on how the child's income will change (in percentage) if the parental income changes by one percentage point. The larger the coefficient (in absolute terms) the stronger the impact. The interpretation of the intergenerational income (or education) correlation is similar to the elasticity but excludes changes in inequality as an explanation for changes between parents and children. Finally, the rank-rank slope gives us information about movements between positions in the income distribution, typically between income percentiles, which is different from the information provided by the elasticity.

In a study about social mobility, the OECD (2018) uncovers, that, as countries become more developed, absolute mobility slows down, meaning that the focus on relative mobility becomes stronger. This is the same as saying that absolute mobility is a consequence of development, therefore the debate on relative mobility gains more attention because it allows to have a better assessment of how unequal a society is.

Finally, we should devote attention to both global and local mobility measures. Deutscher and Mazumder (2023) define global mobility variables as the ones that summarize the joint distribution of income or education, while local measures regard isolated portions of the distributions. Analysing global measures allows policymakers to have an overall understanding of the intergenerational transmission of socioeconomic status, while with local measures they have insights into the mobility of particular groups, namely the children of parents who are poor and can reach the other extreme point of the income distribution (the same applies for educational attainment). Local measures provide information to design tailor-made policies for specific groups. Our local (absolute) measure is the bottom to top income (education) level probability.

Examining both absolute and relative mobility with global and local dimensions provides a full understanding of the mobility landscape in the country, which can't be captured by a single measure, an argument raised by Deutscher and Mazumder (2023) and also by Corak (2019). At the exception of the seminal paper of Chetty et al. (2014), we don't have knowledge of previous research that computed global and local measures for absolute and relative mobility in the same work.

Other concerns appear in the income mobility literature, namely regarding income life-cycle effects since the relationship between current and permanent income changes throughout an individual's life: during the early stages of a career, incomes may be low, increasing with skills and experience acquirement and then stabilizing or even declining during retirement. When not accounted for, mobility estimates may not be well measured. We incorporate this issue in our analysis. To mitigate this problem, we restrict our sample to the individuals' ages where there is a stable relationship between current and permanent income, i.e., between 30 and 50 years old.

Connected with this are the several biases that may appear in the analysis. For example, when there is no information about permanent income for both generations, current income has to proxy for it, introducing a measurement error in mobility estimates. Another example that may lead to sensitive measures is the inclusion of samples in the analysis that are not representative of the total population, as in the case of co-residents or siblings. We are the first developing a sensitive analysis to assess the robustness of our results to the measurement or selection problems that should also exist in other works.

Finally, as pointed out by Chadwick and Solon (2002), "daughters' own earnings often comprise a minority share (…) of her family income", i.e., their individual income, when

married, may not be a true measure of their socioeconomic status. When considering both genders and married women are included in the analysis of income mobility, different authors may not have properly considered the role of marital status. Others simply discard women from the analysis and consider men only to avoid mismeasurement of mobility. Since we advocate that both genders should be analysed, we calculate a measure of the couple's average income for women when they are married and use it when computing the intergenerational mobility measures in income.

We try to overcome these shortcomings identified in the literature, and estimate both mobility in income and education, in relative and absolute terms, with global and local measures, for both genders, while incorporating different types of biases in the analysis and testing how results are sensitive to them. Our approach aims to capture various dimensions of social mobility, offering a broad understanding of the phenomenon.

3 Methodology

In this section, we present the intergenerational mobility measures that are used in this work both in relative and absolute terms. Absolute mobility regards the extent to which the younger generation is better off than the older generation while relative mobility concerns the extent to which the socioeconomic relative position of children is connected to the one of parents, in their respective generations. Intergenerational mobility can also be characterized as global or local measures. The first ones summarize the joint income or education distributions and the second ones comprehend only some parts of those distributions.

Each mobility measure, IM, will have a specific functional form, g, such that $IM = g\left(S_c, S_p\right)$ where c stands for children, p stands for parents and S is a measure of individual's socioeconomic status, as income or education.[1] Grounded on methodological fundamentals on mobility measurement, we describe how the functional form of each measure should be constructed conditional on the type of data we have.

3.1 Intergenerational Mobility in Income

We now present the income mobility measures considered in this work. Table 1 summarizes them according to the framework provided by Deutscher and Mazumder (2023). This regards the relative versus absolute and global versus local criteria.

The larger the value of relative mobility measures the lower mobility is, while the opposite occurs with absolute mobility measures.

3.1.1 Relative Mobility Measures

3.1.1.1 Intergenerational Income Elasticity (IGE) The coefficient (β_1) obtained by regressing the log of child i's permanent income (y_i^c) on the log parental permanent income (y_i^p),[2] which is the canonical measure used for relative mobility:

[1] As a very simple exercise, we present in Appendix A3 a relationship between relative mobility in income and education based on the well-known Mincer (1974) wage equations.

[2] Permanent/lifetime income can be defined as the average income during an individual's lifetime (Friedman, 1957)

$$y_i^c = \beta_0 + \beta_1 y_i^p + \omega_i \tag{1}$$

where $i \in [1;N]$ stands for the pair child-parent, from a total of N pairs. It is an elasticity and therefore interpreted as the child's income percentage change resulting from a one percentage point variation in the parental income. The larger the coefficient is in absolute terms the stronger the impact that parental income has on child's income and vice-versa. It is a measure of global mobility as it will consider the entire income distribution.

The estimation of Eq. (1) is possible only when at least two generations' lifetime income is available. For this purpose, researchers would need long panels to link parents and children during their entire lives. However, data are usually available in short panels where individuals (parents and children) are observed for a few years only and, therefore, different authors use current income (y_{it}) in period t as a proxy for permanent income (y_i) and assume their relationship to be constant and equal to one. The standard least squares estimator for (1) using the current income may have inconsistency problems. In light of the classic errors-in-variables model, this procedure is associated with a measurement error,τ_{it},

$$y_{it} = y_i + \tau_{it} \tag{2}$$

When parental permanent income, i.e., our explanatory variable, is proxied by current income, IGE is subject to an attenuation bias, as pointed out by Solon (1992)[3]: the measurement error leads to an underestimation of the true relationship between both generations' socioeconomic status. Also, as recent non-classic measurement error research points out, the relationship between permanent and current income changes during the life-cycle of individuals (children and parents): current income usually starts low when entering the labour market, increases in mid work life and declines when reaching retirement, fluctuating around permanent/lifetime income (more stable measure for the long-term). Therefore, grounded on Nybom and Stuhler (2016), Eq. (2) should be generalized to account for the changes in time of this relationship (λ_t), as

$$y_{it} = \lambda_t y_i + \tau_{it} \tag{3}$$

meaning that besides the standard attenuation bias, an associated life-cycle bias should also exist.[4]

Our work is no exception in the framework of intergenerational mobility estimates because the survey we use for Portugal contains information only about children's current income. We cannot directly observe parental income as the data are not available, so we use the two-samples two-stage least squares method (TSTSLS). Two samples are needed for this purpose: one for children used in the second step and another for parents used in the first step. In the first step, we predict parental current income ($\widehat{y}_{it}^p$) by proxying their lifetime income with parental characteristics reported by children: we use parental education, occupation and managerial position. In the second stage, we estimate intergenerational mobility by regressing child's observed income on parental predicted current income. Furthermore, we must account for the uncertainty arising from the regressor used in the second stage

[3] For the attenuation bias, we have that $plim\widehat{\beta}_1 = \beta_1 \frac{Var(y_i^p)}{Var(y_i^p)+Var(\tau_{it}^p)} < \beta_1$ and $plim\widehat{\beta}_1 \to 0$ if $Var(\tau_{it}) \to +\infty$, i.e., beta becomes attenuated (Nybom and Stuhler, 2016).

[4] The life-cycle bias (if income profiles change throughout life for both generations) is reflected by $plim\widehat{\beta}_1 = \beta_1 \lambda_{it}^c \lambda_{it}^p \frac{Var(y_i^p)}{\lambda_{it}^{p\,2} Var(y_i^p)+Var(\tau_{it}^p)}$. Depending on λ_{it}^c and λ_{it}^p, different results may arise (Nybom and Stuhler, 2016).

Table 1 Properties of Intergenerational Mobility in Income Measures

	Global Measures	Local Measures
Relative Mobility	- Intergenerational Income Elasticity - Intergenerational Income Correlation - Rank-rank Slope	NA
Absolute Mobility	- Share of Individuals Earning More than their Parents	- Bottom to Top Income Level Probability

NA stands for Not Applicable

(parental income, which is predicted from the first stage, $\widehat{y}_{it}^{p}$). Pagan (1984) pointed out that the final steps' coefficients may be in general consistent but the standard errors not. As suggested by Björlund and Jäntti (1997), Piraino (2015), and OECD (2018), we compute second step standard errors by employing a bootstrapping methodology.

For the life-cycle bias, controlling for individuals' age (A) and its square (A^2) to account for life-cycle effects is by itself not sufficient (Jenkins, 1987). One should therefore restrict the sample to the age range in which there should be a stable relationship between current and permanent income and λ_{it} equals one (Haider & Solon, 2006).[5] The authors found that for the USA economy this should occur between the early thirties and mid-forties (therefore around 40 years old), a result corroborated by Brenner (2010) for Germany, and by Böhlmark and Lindquist (2006) for Sweden. Regarding the attenuation bias, the most common way to deal with it in the literature is to average parents' current income over time (Solon, 1992).[6]

Therefore, the IGE is computed through the following equation:

$$y_{it}^{c} = \beta_0 + \beta_1 \widehat{y}_{it}^{p} + \gamma_1^{c} A_{it}^{c} + \gamma_2^{c} A_{it}^{c\,2} + \omega_{it}^{c} \tag{4}$$

3.1.1.2 Intergenerational Income Correlation Assuming that $\widehat{y}_{it}^{p}$ is orthogonal regarding A_{it}^{c} and $A_{it}^{c\,2}$, we have:

$$\beta_1 = \rho_{y_{it}^{c},\widehat{y}_{it}^{p}} \frac{sd(y_{it}^{c})}{sd(\widehat{y}_{it}^{p})} \Rightarrow \rho_{y_{it}^{c},\widehat{y}_{it}^{p}} = \beta_1 \frac{sd(\widehat{y}_{it}^{p})}{sd(y_{it}^{c})}, \tag{5}$$

where $sd(y_{it}^{c})$ and $sd(\widehat{y}_{it}^{p})$ are the standard deviations of the (logged) child's current income and predicted parental current income, respectively, and $\rho_{y_{it}^{c},\widehat{y}_{it}^{p}}$ is the partial correlation between those two variables. This correlation is the second measure we compute because since $sd\left(y_{it}^{c}\right) \neq sd\left(\widehat{y}_{it}^{p}\right)$, we have an intergenerational income elasticity distinct from the

[5] If we consider $\lambda_{it}^{c} = \lambda_{it}^{p} = 1$ in $plim\widehat{\beta}_1 = \beta_1 \lambda_{it}^{c} \lambda_{it}^{p} \frac{Var(y_i^{p})}{\lambda_{it}^{p\,2} Var(y_i^{p}) + Var(\tau_{it}^{p})}$, we only have to worry about the standard attenuation bias.

[6] If we adopt this approach to compute the average, we will have to drop a lot of observations to guarantee parents remain in the benchmark sample for the periods considered. Besides, that does not guarantee that the bias disappears, as found by Mazumder (2005): the authors shows that even with an average computed for five years results in a 30% bias. Therefore, our study uses a single year to predict parental income, preserving sample size and acknowledging that the true relative income mobility may be lower.

intergenerational income correlation, $\beta_1 \neq \rho_{y_{it}^c \hat{y}_{it}^p}$. In other words, we adjust the elasticity which, as argued by Bukodi and Goldthorpe (2018), reflects earning's association and also changes in inequality across generations. It is also classified as a global mobility measure.

3.1.1.3 Rank-Rank Slope Dahl and DeLeire (2008) suggest another measure of relative intergenerational income persistence, which is the rank-rank slope, adopted also by Chetty et al. (2014). It may be computed by first rank children and parents in their respective permanent income percentiles' distribution. Second, for each parental income percentile rank $r(y_i^p)$, obtain the average children's income percentile ranks, $\bar{r}(y_i^c)$. Third, regressing it against parental income percentile ranks, as follows:

$$\bar{r}(y_i^c) = \kappa_0 + \kappa_1 r(y_i^p) + \psi_i. \tag{6}$$

The resulting coefficient (κ_1) measures the relationship between the positions children and parents have in their respective income distributions. As with the intergenerational income elasticity, the greater is the coefficient the greater intergenerational persistence will be, and vice-versa, in absolute terms.[7] As pointed out by Deutscher and Mazumder (2023), the rank-rank slope, also a global mobility measure, is preferable to the intergenerational income elasticity if the interest lies in positional mobility rather than the regression to the mean rate, i.e., if the focus is on the movements between positions is the distribution of income and not on the incomes that are connected to them.

We rank the predicted values for parental income, $r\left(\hat{y}_{it}^p\right)$. [8]Then, for each one, there is a given number of corresponding children about which we observe their percentile income ranks and compute the average, $\bar{r}(y_{it}^c)$. We should face the same constraints as before in terms of income (mis)measurement. Therefore, we should consider the strategies explained above to smooth the life-cycle associated bias, although we don't know its full extent. Following Chetty et al. (2014), Eq. (6) will therefore be rewritten as

$$\bar{r}\left(y_{it}^c\right) = \vartheta_0 + \vartheta_1 r\left(\hat{y}_{it}^p\right) + \varpi_{it}, \tag{7}$$

We estimate Eq. (7) through OLS. Percentile ranks for children and ranked bins for parents will be based on the entire sample throughout our analysis.

[7] Chetty et al. (2014) argue that the rank-rank slope and the intergenerational income correlation have a close relationship, since they are scale invariant. This does not occur with the intergenerational income elasticity, because inequality should be different across generations. When inequality is greater for the child's generation, an increase in parental income may have a greater effect on children's income when compared to a scenario where inequality is lower. In other words, the rank-rank slope and the intergenerational income correlation are not affected by changes in inequality, while the intergenerational income elasticity is.

[8] Since we predict parental income, our rank-rank slope will not be the same as the standard rank-rank slope used in the literature. This is because parental income will be predicted grounded on the available but limited set of predictors, reducing the number of distinct values it can assume. Therefore, it is not possible to split them into percentile ranks, as we do for children. Though we don't have percentile ranks, we have ordered bins. For the sake of our analysis, we consider that only the interpretation of the slope changes, though the reasoning that can be taken from conclusions is the same. Instead of reflecting what will be the change in the average percentile rank if the parental percentile rank changes, the rank-rank slope will give us the change in the average percentile rank if the parental bin increases to a higher order.

3.1.2 Absolute (Upward) Mobility Measures

Besides looking at relative mobility, one should be interested in measuring absolute upward mobility as well.[9] As Chetty et al. (2014) argue, while improvements in relative mobility may occur at the expense of rich people's income being harmed, improvements in absolute mobility for a given level of income, *ceteris paribus*, should result in a welfare improvement according to the Pareto Principle. This is the same as saying that, holding other things constant, absolute upward mobility de facto reflects beneficial changes in income of individuals from a given background. We follow their work and compute two main measures of absolute upward mobility.

3.1.2.1 Share of Individuals Earning More than their Parents The first measure of absolute upward and also global mobility suggested by Chetty et al. (2014) is the share of individuals whose income exceeds their parents' income in real value.

3.1.2.2 Bottom to Top Income Level Probability Following Chetty et al. (2014), the other measure one can use for upward absolute mobility is the bottom to top quintile probability, which is the probability that children whose parents are in the bottom quintile of the parental income distribution have of reaching the top quintile of the children's income distribution when adults. Since it covers specific sections of the income distribution, it is considered a local measure of mobility. This would be the well-known "American Dream". We measure in this way the bottom to top income level probability because, as mentioned above, we are unable to construct percentile ranks for parents. This also prevents us from transforming data into quartiles or quintiles. Therefore, we consider a specific cell of the Ordered Logit Transition Matrix, which we describe below.

Suppose that we assign each child's income level $inclev_i^c$ in one specific category, i.e., we have $inclev_i^c \in \{1,2,...,H\}$ where H denotes the number of possible income categories, which will be defined later in this work: the same is considered for the parental income level categories.

The ordered logit transition probability will be estimated by

$$Pr(inclev_i^c = h|inclev_i^p) = \begin{cases} G(c_1 - \Psi inclev_i^p), if h = 1 \\ G(c_h - \Psi inclev_i^p) - G(c_{h-1} - \Psi inclev_i^p), if 1 < h \leq H-1 \\ 1 - G(c_{H-1} - \Psi inclev_i^p), if h = H \end{cases} \tag{8}$$

with the cumulative distribution function of the logistic defined by $G(c_h - \Psi inclev_i^p) = \frac{e^{c_h - \Psi inclev_i^p}}{1+e^{c_h - \Psi inclev_i^p}}$. Ψ is estimated using the maximum likelihood estimator. The bottom to top income level probability is given by $Pr(inclev_i^c = H|inclev_i^p = 1)$, i.e., it corresponds to the probability that a child with parents classified as low income has of becoming classified as a high-income level earner.

[9] We acknowledge the possibility of downward movements, but the focus should be on the upward direction, as it is connected with higher income growth and shared prosperity (GDIM, 2018).

3.2 Intergenerational Mobility in Education

The educational mobility measures considered in this work are now presented. As we did for income, Table 2 summarizes them according to Deutscher and Mazumder (2023), namely regarding the relative versus absolute and global versus local criteria.

As it occurred with income, the larger the value of relative mobility measures the lower mobility is, with the opposite occurring with measures of absolute mobility.

The preferred measure in the literature of relative intergenerational mobility in education is analogous to the relative mobility measure used for income and consists of the coefficient obtained by regressing the total years of educational attainment of children on the total years of education of parents. However, our data characteristics do not allow us to compute it.[10]

3.2.1 Relative Mobility Measure

We rely on the Pearson correlation between parental and child's education levels to measure relative mobility in education:

$$P = \frac{\sum_{i=1}^{N} (e_i^c - \overline{e}^c)(e_i^p - \overline{e}^p)}{\sqrt{\sum_{i=1}^{N} (e_i^c - \overline{e}^c)^2} \sqrt{\sum_{i=1}^{N} (e_i^p - \overline{e}^p)^2}}, \tag{9}$$

where e_i^c is a variable for the ordered education levels of children, e_i^p is a variable for the ordered education levels of parents, and the respective average education levels in the sample are $\overline{e}^c = \frac{1}{N} \sum_{i=1}^{N} e_i^c$ and $\overline{e}^p = \frac{1}{N} \sum_{i=1}^{N} e_i^p$.

The coefficient ranges between -1 and 1. From its sign it is possible to infer if we have positive or negative monotonic relationships between the education levels of parents and children, with 0 meaning that no such type of correlation should exist. The closer the coefficient is to the extremes, the stronger the relationships are, while the opposite occurs if it is near zero. It is also a global mobility measure.

3.2.2 Absolute Mobility Measures

In order to measure mobility in education in absolute terms, two measures are considered. The first is the share of individuals with a higher education level than their fathers. The second is the probability of low to high education level, which corresponds to the probability children have of reaching the highest education level conditional on the father's education being the lowest one. Therefore, it is classified as a local measure of mobility. This corresponds to a specific cell of the Ordered Logit Transition Matrix described below.

Similar to the case of income levels, we model the probability of children having attained a specific observed category in terms of education, e_i^c, conditional on the observed educational category of their parents e_i^p. Suppose that for the educational levels of children we have $e_i^c \in \{1,2,...,M\}$ where M denotes the number of educational categories we have

[10] It would only be possible if we had information on both parents' and children's educational attainment, expressed in completed years of education. However, that is not considered in the surveys we use. Instead, educational attainment is reported in categories of completed education levels: the disaggregation is not the same for both generations. Therefore, by making both categorizations comparable and attributing them years of education, we could lose information in the end.

for our dependent variable: the same categories are considered for the case of parents. We have an index model for parental educational attainment described as

$$e_i^{*c} = \Theta e_i^p + \xi_i^p, \tag{10}$$

where e_i^{*c} is an unobserved latent measure of the years of education of children and e_i^p is a variable for the ordered education levels of parents. Θ is the regression coefficient associated with the explanatory variable, estimated using maximum likelihood. ξ_i^p is the error term, which follows a logistic distribution. Furthermore, the latent variable crosses specific thresholds, t_m, which are also unknown, such that:

$$e_i^c = \begin{cases} 1, if e_i^{*c} \leq t_1 \\ m, if t_{m-1} < e_i^{*c} \leq t_m \\ M, if e_i^{*c} > t_{M-1} \end{cases}. \tag{11}$$

For each value of the transition matrix, we will estimate

$$Pr(e_i^c = m | e_i^p) = \begin{cases} G(t_1 - \Theta e_i^p), if m = 1 \\ G(t_m - \Theta e_i^p) - G(t_{m-1} - \Theta e_i^p), if 1 < m \leq M - 1 \\ 1 - G(t_{M-1} - \Theta e_i^p), if m = M \end{cases} \tag{12}$$

with the cumulative distribution function $G(t_m - \Theta e_i^p) = \frac{e^{t_m - \Theta e_i^p}}{1 + e^{t_m - \Theta e_i^p}}$. The low to high education probability is given by $Pr(e_i^c = M | e_i^p = 1)$.

4 Data and Sample Construction

In this section, we present the databases that are used not only to construct the mobility measures but also to estimate the relationship between relative mobility in income and education, through the use of Mincer (1974) equations. Besides, we describe how our sample is constructed.

4.1 Data

To estimate our benchmark measures of mobility in income and education, we use two databases. Both are provided by INE (Instituto Nacional de Estatística, the Portuguese National Statistics Authority) and are the Portuguese components of two main European Union surveys. The first survey is the *Painel dos Agregados Domésticos Privados da União Europeia*, part of the European Community Household Panel (ECHP), developed for 14 Member States. The second is the *Inquérito às Condições de Vida e Rendimento das Famílias,* which is a part of the European Union Statistics on Income and Living Conditions (EU-SILC) and was launched in 2003, replacing the first survey. Individuals are between 16 and 80 years old. Our sample of children is restricted to the latest survey wave, in which there is retrospective data on their parents. We use the 2019 wave of the EU-SILC as it contains a module aimed at providing information on intergenerational transmission of poverty. Individuals considered are between 30 and 50 years old. Here, personal information is used, in particular individuals were asked about their

Table 2 Properties of Intergenerational Mobility in Education Measures

	Global Measures	Local Measures
Relative Mobility	- Intergenerational Education (Pearson) Correlation	NA
Absolute Mobility	- Share of Individuals with a Higher Education Level than their Parents	- Low to High Education Level Probability

NA stands for Not Applicable

parents' characteristics when they were about 14 years old. The pseudo-parents' samples used in our analysis concern the 1995–1999 waves of the ECHP, since they are the ones closer to the periods in which the adults in our main sample are 14 years old. In the EU-SILC survey, an income reference period is defined as the period that income is related to. In most of the EU-member States it corresponds to the previous calendar year (fixed 12-month period). Hence, the outcomes' periods for specific variables considering the 2019 wave is 2018. The same applies to the 1995–1999 ECHP waves, where the reference period is 1994–1998.

Additionally, although research about intergenerational income mobility is mainly focused on fathers and sons, in this work we consider both genders for children. The reason, as stated above, is because Portugal has some very specifics characteristics regarding the female labour market and educational attainment for women.

4.2 Sample Construction

The sample construction is now presented. We describe how we deal with unobserved parental income, life-cycle effects in income measurement, differences between permanent and current income, and income measurement conditional on gender. We also show how we make information comparable across surveys and detail the definitions of income, education, occupation and managerial position related variables.

4.2.1 Income

4.2.1.1 Predicting Father's Income We follow the common methodology of a variety of previous studies in which the datasets share the same characteristics as ours and father's income has to be predicted, namely, Björklund and Jäntti (1997), Leigh (2007), Lee and Solon (2009), and Nuñez and Miranda (2010). Our strategy can be formalized as follows. Consider that the log of parents' current income (in t) can be defined as the sum of permanent income y_i^p and time-varying characteristics, namely age (A) and its square (A^2) to control for life-cycle effects in income:

$$y_{it}^p = y_i^p + \gamma_1^p A_{it}^p + \gamma_2^p A_{it}^{p\,2} + \mu_{it}^p. \tag{13}$$

In the current wave of the survey (main sample) we cannot observe parental current income, y_{it}^p. We also cannot link parents and children across waves. Although this is the case, we can observe in an earlier wave of the survey the current income of individuals, which are assumed to be representative of the same population as the current one. We call it the auxiliary sample of pseudo-parents. Thus, let X_{ij}^p be a vector of dummies for each possible parental characteristic ($j \in J$) which can proxy for lifetime income (again, not observed), such that:

$$y_{it}^{p} = \Phi_{j}^{\prime p} X_{ij}^{p} + \varphi_{ij}^{p} \tag{14}$$

Equation (13) becomes:

$$y_{it}^{p} = \Phi_{j}^{\prime p} X_{ij}^{p} + \gamma_{1}^{p} A_{it}^{p} + \gamma_{2}^{p} A_{it}^{p^{2}} + \mu_{it}^{p} + \varphi_{ij}^{p} \tag{15}$$

We estimate Eq. (15) through an OLS estimator in t (i.e., our results are computed for a cross-section). The resulting coefficients are used to predict the current income of pseudo-parents of children in the main sample, $\hat{y}_{it}^{p}$:

$$\hat{y}_{it}^{p} = \Phi_{j}^{\prime p} X_{ij}^{p} + \hat{\gamma}_{1}^{p} A_{it}^{p} + \hat{\gamma}_{2}^{p} A_{it}^{p^{2}} \tag{16}$$

We consider as potential proxies of parental permanent income their individual characteristics such as occupation, educational attainment and managerial position.

This approach has some issues attached to it that are worth mentioning. First, we use a sample of pseudo-parents which is not the same as using parents, taken from the population in our main sample. Second, the predicted income is not the same as the observed income. Third, results may be biased due to the possible lack of validity of the instruments used. As pointed out by Solon (1992), there is the possibility of these instruments not being exogenous and, in turn, having a relationship with children's income that goes beyond the parental income channel. Grounded in Nicoletti and Ermisch (2008) and supported by the evidence presented by Björklund and Jäntti (1997), Cervini-Plá (2015) argues that these instruments may positively influence the children's income even after controlling for the parental income, promoting an upward bias in the estimate of the elasticity. Thus, most authors that use this method assume that the estimates are upper bounds of the true coefficient. We test how sensitive our results are to the use of different combinations of characteristics that proxy for parental permanent income. Fourth, as parental income is predicted using a small number of different instruments that proxy for their permanent income, we have a limited small set of distinct values that these can assume and a lack of variability in parental income.[11] In line with this, there is the potential problem of missing variables, such as industries or sectors of activity and years of experience. However, there is no more retrospective information about parents reported by children available in the EU-SILC that could be used to predict their individual income. All together these issues may influence the results and conclusions.

4.2.1.2 Life-cycle and Attenuation Bias To account for the life-cycle measurement error we restrict our sample to individuals aged 30–50 years old.[12] Current income is used for both generations. We predict parental income at 40 years old, the age in the middle of the range at which permanent income may be proxied,[13].[14] To address the standard attenuation bias, existing evidence shows that a large time range would be needed to make it disappear. We restrict the parents' sample to fathers only: as we predict parental individual income and the best option for women is to use family income/couple's income (while for men, concerns

[11] This has implications for the rank-rank slope because we cannot rank predicted parental income in percentiles as it is done for children. Nevertheless, parental income is still ranked but in different bins.

[12] Different authors used similar age ranges: e.g., 30–50 in Cervini-Plá (2015), 25–54 in Mendolia and Siminski (2019), and 38–45 in Corak (2019).

[13] We follow authors such as Leigh (2007) and Mendolia and Siminski (2019).

[14] Results for the first stage are presented in Table 16 in the Appendix.

are not that clear in the literature), we do not have an intersection between both conditions. Besides, we don't know the parental marital status when income is measured. We will therefore have estimates for the pairs father-children, father-son, and father-daughter. A father is defined as the individual considered by the interviewed person as his or her father when aged 14, having (or not) a biological relationship, even if the biological father was known and alive. According to Mazumder (2005), a father's income averaged for 5 years will still produce attenuated beta (IGE) estimates, which are 30% biased for the USA, and even using a 25-year range period the bias would remain. As Cervini-Plá (2015) points out for Spain (Spain's data have the same characteristics as ours), when using instruments in the TSTSLS approach to proxy for parental income and then predict parental current income, one is already computing its average. By using a single year for parental income in our benchmark sample, we assume that we are obtaining the most attenuated estimate of relative persistence in income, which means that relative mobility in income may be lower than the one we obtain.[15] Additionally, considering more than a single year implies guaranteeing that individuals are in the cross-sectional samples for all periods, which reduces the number of observations by a large amount. We perform a sensitivity exercise to assess how sensitive our estimates are when using an average for parental income (i.e., using more than one period to compute it).

4.2.1.3 Measurement Issues In our sample of children, individuals can be either single or married. Chadwick and Solon (2002) show that in the case of married daughters, we should use the couple's income to better proxy for their economic status. Although this may justify the use of couple's income for women, it should not rule out the use of the couples' income as well for men. This is because in our sample women earn on average 45% of the couple's income. This makes us consider the couple's income as well for men, when married.

Additionally, since we are studying intergenerational income mobility, we decide to include only individuals with strictly positive income during the income reference period.[16] For singles we use individual income. For married individuals we use the combined income of the couple, i.e., we add the total income of the couple and divide by two, obtaining an average, following Chadwick and Solon (2002) and Raaum et al. (2008). Married individuals who do not work but benefit from the income of his/her spouse are also not considered, as what they earn is not a direct result from being active in the labour market. In a later sensitivity exercise we include the partners with no individual income, but with positive average couple's income and test if results change. We also perform a sensitivity analysis to evaluate the possible differences arising from using individual income instead of average couple's income when individuals are married. When using the ECHP, we measure income as the wage and salary income for employees and self-employment income for self-employed individuals. The corresponding variables available in the EU-SILC are the net employee cash or near cash income and the net cash profits or losses from self-employment. The reason why we use these "narrower" definitions of income is that the

[15] For the standard attenuation bias, when we average the annual income of fathers from 1 to T and regress y_i^c on $\overline{y}_i^p = \frac{1}{T}\sum_{t=1}^{T} y_{it}^p$, we obtain that $plim\widehat{\beta}_1 = \beta_1 \frac{Var(y_i^p)}{Var(y_i^p)+\frac{1}{T}Var(\tau_{it}^p)} < \beta_1$. If $t \to +\infty$, beta becomes less attenuated, which reflects more persistence (Björklund and Jäntti, 1997).

[16] The reason is that the canonical measure considered in the literature and also in our paper is the intergenerational earnings elasticity and we wanted to follow existing research. Income is logged, therefore it has to be strictly positive.

characteristics reported about parents by children, in the EU-SILC database, mainly consider labour-related income. To make both generations comparable, this is also the type of income chosen for the children's subsample.

In the second survey, the first variable is defined as the gross cash or near cash income, deducted from tax at source and/or social insurance contributions. In turn, gross cash or near cash income consists of the cash monetary component of employees' compensation paid by an employer, including the value of income taxes and social contributions that are paid either by the employee or by the employer to tax authorities and/or social insurance schemes (on behalf of the employee).[17] The second variable can be defined as the net of tax at source and/or social insurance contributions net operating profit or loss for owners/partners that work in an unincorporated company, with interest on business loans deducted, plus royalties (writing, inventions, among others) and rentals from equipment.[18] To make income comparable across surveys we use the Consumer Price Index (CPI with a base year in 2010 to obtain income in real values).

We also define income levels for both children and parents. We ground our definition for each income category on the OECD definition for low and high pay workers.[19] We consider the low-income level to be the one in which individuals earn less than two-thirds of the median national income, while the high-income level comprehends individuals earning one and a half the median income. Individuals classified as middle-level earners are those between, and are split into two categories, middle-low and middle-high, according to the intermediate value of the category's possible values' range. We again apply the CPI base year 2010. For parents, the log income' bounds separating classifications are 8.81, 9.29, and 9.62. For children we have 8.96, 9.45, and 9.77.

4.2.2 Education

Data for educational attainment is taken from the ECHP and the EU-SILC. Education is classified using the International Standard Classification of Education (ISCED) of the United Nations Scientific and Cultural Organization (UNESCO). There exist two categorizations. The first one, ISCED 1997, considers 7 levels of education. Data in the 1995 wave of the ECHP cover three valid groups, which have correspondence with the ISCED 1997 classification. The second categorization, ISCED 2011, was used in the 2019 wave, covering 9 levels. When asked about their parents' education, children's responses are divided into low, medium, and high educational levels, which have correspondence with ISCED 2011 classification. This means that to estimate intergenerational mobility in income—in

[17] As described in the EU-SILC variables definitions, it includes wages and salaries, payments for time not worked as holidays, overtime rates, directors' fees, piece rate payments, commissions, gratuities and tips, supplementary payments as the thirteenth month, shared profits and bonuses, productivity payments, allowances for remote working and transport, sickness, disability and maternity supplements. It excludes reimbursements, severance and termination pay, purely work-related expenses, lump sum transfers at retirement time and union strike pay.

[18] According to the EU-SILC documentation, when computing the net operating profit, one should sum market output, market value of goods and services consumed by the entrepreneur but bought for the unincorporated company, property income, subsidies, and subtract intermediate goods, compensation of employees, taxes, interest, rents and fixed capital consumption. The documentation also states that income from self-employment excludes directors' fees earned by owners of incorporated enterprises (included in the gross employee cash or near cash income), dividends paid by incorporated companies, profits from capital invested in other enterprise where the individual does not work, rent from land and rentals from dwellings.

[19] https://data.oecd.org/earnwage/wage-levels.htm.

which we predict parental income grounded on educational attainment—as well as in intergenerational education mobility, we must match children's own education levels in the pseudo-fathers' education categories, which is presented in Table 3 below.

Information about education in the pseudo-parents' sample is only used to proxy for their permanent income and then predict their current income (which is not available) in a first stage, which is the estimation of intergenerational mobility in income. For the estimation of intergenerational mobility in education we only need to use the children's samples where retrospective information about education is directly available. As we aim not only to analyse mobility in education, but also to identify patterns regarding its joint behaviour with mobility in income, we should consider the same individuals in both analyses, which implies that the age range we first chose is the same. We also have to ensure that individuals are not enrolled in school. Therefore, we include in the analysis only individuals between 30 and 50 years old, which have finished school and are not enrolled in any type of education at the time of the survey, following Urbina (2018). In 2018, 5% of the Portuguese individuals aged 30–34 where still enrolled in school, 4% for the age range of 34–39, and 2% for 40–64 years old.[20]

4.2.3 Occupation

The ECHP and the EU-SILC are the sources for occupation related data. The International Standard Classification of Occupations (ISCO) from the International Labour Organization (ILO) is considered in our work. For the 1995 wave of the ECHP the ISCO-88 classification is used, while for the 2019 wave of the EU-SILC the ISCO-08 classification is considered. The correspondence is in Table 4.

4.2.4 Managerial Position

Another characteristic we use to proxy for father's permanent income is his managerial position. The parent can be either in a supervisory or non-supervisory position. We create a dummy variable that is equal to 1 in the first case, if the individual has formal responsibility for an employees' group, with direct supervision of the work, and 0 otherwise. Expectedly, for the same occupation category and education level, an individual in a superior managerial position should have higher income than one in a lower managerial stage. Data for managerial position is also taken from the ECHP and the EU-SILC.

Summary statistics are presented in Tables 14 and 15 in the Appendix.

5 Empirical Results and Discussion

In this section we present our benchmark results for the measures of intergenerational mobility in income and education for the Portuguese economy.[21] As pointed out by Deutscher and Mazumder (2023), there are no correct or incorrect mobility measures. Therefore, the information contained in the different mobility measures is distinct and

[20] https://stats.oecd.org/Index.aspx?DataSetCode=EAG_ENRL_RATE_AGE.

[21] The surveys we use provide individual weights that are computed accounting for the sample design and individuals' characteristics. They reflect the structure of the population: the greater the weight the stronger the representativeness an individual has on the population, which cannot be ignored. We therefore use population weights in our analysis.

serves the heterogeneous interests that policymakers may have. We also present possible explanations for our evidence, which do not imply causality, but may be explored in future research. Policy directions are addressed.

5.1 Intergenerational Mobility in Income

Table 5 presents the benchmark results for the intergenerational mobility in income for all children regardless of gender and also for male and female children separately.[22]

The evidence presented shows that the income elasticity, equal to 0.26, is higher relative to the intergenerational income correlation of 0.20. This result is expected because the standard deviation of children's income (0.56) is higher than the one of parents (0.44), i.e., inequality is expected to have increased throughout time. This resembles the evidence presented by the World Inequality Database on which inequality has been increasing throughout time for this country.[23] Results also suggest that, although 53.11% of the individuals have experienced upward income mobility relative to their parents, the probability that individuals have of reaching the top income level when raised in the low-income level is still low given that only 7.15% managed to do so. In other words, although more than half the population is better off than their parents, it is still not easy for someone born in the worst income scenario to attain full prosperity.

Gender differences also evident. Women show more intergenerational income mobility than men, with the exception of the bottom to top income level probability. Our evidence is also verified in the literature regarding other countries. Borisov and Pissarides (2019) show that mobility is higher in correlation ranks for females in Russia. For this measure as well as for the intergenerational income elasticity, Helsø (2020) finds daughters to be more mobile than sons for Denmark and USA, while ambiguous findings are reported by Kyzyma and Groh-Samberg (2020) for Germany. Acciari et al. (2022) show that mobility is higher for women when considering the rank-rank slope for Italy. Considering the work of Comi (2004), for an older generation and with differences in variables' definitions and sample construction, the same finding is presented for Portugal regarding the intergenerational income elasticity, according to which girls show more mobility. Regarding the evidence of the OECD (2018), also following an instrumental variable approach and similar sample restrictions, men present higher mobility than women, as opposed to our evidence.

When analysing intergenerational mobility measures, a main goal is to stress how high or low mobility is. This is done through comparisons between countries. We must be careful in the comparisons because estimates are sensitive to measures of income, estimation methods, and sample selection, among others. This means that we try to choose works that make choices to ours in terms of sample and methods.[24] Most of these studies address mainly the case for intergenerational income elasticity for a single gender (usually men).

By country and for sons, we have elasticities being around: 0.1–0.3 (Blanden et al., 2004), 0.20–0.25 (Nicoletti & Ermisch, 2008), and 0.56–0.59 (Dearden et al., 1997) for the UK[25]; 0.19–0.22 for Canada (Fortin & Lefebvre, 1998); 0.28 for Sweden (Björklund & Jäntti, 1997); 0.2–0.3 (Leigh, 2007), 0.35 (Mendolia and Siminski, 2019) for Australia;

[22] Results are the same when age is centred at 40 years old for both generations, regarding income mobility.

[23] https://wid.world/country/portugal/.

[24] Slight differences between ours and the cited studies may lead to wrong conclusions (see Solon, 2002). This is also true for education mobility estimates.

[25] Large differences for the UK may be due to differences in the cohorts or the surveys used by the authors.

0.4 for France (Lefranc & Trannoy, 2005); 0.42 for Spain in Cervini-Plá (2015); 0.45–0.53 (Solon, 1992), 0.34–0.49 (Lee & Solon, 2009), and 0.52 (Björklund & Jäntti, 1997) regarding the USA; 0.5 for Italy (Mocetti, 2007; Piraino, 2007); 0.58 (Ferreira & Veloso, 2006) and 0.69 (Dunn, 2007) for Brazil. Our estimated value for the elasticity of males, 0.3, is similar to some of the estimates for the UK, Sweden, and Australia, but higher than the estimates found for Canada, and lower than the ones for France, Spain, the USA, Italy, and Brazil. In the OECD (2018), when comparing persistence across countries, Portugal, with an elasticity of almost 0.4 (higher than ours) is also above Canada and below the USA, Italy, France and Brazil. The UK and Australia surpass Portugal, as in some of the cases presented, while Spain is below the country's estimate.

For daughters we have elasticities ranging about: 0.05–0.46 in the USA (Lee & Solon, 2009); 0.1–0.3 (Blanden et al., 2004) and 0.63–0.70 (Dearden & Reed, 1997) in the UK; 0.3 in France (Lefranc & Trannoy, 2005). Our estimate of 0.22 fits in the interval of some of the estimates made for the USA and the UK, but lower than the estimate made for France. This is in line with results presented by the OECD (2018), though results for France are not presented: Portugal presents an elasticity slightly above 0.4 (also higher than ours).

The Global Database on Intergenerational Mobility (GDIM, 2018), constructed by Narayan et al. (2018), also presents elasticity estimates for Portugal, finding that is equal to 0.28, for each gender separately as well as together.

Mendolia and Siminsky (2019) also compute the intergenerational income correlation, which is around 0.233 for men in Australia, similar to our findings. We can only compare our estimates for men and women with those in the literature. None of the authors instrumenting and predicting parental income compute the other mobility measures. For sons, Portugal may stand amongst the most relative mobile countries in income, being similar to the UK and Australia. Regarding daughters, it fits in all the estimates for the countries described.

Figure 1 presents the transition probabilities between father and children (sons and daughters) income levels in the respective generations, which complements the previous measures.

There is a strong degree of intergenerational mobility when the father is classified as low-income earner: the majority of individuals are likely to arrive at higher income levels when adults. This means that almost no child with low-income fathers keeps that position and the majority is able to be better off when adults. At the same time, about 75% of individuals remain in the low- and medium–low income levels. Connected with this, the majority of children with medium–low income level earners keep that position, which reveals that for children born below the medium–high and high-income levels, persistence is high. The probability of keeping a high income level is lower than the one of reaching a lower income level (downward mobility is high for children of high income fathers). Besides, the upward probabilities decrease the higher the fathers' income levels, as expected (the more fathers earn, the less room for being surpassed by children there is). The chances of reaching a high-income level are lower for all fathers' income levels. The likelihood of departing from a low-income level and reaching the highest is lower than the opposite movement. The chances of ending up in the medium–low income level are the highest. These are higher for females with fathers in the medium high and high-income levels (39.93% and 36.72% for women when compared to the 39.25% and 34.01% for men, respectively), and higher for males with fathers in the low and medium low-income levels (39.60% and 40.96% for women when compared to the 42.83% and 42.43% for men with fathers, respectively).

Table 3 Correspondence between ISCED Classifications across Surveys

ECHP 1995 (ISCED 1997)	EU-SILC 2019 (ISCED 2011)	Retrospective question about parents
Less than second stage of secondary education	Primary	Low level
	Lower secondary	
Second stage of secondary education	Upper secondary	Medium level
Recognized third level education	Short cycle tertiary	High level
	Bachelor or equivalent	
	Master or equivalent	
	Doctorate or equivalent	

Adapted from Eurostat online tables (correspondence between ISCED 2011 and 1997 levels). *Source* http://www.uis.unesco.org/Education/Pages/internationalstandard-classification-of-education.aspx

5.2 Intergenerational Mobility in Education

We present the benchmark results for intergenerational mobility in education in Table 6.

Results show that there is a positive association between children and father' educational attainment according to which children will have, on average, higher education levels when their father also have higher levels of education, as reflected by the intergenerational education correlation of 0.26. We also see that there is a 44.35% chance of individuals born into low-educated environments reaching the highest education level, with 84.47% of individuals attaining improving their education in comparison with the oldest generation. This means that less than 20% of individuals keep their father's education level or reach a lower one, which appears to be good news for a country where, according to International Organizations, low education levels were likely to perpetuate, i.e., there was a high chance of individuals keeping the same education level than their parents.

The last result may be connected with the decrease in school drop-out rates between 1968 and 2018: for the primary and secondary education levels, the percentage changes were approximately equal to 99.6% and 96.35%, respectively. The reasoning is that opportunities are equalized across individuals from different educational backgrounds as pointed outby Narayan et al. (2018). This is in line with the description made in Clements (1999) from the IMF to highlight an education reform that took place in the nineties and that substantially decreased school dropout rates which were found to be responsible for the low education levels by the OECD (1995). The measures adopted by the Portuguese Government included the expansion of preschool on which participation increased by 30% points (from 34 to 64% between 1988 and1997/1998; the Guaranteed Minimum Income Program which requires children from recipients to be at school; the expansion of professional schools at the secondary level, associated with an increase in enrolled individuals of about 26 p.p. (from 13 to 29%) between 1991/1992 and 1998/1999. Some of the measures are still in place nowadays, and the OECD (2019) corroborates that progress in the last decade continued to be made, as continued policy efforts to reduce out-of-school rates made the share of individuals attaining upper-secondary or post-secondary non-tertiary education level increased 13 p.p. between 2008 and 2018.

Men are more relatively mobile than women (0.24 compared to 0.29 for the intergenerational correlation) while more persistent in absolute terms (36.93% compared to 49.98%

Table 4 Correspondence between ISCO Classifications across Surveys

ECHP 1995 (ISCO-88)	EU-SILC 2019 (ISCO-08)
Legislators, senior officials and managers	Managers
Professionals	Professionals
Technicians and associate professionals	Technicians and associate professionals
Clerks	Clerical support workers
Service workers and shop and market sales workers	Services and sales workers
Skilled agricultural and fishery workers	Skilled agricultural, forestry and fishery workers
Craft and related trades workers	Craft and related trades workers
Plant and machine operators and assemblers	Plant and machine operators and assemblers
Elementary occupations	Elementary occupations

Source International Labour Organization (https://www.ilo.org/public/english/bureau/stat/isco/)

Table 5 Benchmark Results for Intergenerational Mobility in Income

	Elasticity	Corr	Rank-rank	Prob	Share
All individuals n = 2549 | N = 980,083	0.26*** (0.04)	0.20*** (0.03)	0.45*** (0.01)	7.15*** (0.01)	53.11
Males n = 1027 | N = 431,849	0.3*** (0.05)	0.24*** (0.04)	0.48*** (0.02)	8.21*** (0.01)	52.90
Females n = 1522 | N = 548,234	0.22*** (0.06)	0.17*** (0.04)	0.42*** (0.02)	6.42*** (0.01)	53.28

Standard errors are presented in parentheses. *,**,*** stands for statistically significant at 10%, 5%, 1% levels, respectively. Elasticity stands for the Intergenerational Income Elasticity (IGE), Corr. stands for the Intergenerational Income Correlation. Rank-rank stands for the Rank-Rank Slope. Prob. stands for the Bottom to Top Income Level Probability. Share stands for the Share of Individuals Earning More than their Fathers. These are described in Sect. 3.1. Only fathers are considered. Probabilities obtained using an ordered logit and the share of individuals earning more than their fathers are expressed in %. The share of individuals earning more than their fathers does not have an associated significance level. n stands for the number of observations in the sample and N for the total population represented by those observations using survey weights

for the low to high education level probability and 82.54% compared to 85.99% for the share of individuals with more education than their fathers). Gender differences in relative mobility may be also related with differences in school drop-out rates, resembling the findings of Hilger (2016) for the USA regarding high school enrolment. In Portugal, women appear to have higher dropout rates than men in more than 90% of times, considering the primary education level between 1968 and 2018. For the lower secondary level, this share is close to 89%.[26] Besides, regarding the primary level of education, the reduction in school dropouts in the same period was more pronounced for men than for women (99% for men

[26] Data on dropout rates for the primary education level for males and females are available in https://data.worldbank.org/indicator/SE.PRM.UNER.MA.ZS and https://data.worldbank.org/indicator/SE.PRM.UNER.FE.ZS, respectively. For the lower secondary level, these are presented in https://data.worldbank.org/indicator/SE.SEC.UNER.LO.MA.ZS and https://data.worldbank.org/indicator/SE.SEC.UNER.LO.FE.ZS, respectively.

and 90% for women), while these were similar between genders for the lower secondary education level. All together may have made women present more relative education persistence than men.

Some authors compute an analogous measure to our probability measure. Lam and Liu (2019) find that for primary and lower secondary educated fathers (both in our low level of education), the chances children have of reaching the high education level are in the 26.63–33.07% range, for both-generation Hong Kong born individuals, 32.78–40.61% for second-generation Mainland immigrants, and 16.11–20.35% for both-generation Mainland immigrants. Schneebaum et al. (2016) show that for Austria, this likelihood is around 8% for males and 7% for daughters. For Portugal, Bago d'Uva and Fernandes (2017) find that this is around 20% considering male children, which is about 17% points below our 36.93% estimate. Although cohorts used are similar to ours (1970–1985), differences should be noted in the methodology. They use a multinomial logit and their calculations involve the 2005 and 2011 waves of the EU-SILC. All these are below our estimates and the differences between genders are the opposite to what we obtain. The share of individuals with more education than their fathers is higher than 80%. This value is larger than the one found in Lam and Liu (2019) for Hong Kong-born children with Hong Kong-born fathers (78.06%), while lower than the one for Hong Kong-born children of Mainland immigrant fathers (89.47%). Both generation Mainland immigrants fall in the middle (86.54%). Due to the lack of comparability in the literature that, for our measures, is scarce, we cannot infer if Portugal has high absolute mobility in education (or not) in the World.

Education correlations are the most studied measure in the literature and mainly use years of education instead of education levels. Considering that there may be a strong link between years of education and education level attained, we abstract from this last issue. Urbina (2018) is the only investigator studying the pair father-children and finds a correlation that is between 0.45 and 0.51 regarding Mexico. As before, reported studies often confront the analysis for each gender separately. Schneebaum et al. (2014) consider 20 European countries. In general, mobility is lower for sons (0.33) when compared to daughters (0.26). They include Portugal in their analysis, finding values similar to ours: the intergenerational correlation for Portugal for the pair father-son is equal to 0.24 (the same as we obtain), while the pair father-daughter is equal to 0.26 (lower than our estimate). This country presents the highest mobility when considering men. Regarding daughters, Portugal is surpassed in terms of mobility by France (0.24), all the Nordic countries (average correlation of 0.20), the Anglo-Saxon countries (average correlation of 0.23), Greece (0.22), Czech Republic (0.20), and Poland (0.21). The highest persistence value is found for Italy (0.40). Latif (2018) shows for Canada that boys are on average less mobile than girls with the education correlation being equal to 0.33 for boys and 0.32 for girls. Schneebaum et al. (2016) found that persistence appears to be greater for girls, 0.43, than for boys, 0.41, for Austria. Azam and Bhatt (2015) find that the correlation between father and son's education is around 0.64 for India. To sum up, Portugal is the most relatively mobile country in education for sons when considering the intergenerational correlation in education whereas for daughters it is in the middle of known World's estimates.

The fact that Portugal is the one presenting a larger relative change in the government expenditures as a share of GDP may be leading our evidence (an increase around 186% between 1968 and 2018[27]). According to Narayan et al. (2018), this may be the result of

[27] https://data.worldbank.org/indicator/SE.XPD.TOTL.GD.ZS

higher public spending on education is associated with larger relative mobility in education in richer countries, by compensating the inequality in private investments in education between poor and rich parents, in line with the findings of Ferreira and Gignoux (2014). It also should be connected with the policies implemented to improve enrolment in schools which can be again considered to explain differences between countries. Portugal is the country with the highest decrease in the school drop-out rate for men, considering primary education, while for women it lays in the middle of the group of countries' estimates. However, women do not maintain the same position when compared to other countries in terms of primary school dropout rates' decrease as the one they have regarding relative education mobility. This reinforces the argument of Clements (1999) that early education is one of the main drivers of educational achievement in the Portuguese economy.

Figure 2 presents the transition probabilities for education levels considering both generations.

An interesting result emerges when we analyse the transition probabilities for intergenerational mobility in education. The probability of staying in the same low education level as the father is equal to 0%, i.e., individuals present full absolute mobility when raised in a low educated environment. This result appears to be stronger than the one found by Bago d'Uva and Fernandes (2017): noting the same differences in methodology mentioned above, sons with low educated fathers appear to have almost 50% chance of reaching a higher education level. When the father is classified as medium educated, children's chance of surpassing that level is higher than the one they have of obtaining the same level. The probability of remaining in the same education level of the father is higher for men regarding the medium education level and for women regarding the high education level (45.07% compared to 24.35% for the first case and 90.62% compared to 71.72% in the second case). Moreover, the chances of completing the highest education level is always higher for females when compared to males for all the father's education levels. Finally, the likelihood that an individual has of reaching or remaining in the high-education level is increasing on the father education level, which reflects a high persistence at the top of the education classification: this finding is similar to that presented by Bago d'Uva and Fernandes (2017), regarding sons born from 1950 on.

As we stated before, we perform several sensitivity analysis, which we present in the Appendix 2. Overall, our analysis shows that results are robust to most of the sensitivity exercises. The rank-rank slope may be upward or downward biased, as found when performing the sensitivity analysis for different instruments for parental income. The other measures are likely to be attenuated. We also show that it is a fair choice to consider average total household income for married individuals instead of individual income, because household structure persistence influences the transmission of socioeconomic status.

5.3 Results by Individual Characteristics

Literature reports that individual's characteristics are associated with more or less mobility. Examples include Causa and Johansson (2010) and Gallagher et al. (2019) that find that there is a connection between parental education and income mobility, in OECD countries and the USA, respectively. Emran et al. (2019) and Alesina et al., (2021, 2023) also find that different occupations or sectors of activity present heterogeneous education mobility patterns, respectively considering India and China, and African countries. Acciari et al.

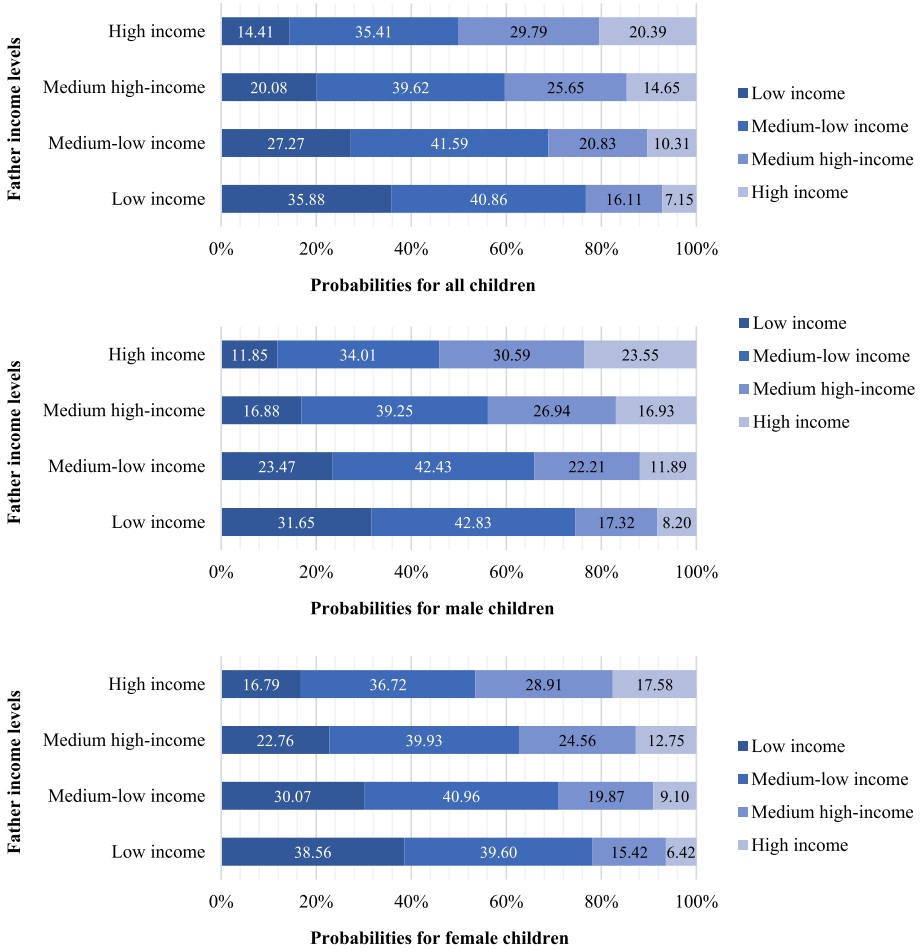

Fig. 1 Intergenerational Transition Probabilities in Income Using an Ordered Logit. Probabilities obtained using an ordered logit are expressed in % and are all statistically significant at 1%. Parental individual income (in logs) is predicted at the age of 40 years old, with results for the first stage presented in Table 16 in the Appendix and using father's education, occupation, and managerial position as instruments for permanent income. Children's income (in logs) correspond to the average of the couple's income when married and to individual income when not married. Results can be found in Table 17

(2022) analysed Italy and distinct status in employment also appeared to be associated with differences in income mobility. We analyse intergenerational mobility in income and education in different subsamples according to individual characteristics to assess these previous findings. Hence, the benchmark analysis is extended by children/father education, occupation, income levels, and employment status. This analysis allows us to understand which characteristics are associated with more or less mobility. We are not however capturing the relative importance of any of those variables, but exploring the within-group inequality that may exist for each characteristic.

Table 6 Results for Intergenerational Mobility in Education

	Correlation	Prob	Share
All individuals n = 2549 | N = 980,083	0.26***	44.35*** (0.01)	84.47
Males n = 1027 | N = 431,849	0.24***	36.93*** (0.02)	82.54
Females n = 1522 | N = 548,234	0.29***	49.98*** (0.02)	85.99

Standard errors are presented in parentheses. *,**,*** stands for statistically significant at 10%, 5%, 1% levels, respectively. Probabilities obtained using an ordered logit and the share of individuals with more education than their fathers are expressed in %. The share of individuals with more education than their fathers does not have an associated significance level. n stands for the number of observations used and N for the total population represented by those observations using survey weights

5.3.1 Education

We present the disaggregation by own and father's education levels, in Tables 7 and 8, respectively.

In the majority of the indicators, individuals with a high education level present the highest relative and absolute mobility in income, pointing to the possibility that there is an absolute advantage in income of completing the highest education level.

The share of individuals earning more than their fathers is the measure for which results appear to have opposite findings, as reported in the work of Causa and Johansson (2010) for the OECD. The authors show that highly educated households are associated with more relative mobility, while we observe that children whose fathers have a low education level are the ones with higher relative mobility. The opposite happens for indicators of absolute mobility in comparison with the entire sample. Regarding education, when fathers have a low education level, children have more absolute mobility in comparison to the entire sample. Also, children of high educated fathers show more persistence in income than the sample for which we consider all individuals.

5.3.2 Occupation

Results by own occupation and father occupation categories are in Table 9 and 10 respectively.

Mobility in income is always higher than in the benchmark sample when considering the (significant) subsamples of individuals with occupations in the following categories: legislators, senior officials, and managers, and professionals. The opposite occurs for skilled agricultural and fishery workers, plant and machine operators and assemblers, and elementary occupations. Subsamples where individuals have occupations classified in the technicians and associate professionals and also service workers and shop and market sales workers categories are the ones presenting more relative mobility but less absolute mobility in income in comparison with the entire sample. Regarding education, relative mobility is higher than in the benchmark sample, except when considering the subsamples where individuals work as skilled agricultural and fishery workers or have elementary occupations. Absolute mobility is also lower than in the sample with

all individuals for the technicians and associate professionals' category and also for the elementary occupations.

In comparison with the entire sample, when fathers' occupations are classified in the legislators, senior officials, and managers as well in the professional's category, children always have lower relative mobility in income. In turn, the absolute income mobility is always higher than in the benchmark case when fathers belong to clerks and skilled agricultural and fishery workers occupations. Regarding the rank-rank slope, most of the professional categories show lower mobility, with exceptions being for technicians and associate professionals. Relative mobility in education presented in each subsample is higher than in the benchmark case for legislators, senior officials, and managers, technicians, and associate professionals, and craft and related trades workers, but lower for professionals. Absolute mobility in education is higher than in the benchmark subsample when children have fathers working as clerks, but lower than in the entire sample when considering the subsample of children whose fathers are classified as professionals.

5.3.3 Income Level

Tables 11 and 12 present the results by own and father income levels, respectively.

Mobility in income is in most cases higher than the one verified in the entire sample. For the majority of measures of intergenerational mobility in education, relative mobility is also higher in each income level partition when compared to the entire sample, while absolute mobility is always higher than in the benchmark case when individuals' income belongs to the medium–high category.

Only when fathers are classified as medium–low income earners do children present more (relative and absolute) mobility in income than the one in the entire sample. When individuals have fathers in medium–high- and high-income levels, (relative and absolute) mobility in income appears to be lower than in the benchmark case. Relative mobility in education is higher than the entire sample when parents have a medium–low income level and is lower than in the entire sample when parents have a high-income level. In terms of absolute mobility in education, for children of parents with medium–high- and high-income level, mobility is higher.

5.3.4 Status in Employment

In this section we analyse children by their status in employment (either self-employed or employees), with results in Table 13.[28]

Overall, children who are self-employed present higher persistence in income and education when compared to the entire sample, while the opposite occurs for the subsample of children who are employees. For the first group the exception is the low to high education level probability. For the last group, lower mobility is verified for the bottom to top income level probability and the low to high education level probability.

[28] This exercise cannot be performed by fathers' employment status, because we cannot distinguish in the sample of children the cases for which their fathers were employees only, employers only, or both.

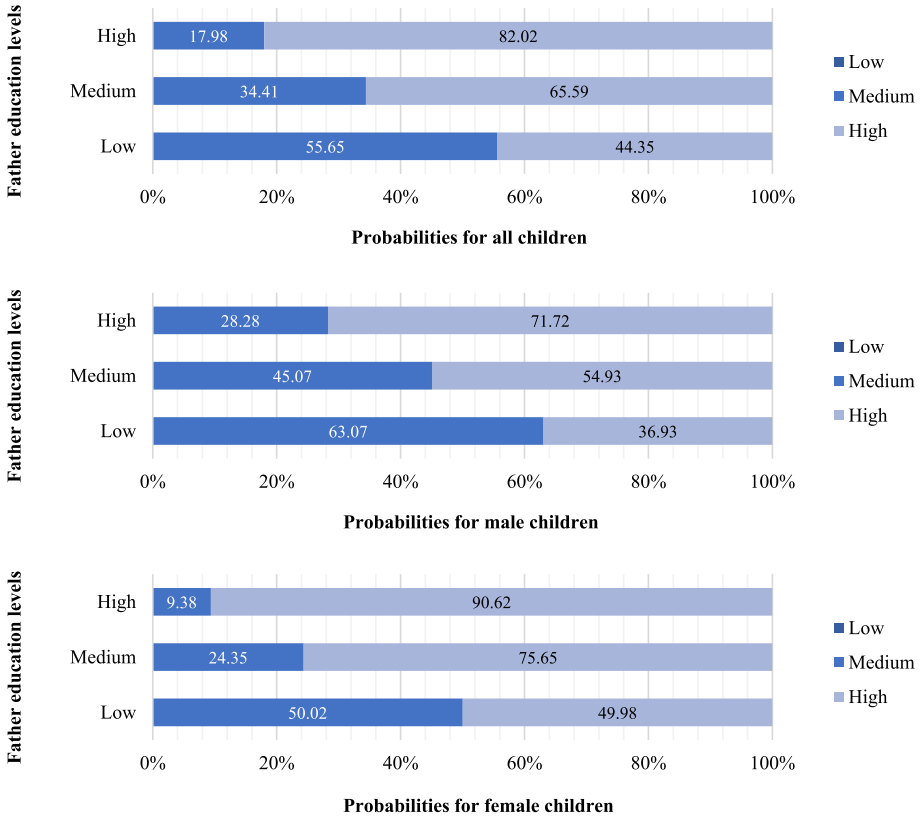

Fig. 2 Intergenerational Transition Probabilities Using an Ordered Logit. Probabilities obtained using an ordered logit are expressed in % and are all statistically significant at 1%. Results can be found in Table 18

5.4 Policy Directions

Although Portugal exhibits a positive evolution in terms of intergenerational mobility, the above results allow us to conclude that differences across groups in the Portuguese economy still exist. This research aims to present the current framework of intergenerational mobility in income and education. Some of our findings are in line with the results of existing research that point to possible mechanisms for the evidence presented and therefore are highlighted when applicable. This does not mean that we are defining causality for the evidence presented, which should be a topic of further research. However, given that there is a likelihood that these factors are possible explanations for the results we get, we address aligned possible policy directions, that should be properly evaluated in what concerns efficiency and applicability, given that these are context-dependent. These are targeted at closing the gap between advantaged and disadvantaged individuals by improving the outcomes of the latter. All of these find support in the World Bank report of Narayan et al. (2018).

First, early childhood development should be part of policymakers' agenda, as it is supposed to make children succeed in school, developing skills that are rewarded later in life through, for example, productivity. A positive empirical relationship with education

Table 7 Results by Own Education Level

	Intergenerational Mobility in Income					Intergenerational Mobility in Education		
Own Education Level	Elasticity	Corr	Rank-rank	Prob	Share	Corr	Prob	Share
Medium n = 1291 | N = 477,439	0.19*** (0.05)	0.13*** (0.04)	0.33*** (0.04)	4.85*** (0.01)	49.44	–	–	87.51
High n = 1258 | N = 502,644	0.18*** (0.05)	0.20*** (0.06)	0.3*** (0.02)	11.51*** (0.02)	56.6	–	–	87.00

Standard errors are in parentheses. *,**,*** stands for statistically significant at 10%, 5%, 1% levels, respectively. Probabilities obtained using an ordered logit and the share of individuals earning more/with more education than their fathers are expressed in %. Correlations and the share of individuals earning more/with more education than their fathers does not have an associated significance level. n stands for the number of observations used and N for the total population represented by those observations using survey weights

mobility is also found in the works of Bauer and Riphahn (2006) for Switzerland and Daude and Robano (2015) for Latin American countries. This also finds support in the theory designed by Daruich (2018) on which the macroeconomic life-cycle general-equilibrium model incorporates parental investments in their children's skills through time and money over several periods. Early childhood development is considered to improve social mobility. It gains relevance since differences and changes in school dropouts may be responsible for the results we present, particularly for the early stages of education. It reinforces the idea of Clements (1999) that with the expansion of preschool as a part of early childhood development, higher educational attainment in a country where low education levels were likely to perpetuate is now in place.

The work of Clements (1999) also shows that offering technology and vocational courses through the regular education system may have led to a considerable increase in the secondary school enrolment rate, which appears to be improved according to the OECD (2019). This highlights the importance of our second policy direction which is the access to education as well as its quality, as found by Chetty et al., (2014, 2020a, 2020b), Chetty and Hendren (2018b) and Hilger (2016) for the USA, Acciari et al. (2022) for Italy, and Nimubona and Vencatachellum (2007) for South Africa. All together appear to ground our result on which more than 80% of individuals attain a higher education level than their fathers and a chance of about 44% of being raised in a low educated environment and reaching the highest education level.

The third policy implication is the basis of the other already described. Now we have the relevance of an efficient investment of public resources in education, by equalizing opportunities across individuals from different backgrounds. First, there is evidence that government expenditures on early education are positively connected with education mobility in the works of Daude and Robano (2015) for Latin America, Urbina (2018) for Mexico and Lee and Lee (2020). This supports the points raised for early childhood development-related policies and their role in achieving better outcomes in the country. For government total spending on education, the same is presented by Chu and Lin (2020) for Taiwan regarding income mobility, Daude and Robano (2015) for Latin American countries, Latif (2017) for Canada, and Urbina (2018) for Mexico regarding education mobility. In the theoretical model of Solon (2004), it is also shown that a progressive public investment

Table 8 Results by Father Education Level

	Intergenerational Mobility in Income					Intergenerational Mobility in Education		
Father Education Level	Elasticity	Corr	Rank-rank	Prob	Share	Corr	Prob	Share
Low n = 2040 | N = 745,593	0.2*** (0.05)	0.12*** (0.03)	0.37*** (0.02)	6.74*** (0.01)	44.38	–	–	100.00
Medium n = 275 | N = 124,035	0.36** (0.15)	0.19** (0.08)	0.49*** (0.08)	9.84* (0.03)	49.44	–	–	66.34
High n = 234 | N = 110,455	0.22 (0.35)	0.06 (0.09)	1.66*** (0.22)	–	17.69	–	–	0.00

Standard errors are in parentheses. *,**,*** stands for statistically significant at 10%, 5%, 1% levels, respectively. Probabilities obtained using an ordered logit and the share of individuals earning more/with more education than their fathers are expressed in %. Correlations and the share of individuals earning more/with more education than their fathers does not have an associated significance level. n stands for the number of observations used and N for the total population represented by those observations using survey weights

in human capital will decrease the income elasticity's steady state value, contributing to promote mobility in income. Our findings suggest that more mobility is associated with a higher education level, so investing in that stage of education is of utmost importance in the Portuguese context.

Connected with higher mobility being verified in high education levels but also in occupations requiring a high education level, easing the access to capital markets through credit to finance not only education but also entrepreneurial undertakings may be another strategy to implement. Becker et al. (2018) developed a stylized model of intergenerational mobility, which is connected with cross-sectional inequality. The authors show that even without credit constraints or innate ability differences, richer parents invest more in their children's education in comparison with poorer ones which reduces intergenerational mobility. Therefore, as pointed in the work of Piketty (2000), it is expected that with credit-constrained economies, as it is the common case, persistence becomes stronger, because parental investments are constrained by the availability of resources, a restriction which impacts to a greater extent the poor.

Policymakers can also target education and income mobility to promote a feedback effect, having a long-term perspective. This is because if the current generation sees its mobility in income improved, their ability to invest in their children is promoted, which impacts education mobility and therefore income mobility again.

6 Conclusion

Published work on intergenerational mobility in Europe has been focused on Scandinavian countries while research on Southern Europe is still limited. In this group, literature is scarce for Portugal in terms of income mobility, although some developments have been made regarding the study of educational mobility. Our work analyses intergenerational mobility in income and education for this country by constructing several relative and absolute measures of intergenerational mobility. For income mobility we compute the intergenerational income elasticity,

Table 9 Results by Own Occupation Category

	Intergenerational Mobility in Income					Intergenerational Mobility in Education		
Own occupation	Elasticity	Corr	Rank-rank	Prob	Share	Corr	Prob	Share
Legislators, senior officials, and managers n = 183 | N = 82,768	0.25(0.15)	0.18(0.10)	0.29***(0.08)	17.87***(0.06)	59.87	0.2***	61.71***(0.05)	82.68
Professionalsn = 858 | N = 328,837	0.15**(0.07)	0.12**(0.06)	0.21***(0.03)	14.87***(0.02)	59.5	0.03	95.27***(0.01)	80.46
Technicians and associate professionals n = 410 | N = 157,272	0.2**(0.09)	0.17**(0.08)	0.36***(0.07)	6.03***(0.02)	52.21	0.2***	33.78***(0.04)	81.45
Clerks n = 298 | N = 110,206	0.02(0.11)	0.02(0.09)	0.11(0.07)	4.51**(0.02)	53.34	0.24**	19.85***(0.03)	88.38
Service workers and shop and market sales workers n = 474 | N = 163,753	0.09(0.08)	0.07(0.06)	0.18**(0.07)	2.62**(0.01)	41.91	0.04	14.67***(0.02)	89.81
Skilled agricultural and fishery workersn = 12 | N = 3318	0.13(0.59)	0.11(0.49)	1.7**(0.75)	-	48.5	0.68*	3.25(0.04)	84.88
Craft and related trades workers n = 103 | N = 44,842	0.31(0.2)	0.19(0.13)	0.32***(0.09)	3.21(0.03)	53.14	0.33	9.78**(0.04)	95.34
Plant and machine operators and assemblers n = 94 | N = 48,608	0.13(0.09)	0.13(0.10)	0.22(0.19)	1.82(0.01)	50.56	0.17	10.01**(0.04)	86.27
Elementary occupations n = 103 | N = 34,717	−0.03(0.12)	−0.02(0.08)	−0.01(0.11)	1.2*(0.01)	36.21	0.38**	9.14**(0.05)	81.92

Standard errors are in parentheses. *,**,*** stands for statistically significant at 10%, 5%, 1% levels, respectively. Probabilities obtained using an ordered logit and the share of individuals earning more/with more education than their fathers are expressed in %. Correlations and the share of individuals earning more/with more education than their fathers does not have an associated significance level. n stands for the number of observations used and N for the total population represented by those observations using survey weights

Table 10 Results by Father Occupation Category

	Intergenerational Mobility in Income					Intergenerational Mobility in Education		
Father occupation	Elasticity	Corr	Rank-rank	Prob	Share	Corr	Prob	Share
Legislators, senior officials, and managersn = 126 | N = 64,302	0.46**(0.22)	0.23**(0.11)	0.75***(0.06)	7.85*(0.05)	41.59	0.16*	71.86***(0.06)	67.36
Professionals								
n = 213 | N = 98,992	0.06(0.27)	0.02(0.09)	0.69***(0.07)	4.42(0.14)	14.58	0.34***	39.18***(0.11)	20.51
Technicians and associate professionalsn = 403 | N = 170,812	0.27*(0.15)	0.12*(0.07)	0.2***(0.06)	15.33*(0.08)	33.14	0.12*	54.01***(0.04)	82.66
Clerksn = 186 | N = 65,185	0.17(0.23)	0.06(0.08)	−0.47***(0.16)	11.92*(0.07)	45.07	0.11	54.65***(0.06)	94.21
Service workers and shop and market sales workersn = 359 | N = 114,019	0.36**(0.15)	0.16**(0.07)	0.69***(0.13)	5.55***(0.02)	41.14	0.1	42.18***(0.04)	93.40
Skilled agricultural and fishery workersn = 122 | N = 26,053	−0.17 (0.35)	−0.05 (0.10)	−1.39*** (0.25)	7.03 (0.05)	80.67	−0.07	31.83*** (0.07)	97.24
Craft and related trades workersn = 593 | N = 246,746	0.12(0.17)	0.04(0.05)	0.13(0.1)	6.2***(0.02)	77.5	0.11*	43.24***(0.03)	96.17
Plant and machine operators and assemblersn = 362 | N = 143,457	0.49**(0.23)	0.01**(0.003)	0.71***(0.04)	5.37**(0.02)	62.59	0.04	35.45***(0.03)	99.01
Elementary occupationsn = 185 | N = 50,517	−0.61(0.6)	− 0.12(0.12)	−1.32***(0.41)	5.54**(0.02)	87.96	0.18	-	100

Standard errors are presented between parentheses. *,**,*** stands for statistically significant at 10%, 5%, 1% levels, respectively. Probabilities obtained using an ordered logit and the share of individuals earning more/with more education than their fathers are expressed in %. Correlations and the share of individuals earning more/with more education than their fathers do not have an associated significance level. n stands for the number of observations used and N for the total population represented by those observations using survey weights

Table 11 Results by Own Income Level

	Intergenerational Mobility in Income					Intergenerational Mobility in Education		
Own income level	Elasticity	Corr	Rank-rank	Prob	Share	Corr	Prob	Share
Low n = 609 | N = 230,374	-0.09 (0.1)	-0.07 (0.08)	-0.03*** (0.01)	–	11.55	0.26***	28.11*** (0.03)	87.15
Medium–low n = 1007 | N = 390,927	0.03** (0.01)	0.10** (0.04)	0.07*** (0.02)	–	55.00	0.22***	37.31*** (0.02)	87.28
Medium–high n = 602 | N = 228,948	0.03*** (0.01)	0.14*** (0.05)	0.06*** (0.01)	–	71.68	0.22***	64.62*** (0.03)	85.23
High n = 331 | N = 129,834	0.14*** (0.05)	0.21*** (0.07)	0.06*** (0.01)	–	88.43	0.19***	69.05*** (0.04)	69.93

Standard errors are in parentheses. *,**,*** stands for statistically significant at 10%, 5%, 1% levels, respectively. Probabilities obtained using an ordered logit and the share of individuals earning more/with more education than their fathers are expressed in %. Correlations and the share of individuals earning more/with more education than their fathers does not have an associated significance level. n stands for the number of observations used and N for the total population represented by those observations using survey weights

the intergenerational correlation coefficient, the rank-rank slope, the share of individuals earning more than their fathers, and the bottom to top income level probability. For education mobility we compute the intergenerational education (Pearson) correlation, the low to high education level probability, and the share of individuals with more education than their fathers. Both income and education mobility measures are complemented by ordered logit transitions matrices. We uncover the patterns that exist and which individual characteristics present more or less mobility, for individuals born in 1968–1988. Both genders are considered. Two Portuguese components of European datasets are used: the European Community Household Panel and the European Union Statistics on Income and Living Conditions.

Our benchmark results reveal gender differences, showing that women generally present higher mobility in income than men, a finding also for Russia, Denmark, the USA, Italy, and in other studies that included Portugal. When considering transition probabilities between income levels, we observe that there is a strong degree of intergenerational mobility when fathers are at the low-income level. At the same time, persistence is high for children born below the medium–high and high income levels. Additionally, upward probabilities decrease the higher the father's income level. Our value estimates are according to estimates previously done. As in the case of income, women have a higher probability of passing from a low to a high education level than men, with previous studies for Portugal reaching lower probabilities than ours. In Portugal the share of individuals with more education than their fathers is higher than 80% and the probability of staying in a low education level, if that is the case of the father, is 0%, a finding that improved relative to other estimates for Portugal and is higher than previous estimates for Hong Kong and Austria. The likelihood that an individual has of reaching or remaining in the high-education level is increasing on the father's education level, confirming published findings.

We analyse intergenerational mobility in different subsamples according to individual characteristics to check which own and father's characteristics are associated with more or less income and education mobility when compared to the benchmark sample. We assess characteristics such as education level, occupation, income level, and status in employment. Contrary to what is found in the literature, individuals with a high education level show higher income and education

Table 12 Results by Father Income Level

	Intergenerational Mobility in Income							Intergenerational Mobility in Education
Father income level	Elasticity	Corr	Rank-rank	Prob	Share	Corr	Prob	Share
Low n = 275 | N = 68,264	5.33 (4.48)	0.18 (0.15)	6.18* (3.17)	-	89.27	0.07	35.68*** (0.05)	98.95
Medium–low n = 1262 | N = 488,814	0.12 (0.12)	0.03 (0.03)	0.22*** (0.02)	-	67.86	0.13***	40.68*** (0.02)	97.84
Medium–high n = 451 | N = 182,071	0.41 (0.37)	0.08 (0.07)	0.82*** (0.17)	-	43.8	0.04	58.67*** (0.04)	91.08
High n = 561 | N = 240,934	0.22 (0.17)	0.08 (0.06)	0.63*** (0.08)	-	19.99	0.33***	47.62*** (0.04)	48.25

Standard errors are in parentheses. *,**,*** stands for statistically significant at 10%, 5%, 1% levels, respectively. Probabilities obtained using an ordered logit and the share of individuals earning more/with more education than their fathers are expressed in %. Correlations and the share of individuals earning more/with more education than their fathers does not have an associated significance level. n stands for the number of observations used and N for the total population represented by those observations using survey weights

Table 13 Results by Status in Employment

	Intergenerational Mobility in Income					Intergenerational Mobility in Education		
	Elasticity	Corr	Rank-rank	Prob	Share	Corr	Prob	Share
Self-employed n = 155 | N = 70,831	0.44** (0.18)	0.23** (0.10)	0.62*** (0.11)	6.76** (0.03)	53.11	0.29***	53.18*** (0.06)	80.64
Employee n = 2260 | N = 851,447	0.23*** (0.04)	0.19*** (0.04)	0.41*** (0.02)	6.61*** (0.01)	53.89	0.25***	42.66*** (0.02)	85.70

Standard errors are in parentheses. *,**,*** stands for statistically significant at 10%, 5%, 1% levels, respectively. Probabilities obtained using an ordered logit and the share of individuals earning more than their fathers are expressed in %. Correlations have the associated significance level of the elasticities used to compute them. The share of individuals earning more than their fathers does not have an associated significance level. n stands for the number of observations used and N for the total population represented by those observations using survey weights

mobility. This is a further advantage of having more education and corroborates the findings for occupations in the legislators, senior officials, and managers and professionals' categories for which mobility in income is higher: they require a higher education level than occupations as skilled agricultural and fishery workers, and plant and machine operators and assemblers, which show lower income mobility when compared to the benchmark sample. Also, individuals with elementary occupations always present lower mobility and mobility in education is higher when fathers work as clerks. Also, a finding against previous literature, children whose fathers have a low education level are those presenting higher relative income mobility. Mobility in income and education is higher for individuals in the medium–high income level and more mobility in education occurs for these individuals when fathers also belong to the medium–high-income level category. However, medium–low income fathers bring more mobility in income to their offspring. Self-employed individuals present lower income mobility when compared to the entire sample. *Vis-à-vis* these results and noting that any policy-making targeting mobility improvements needs a strong study justifying it (meaning we are not addressing causality here), policies such as the ones proposed in Narayan et al. (2018), which promote early childhood development, provide access to quality education, aim to reduce segregation, strengthen institutions and infrastructures, and an efficient public investment in education should help to close the gap between advantaged and disadvantaged individuals and serve as basis for new research on the topic. The same applies to the ease of access to capital markets and a robust economic growth which should have a feedback effect of education and income mobility in future generations.

We have also performed sensitivity analyses to some of our initial methodological hypotheses, namely in terms of income definition (average total income and individual income, parental income, inclusion of individuals with no individual income, co-resident bias, presence of siblings and attenuation bias) to determine if our benchmark results hold. There is some degree of intergenerational persistence in household structure, as reported in previous literature. Furthermore, if we consider four years, instead of one year, to estimate parental income, the designated attenuation bias, this changes the results. However, neither the inclusion of individuals with no individual income or taking in consideration two generations living in the same home affect our benchmark results.

Some shortcomings can be pointed to our work. First, the datasets we use do not provide direct information on father's income when children were around 14 years old. Following the literature, we predict parental income which is not observed, through education, occupation,

and managerial position information, i.e., by using a pseudo-parent's sample, which has implications for results. Second, our datasets provide a set of retrospective questions about parental characteristics, which allow us to predict their income. But the range of available characteristics is insufficient: the higher the number of instruments to proxy for parental permanent income, the more unique values parental income could assume, which increases the heterogeneity of the pseudo-parents' sample. Additionally, there is the potential problem of missing variables, such as industries or sectors of activity and years of experience. However, there are no more retrospective questions reported by children in the EU-SILC survey that could be used to predict their parents' individual income. Regional proxies are a simple example that would fill this need. Third, it is possible to follow individuals in both generations over time, but for the children's subsample this is done at the expense of no retrospective questions about parents, and hence mobility could not be computed. This implies that analyses that require addressing temporal behaviours for the measures we compute to complement our cross-sectional framework cannot be performed. Although we try to make the possible adaptations, the final analysis of the effect of education mobility on income mobility is not performed using the same sample as in the other analysis, which can influence the results. Overcoming these problems would improve our work, although it is a difficult task, since the majority of problems are due to the nature of the data supplied by the existing surveys. Finally, the biases we address are mainly studied in the literature for relative mobility measures, but the restrictions to avoid them should influence absolute mobility measures as well. This topic needs further research. As before, we also recognize the need for future research to investigate what drives mobility in Portugal to uncover which specific policy actions should take place to improve mobility in this country. This can be done by studying the role of different mediators of the relationship between parents and children's incomes, as in the work of Blanden et al. (2005). Finally, given our evidence and that Deutscher and Mazumder (2023) find intergenerational persistence measures and inequality of opportunity to have a strong correlation, we consider that there should be a further analysis with a more profound study about the role of inequality of opportunity in shaping intergenerational mobility. Some research on inequality of opportunity has covered Portugal (e.g., Carranza, 2022), although the relationship between both has not been examined.

Appendix 1: Descriptive Tables

See Tables 14, 15, 16, 17 and 18

Table 14 Summary (unweighted) statistics: pseudo-parents sample

Variables	Obs	Mean	Std. Dev	Min	Max
Age	1025	39.23	5.85	30	50
Education: Low level	1025	0.84	0.36	0	1
Education: Medium level	1025	0.11	0.31	0	1
Education: High level	1025	0.05	0.21	0	1
Main occupation: Legislators, senior officials and managers	1025	0.02	0.13	0	1
Main occupation: Professionals	1025	0.04	0.20	0	1
Main occupation: Technicians and associate professionals	1025	0.09	0.29	0	1
Main occupation: Clerks	1025	0.10	0.30	0	1
Main occupation: Service workers and shop and market sales workers	1025	0.14	0.35	0	1
Main occupation: Skilled agricultural and fishery workers	1025	0.04	0.20	0	1
Main occupation: Craft and related trades workers	1025	0.29	0.45	0	1
Main occupation: Plant and machine operators and assemblers	1025	0.16	0.37	0	1
Main occupation: Elementary occupations	1025	0.12	0.32	0	1
Managerial position: Supervisory	1025	0.07	0.26	0	1
Managerial position: Non-supervisory	1025	0.93	0.26	0	1
Individual income (in logs)	1025	9.07	0.56	6.31	11.03

Table 15 Summary (unweighted) statistics

Variables	Obs	Mean	Std. Dev	Min	Max
Children's characteristics					
Age	2549	40.70	5.93	30	50
Education: low level	2549	0	0	0	0
Education: medium level	2549	0.51	0.50	0	1
Education: high level	2549	0.49	0.50	0	1
Individual income (in logs)	2549	9.10	0.73	4.54	11.64
Father's characteristics (recalled by children)					
Education: low level	2549	0.80	0.40	0	1
Education: medium level	2549	0.11	0.31	0	1
Education: high level	2549	0.09	0.29	0	1
Main occupation: Legislators, senior officials and managers	2549	0.05	0.22	0	1
Main occupation: Professionals	2549	0.08	0.28	0	1
Main occupation: Technicians and associate professionals	2549	0.16	0.36	0	1
Main occupation: Clerks	2549	0.07	0.26	0	1
Main occupation: Service workers and shop and market sales workers	2549	0.14	0.35	0	1
Main occupation: Skilled agricultural and fishery workers	2549	0.05	0.21	0	1
Main occupation: Craft and related trades workers	2549	0.23	0.42	0	1
Main occupation: Plant and machine operators and assemblers	2549	0.14	0.35	0	1
Main occupation: Elementary occupations	2549	0.07	0.26	0	1
Managerial position: Supervisory	2549	0.28	0.45	0	1
Managerial position: Non-supervisory	2549	0.72	0.45	0	1
Father's predicted individual income (in logs)	2549	9.25	0.62	3.95	11.94

Table 16 First stage results: 1995 pseudo-parents' sample

Variable	Benchmark	Education	Occupation	Managerial position	Education and occupation	Education and managerial position	Occupation and managerial position
Education: Low level (omitted)							
Education: Medium level	0.10*	0.32***			0.12**	0.26***	
	(0.06)	(0.08)			(0.06)	(0.07)	
Education: High level	0.46***	1.10***			0.53***	0.84***	
	(0.13)	(0.06)			(0.15)	(0.08)	
Main occupation: Managers (omitted)							
Main occupation: Professionals	0.33**		0.38*		0.18		0.52***
	(0.17)		(0.22)		(0.18)		(0.20)
Main occupation: Technicians and associate professionals	0.19		-0.20		-0.02		0.05
	(0.19)		(0.22)		(0.21)		(0.20)
Main occupation: Clerks	-0.001		-0.51**		-0.29		-0.17
	(0.19)		(0.22)		(0.21)		(0.20)
Main occupation: Service workers and shop and market sales workers	0.05		-0.46**		-0.21		-0.15
	(0.20)		(0.22)		(0.22)		(0.20)
Main occupation: Skilled agricultural and fishery workers	-0.54**		-1.09***		-0.83***		-0.74***
	(0.22)		(0.24)		(0.24)		(0.23)
Main occupation: Craft and related trades workers	-0.28		-0.82***		-0.56***		-0.48**
	(0.19		(0.21)		(0.21)		(0.20)
Main occupation: Plant and machine operators and assemblers	-0.20		-0.73***		-0.47**		-0.40**
	(0.20)		(0.21)		(0.22)		(0.20)
Main occupation: Elementary occupations	-0.55***		-1.09***		-0.84***		-0.75***
	0.21)		(0.22)		(0.23)		(0.21)
Managerial Position: Supervisory	0.40***			0.86***		0.52***	0.53***
	(0.08)			(0.07)		(0.05)	(0.08)
Managerial Position: Non-supervisory (omitted)							
Age	-0.002	0.01	0.01	0.01	0.002	0.005	-0.0001
		(0.06)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)

Table 16 (continued)

Variable	Benchmark	Education	Occupation	Managerial position	Education and occupation	Education and managerial position	Occupation and managerial position
Age^2	0.00005 (0.001)	-0.0001 (0.001)	-0.0001 (0.001)	-0.0001 (0.001)	-6.43e-06 (0.001)	0.00001 (0.001)	0.00001 (0.001)
Intercept	9.20*** (0.95)	8.61*** (1.05)	9.60*** (0.98)	8.64*** (1.06)	9.37*** (0.98)	8.78*** (1.01)	9.38*** (0.95)
No. Of observations	**1025**	**1025**	**1025**	**1025**	**1025**	**1025**	**1025**
Total Population	**774,800**	**774,800**	**774,800**	**774,800**	**774,800**	**774,800**	**774,800**
R^2	**43.13%**	**26.25%**	**38.65%**	**20.28%**	**40.45%**	**31.75%**	**41.83%**

Standard errors are in parentheses. *,**,*** stands for statistically significant at 10%, 5%, 1% levels, respectively. Parental individual income (in logs) is predicted at the age of 40 years old

Table 17 Predicted Probabilities for Income Mobility using an Ordered Logit

	Father Income Levels	Children's Income Levels			
		Low	Medium–low	Medium–high	High
All individuals	Low n = 275 | N = 68,264	35.88*** (0.02)	40.86*** (0.01)	16.11*** (0.01)	7.15*** (0.01)
	Medium–low n = 1262 | N = 488,814	27.27*** (0.01)	41.59*** (0.01)	20.83*** (0.01)	10.31*** (0.01)
	edium–high n = 451 | N = 182,071	20.08*** (0.01)	39.62*** (0.01)	25.65*** (0.01)	14.65*** (0.01)
	High n = 561 | N = 240,934	14.41*** (0.01)	35.41*** (0.02)	29.79*** (0.02)	20.39*** (0.02)
Males	Low n = 98 | N = 29,180	31.65*** (0.03)	42.83*** (0.02)	17.32*** (0.02)	8.20*** (0.01)
	Medium–low n = 484 | N = 203,553	23.47*** (0.02)	42.43*** (0.02)	22.21*** (0.02)	11.89*** (0.01)
	Medium–high n = 185 | N = 81,735	16.88*** (0.02)	39.25*** (0.02)	26.94*** (0.02)	16.93*** (0.02)
	High n = 260 | N = 117,382	11.85*** (0.02)	34.01*** (0.02)	30.59*** (0.02)	23.55*** (0.03)
Females	Low n = 177 | N = 39,084	38.56*** (0.03)	39.6*** (0.02)	15.42*** (0.02)	6.42*** (0.01)
	Medium–low n = 778 | N = 285,261	30.07*** (0.02)	40.96*** (0.02)	19.87*** (0.01)	9.10*** (0.01)
	Medium–high n = 266 | N = 100,336	22.76*** (0.02)	39.93*** (0.02)	24.56*** (0.02)	12.75*** (0.01)
	High n = 301 | N = 123,552	16.79*** (0.02)	36.72*** (0.02)	28.91*** (0.02)	17.58*** (0.02)

Standard errors are in parentheses. *,**,*** stands for statistically significant at 10%, 5%, 1% levels, respectively. Probabilities are expressed in %. n stands for the number of observations used and N for the total population represented by those observations using survey weights

Table 18 Predicted Probabilities for Education Mobility using an Ordered Logit

	Father Education Levels	Children's Education Levels	
		Medium	High
All individuals	Low n = 2040 | N = 745,593	55.65*** (0.01)	44.35*** (0.01)
	Medium n = 275 | N = 124,035	34.41*** (0.02)	65.59*** (0.02)
	High n = 234 | N = 110,455	17.98*** (0.03)	82.02*** (0.03)
Males	Low n = 800 | N = 321,123	63.07*** (0.02)	36.93*** (0.02)
	Medium n = 131 | N = 60,726	45.07*** (0.03)	54.93*** (0.03)
	High n = 96 | N = 50,001	28.28*** (0.05)	71.72*** (0.05)
Females	Low n = 1240 | N = 424,470	50.02*** (0.02)	49.98*** (0.02)
	Medium n = 144 | N = 63,309	24.35*** (0.02)	75.65*** (0.02)
	High n = 138 | N = 60,454	9.38*** (0.02)	90.62*** (0.02)

Standard errors are in parentheses. *,**,*** stands for statistically significant at 10%, 5%, 1% levels, respectively. Probabilities are expressed in %. n stands for the number of observations used and N for the total population represented by those observations using survey weights

Appendix 2: Sensitivity Analysis

In this section, we check how sensitive our benchmark estimates of intergenerational mobility are to changes in variables definitions and sample construction.

Income Definitions

We start by considering different income definitions. We use individual income as opposed to the benchmark estimation in which the average couples' income is used. We are able to do this exercise just for children, not only because the characteristics used to proxy for father's permanent income pertain to individual income, but also because the father's marital status is not known. Results are presented in Table 19.

The intergenerational income elasticity and the share of individuals earning more than their fathers are the ones for which there is only a slight increase in persistence compared to the benchmark (and therefore they may be considered as reasonably robust to the income definition). On other hand, when analysing the intergenerational income correlation and the rank-rank slope, one may conclude that there is a change of about 10% and 13%, respectively, meaning that persistence is higher in the first scenario. The bottom to top income level probability shows a 31% increase between the two cases (7.15% in the benchmark compared to 9.36% when using an individual measure of income), which is the biggest

Table 19 Sensitivity of intergenerational mobility in income to alternative income definitions for the benchmark sample

	Income definitions for children	Elasticity	Correlation	Rank-rank slope	Prob	Share
All individuals n = 2549 N = 980,083	Average total family income	0.26*** (0.04)	0.20*** (0.03)	0.45*** (0.01)	7.15*** (0.01)	53.11
	Individual income only	0.27*** (0.05)	0.18*** (0.03)	0.39*** (0.01)	9.36*** (0.01)	52.30
Males n = 1027 N = 431,849	Average total family income	0.30*** (0.05)	0.24*** (0.04)	0.48*** (0.02)	8.21*** (0.01)	52.90
	Individual income only	0.27*** (0.07)	0.18*** (0.05)	0.31*** (0.02)	16.1*** (0.02)	59.30
Females n = 1522 N = 548,234	Average total family income	0.22*** (0.06)	0.17*** (0.04)	0.42*** (0.02)	6.42*** (0.01)	53.28
	Individual income only	0.23*** (0.06)	0.16*** (0.04)	0.40*** (0.02)	5.14*** (0.01)	46.49

Standard errors are in parentheses. *,**,*** stands for statistically significant at 10%, 5%, 1% levels, respectively. Probabilities obtained using an ordered logit and the share of individuals earning more than their fathers are expressed in %. Correlations have the associated significance level of the elasticities used to compute them. The share of individuals earning more than their fathers does not have an associated significance level. n stands for the number of observations used and N for the total population represented by those observations using survey weights

change. This is in line with relative persistence increases when using household related measures in the work of Murray et al. (2018). Although the most obvious reason for the correlation change is related with the increase in the variability in children's income, when considering individual income, it is likely that assortative mating had play its role for both measures: this is the process according to which individuals select a partner with similar backgrounds. Torche (2015) argues that if the characteristics of individuals with which one shares a life are approximately the same, it is therefore expected that persistence will be higher in those cases, when compared to the scenario for which this type of mating does not occur. A simple exercise allows us to have a clue on the likelihood this has of occurring in our estimation sample. About 32.19% of individuals who are married and have fathers in the medium–high and high-income levels, have selected individuals with fathers in those same levels. The scenario is more evident when considering married individuals with parents in the low and medium–low income levels, with that share being approximately 43.74%.

When individual income is considered, men have the intergenerational income correlation and the rank-rank slope decreasing more than women. Persistence increases when the couples' income is considered, with a higher percentage change for men. This may reflect the fact that men are more likely to be married to individuals with similar backgrounds than women. From the medium–low parental income level on, the shares of men in this situation are approximately 51.37, 31.29, and 34.12% against 48.95, 29.14, and 33.43% for women. The exception is the low level, where women surpass men by 2% points, with a share equal to 4%. Interestingly, absolute persistence for men increases when the couples' income is used in comparison with individual income (the opposite occurs for women, who benefit in terms of mobility when average couples' income is considered).

All in all, the exercise of using individual income instead of average couple's income provides different results from the benchmark analysis. This reinforces our

decision to consider average total income instead of individual income only, since the marital status of individuals plays a role. In other words, the point made by Chadwick and Solon (2002) is clear: there is some degree of intergenerational persistence in household structure which cannot be ignored.

Alternative Specifications for Parental Income

As mentioned above, it is likely that our estimators may suffer from an upward bias, since the instruments used to proxy parental permanent income and then predict the current income may be endogenous. Table 20 presents our estimates using different combinations of the available instruments (we exclude those using one instrument only).

Results are robust to this sensitivity exercise with the exception of the rank-rank slope, which is unstable when different combinations of instruments are considered. This makes us unable to guarantee the direction of the bias which is very likely to be present and may be a consequence of not observing parental income. However, we also recognize that the case with more instruments makes the rank-rank slope more efficient, with lower standard errors.

Inclusion of Individuals with No Individual Income

There may exist mobility mismeasurement in our benchmark analysis by including only individuals that work. Hence, we tested the sensitivity of the results by including individuals with no individual income derived from work. Results are presented in Table21

Results are almost unchanged for all measures, both for all individuals and for each gender. Percentage changes in the estimates are no higher than 5%.

Co-residents Bias

Following Azam and Bhatt (2015), the co-resident bias may exist in our context. The idea is that if parents are part of the same household as children, they can still influence their offspring's decisions about education. The authors point out that the use of samples with co-residents (children-parents) may lead to problems related to sample selection, as co-resident individuals may not represent the adult population. We consider this to be true also for work-related decisions and therefore income, although published research is mainly related to education. Our benchmark sample includes not only co-resident fathers and children, but also individuals who do not live with their fathers. Now, we compare the original estimates to a sample with no co-residents and see whether the results change significantly. Results are presented in Table 22 for income mobility and Table 23 for educational mobility.

Table 20 Sensitivity of Intergenerational Mobility in Income to Alternative Instruments for Father Income for the Benchmark Sample

	Instruments	Elasticity	Correlation	Rank-rank slope	Prob	Share
All individuals n = 2549 | N = 980,083	Education, managerial position	0.26*** (0.04)	0.19*** (0.03)	3.75*** (0.06)	6.99*** (0.01)	55.66
	Occupation, managerial position	0.25*** (0.04)	0.28*** (0.04)	1.12*** (0.02)	7.13*** (0.01)	50.85
	Education, occupation	0.27*** (0.04)	0.20*** (0.03)	0.99*** (0.02)	6.95*** (0.01)	56.04
	Education, occupation, managerial position	0.26*** (0.04)	0.20*** (0.03)	0.45*** (0.01)	7.15*** (0.01)	53.11
Males n = 1027 | N = 431,849	Education, managerial position	0.31*** (0.06)	0.23*** (0.04)	3.98*** (0.12)	7.51*** (0.01)	59.07
	Occupation, managerial position	0.28*** (0.05)	0.22*** (0.04)	1.16*** (0.05)	8.17*** (0.01)	51.08
	Education, occupation	0.31*** (0.06)	0.23*** (0.05)	1*** (0.05)	8.05*** (0.13)	57.19
	Education, occupation, managerial position	0.3*** (0.05)	0.24*** (0.04)	0.48*** (0.02)	8.21*** (0.01)	52.9
Females n = 1522 | N = 548,234	Education, managerial position	0.22*** (0.07)	0.15*** (0.05)	3.45*** (0.07)	6.53*** (0.01)	52.98
	Occupation, managerial position	0.21*** (0.06)	0.17*** (0.04)	1.06*** (0.03)	6.4*** (0.01)	50.67
	Education, occupation	0.24*** (0.06)	0.17*** (0.04)	0.96*** (0.04)	6.15*** (0.01)	55.12
	Education, occupation, managerial position	0.22*** (0.06)	0.17*** (0.04)	0.42*** (0.02)	6.42*** (0.01)	53.28

Standard errors are in parentheses. *,**,*** stands for statistically significant at 10%, 5%, 1% levels, respectively. Probabilities obtained using an ordered logit and the share of individuals earning more than their fathers are expressed in %. Correlations have the associated significance level of the elasticities used to compute them. The share of individuals earning more than their fathers does not have an associated significance level. n stands for the number of observations used and N for the total population represented by those observations using survey weights

Table 21 Sensitivity of Intergenerational Mobility in Income to the Inclusion of Individuals with no Individual Income

		Elasticity	Correlation	Rank-rank slope	Prob	**Share**
All individuals	Benchmark sample n = 2549 | N = 980,083	0.26*** (0.04)	0.20*** (0.03)	0.45*** (0.01)	7.15*** (0.01)	**53.11**
	Considering individuals with no individual income n = 2665 | N = 1,024,434	0.27*** (0.04)	0.20*** (0.03)	0.45*** (0.01)	6.93*** (0.01)	51.84
Males	Benchmark sample n = 1027 | N = 431,849	0.3*** (0.05)	0.24*** (0.04)	0.48*** (0.02)	8.21*** (0.01)	**52.9**
	Considering individuals with no individual income n = 1059 | N = 441,624	0.31*** (0.06)	0.24*** (0.04)	0.48*** (0.02)	8.11*** (0.01)	52.1
Females	Benchmark sample n = 1522 | N = 548,234	0.22*** (0.06)	0.17*** (0.04)	0.42*** (0.02)	6.42*** (0.01)	**53.28**
	Considering individuals with no individual income n = 1606 | N = 582,810	0.23*** (0.06)	0.17*** (0.04)	0.41*** (0.02)	6.14*** (0.01)	51.64

Standard errors are in parentheses. *,**,*** stands for statistically significant at 10%, 5%, 1% levels, respectively. Probabilities obtained using an ordered logit and the share of individuals earning more than their fathers are expressed in %. Correlations have the associated significance level of the elasticities used to compute them. The share of individuals earning more than their fathers does not have an associated significance level. n stands for the number of observations used and N for the total population represented by those observations using survey weights

Table 22 Sensitivity of Intergenerational Mobility in Income to the Exclusion of Co-residents

		Elasticity	Correlation	Rank-rank slope	Prob
All individuals	Benchmark sample n = 2549 | N = 980,083	0.26***(0.04)	0.20***(0.03)	0.45***(0.01)	7.15***(0.01)
	Without co-resident fathers n = 2279 | N = 901,644	0.27***(0.04)	0.21***(0.03)	0.47***(0.02)	7.42***(0.01)
Males	Benchmark sample n = 1027 | N = 431,849	0.3***(0.05)	0.24***(0.04)	0.48***(0.02)	8.21***(0.01)
	Without co-resident fathers n = 902 | N = 395,392	0.31***(0.06)	0.25***(0.04)	0.5***(0.03)	8.41***(0.01)
Females	Benchmark sample n = 1522 | N = 548,234	0.22***(0.06)	0.17***(0.04)	0.42***(0.02)	6.42***(0.01)
	Without co-resident fathersn = 1377 | N = 506,252	0.23***(0.07)	0.18***(0.05)	0.43***(0.02)	6.69***(0.01)

Standard errors are in parentheses. *,**,*** stands for statistically significant at 10%, 5%, 1% levels, respectively. Probabilities obtained using an ordered logit and the share of individuals earning more than their fathers are expressed in %. Correlations have the associated significance level of the elasticities used to compute them. The share of individuals earning more than their fathers does not have an associated significance level. n stands for the number of observations used and N for the total population represented by those observations using survey weights

Overall, we can observe a slight change in the income mobility measures when comparing the original (benchmark) sample and the one without co-residents, i.e., an increase in persistence. However, although differences exist, the sizes of the potential biases may be considered negligible, as mobility measures are around the same values with and without co-residents in the sample. Previous literature on the topic, (e.g., Nicoletti & Francesconi, 2006) found a lower intergenerational income elasticity when using a sample of co-residents, only in comparison with a sample of parents and children who do not co-reside.

For education, marginal differences are also verified. The work of Muñoz and Siravegna (2023), who use the first two measures, confirms this behaviour.

Summing up, both income and education mobility sensitivity analysis contain similar results to the benchmark estimates. Almost unchanged results may result from the small disparity regarding the sizes of the samples represented in the two scenarios analysed. This happens because there is not a high degree of co-residency. Our evidence is consistent with individuals leaving their parents' home, on average, before their 30 s. According to the Eurostat,[29] in 2018 the estimated age at which young people leave their parents' home is 26.3 years (27.2 for males and 25.2 for females) for the EU-27—below Portugal, for which the age is around 28.2 years old (29.9 for men and 28 for women). In turn, the influence parents might exert on children is residual and this bias can also be ignored.

[29] https://ec.europa.eu/eurostat/databrowser/view/ILC_LVPS08$DV_1041/default/table?lang=en

Table 23 Sensitivity of Intergenerational Mobility in Education to the Exclusion of Co-residents

		Corr	Prob	Share
All individuals	Benchmark sample n = 2549 | N = 980,083	0.26***	44.35*** (0.01)	84.47
	Without co-resident fathers n = 2279 | N = 901,644	0.26***	44.69*** (0.02)	84.66
Males	Benchmark sample n = 1027 | N = 431,849	0.24***	36.93*** (0.02)	82.54
	Without co-resident fathers n = 902 | N = 395,392	0.24***	37.19*** (0.02)	82.80
Females	Benchmark sample n = 1522 | N = 548,234	0.29***	49.98*** (0.02)	85.99
	Without co-resident fathers n = 1377 | N = 506,252	0.28***	50.36*** (0.02)	86.11

Standard errors are in parentheses. *,**,*** stands for statistically significant at 10%, 5%, 1% levels, respectively. Probabilities obtained using an ordered logit and the share of individuals with more education than their fathers are expressed in %. The share of individuals with more education than their fathers does not have an associated significance level. n stands for the number of observations used and N for the total population represented by those observations using survey weights

Siblings

We also analyse the role of siblings in influencing our benchmark mobility measures, because they share many characteristics that are specific to their family, namely parental involvement, schools or neighbourhoods. Therefore, their socioeconomic status may be strongly correlated (Fletcher et al., 2023), and may influence the mobility estimates made for income and education. In the same line as the analysis for co-residents, the use of samples with over-representation of siblings may lead to problems related to sample selection, since they do not represent the adult population. Our benchmark sample includes individuals together with their brothers and sisters. This way, we evaluate if results are influenced by the existence of such relationships. Results are presented in Tables 24 and 25 for income and educational mobility, respectively.

Overall, most mobility values remain unchanged, when the benchmark sample and the one with no siblings are compared. The differences are predominant in the bottom to top income level probability and the share of individuals earning more than their fathers. Nevertheless, these differences are negligible and therefore can be discarded along with any potential bias.

For education, again relative mobility does not appear to change, while for absolute mobility the differences that take place are too small.

We can conclude that our benchmark evidence for income and education is robust to the exclusion of siblings. As it occurred in the case of co-residency, the sample size of siblings is not large, which makes these sensitivity results very similar to the benchmark ones.

Attenuation Bias

For the parental income measure, we now compare our benchmark estimates using a single year to an estimate obtained by using a 4 year period average. Here the estimates based on income measured using a single year will be different from the ones presented in Table 3. This is because we must ensure that the pseudo-parental sample remains

Table 24 Sensitivity of Intergenerational Mobility in Income to the Exclusion of Siblings

		Elasticity	Correlation	Rank-rank slope	Prob	Share
All individuals	Benchmark sample n = 2549 | N = 980,083	0.26*** (0.04)	0.20*** (0.03)	0.45*** (0.01)	7.15*** (0.01)	53.11
	Without siblings n = 2519 | N = 973,655	0.26*** (0.04)	0.20*** (0.03)	0.45*** (0.01)	7.20*** (0.01)	53.10
Males	Benchmark sample n = 1027 | N = 431,849	0.3*** (0.05)	0.24*** (0.04)	0.48*** (0.02)	8.21*** (0.01)	52.9
	Without siblings n = 1010 | N = 428,503	0.3*** (0.06)	0.24*** (0.03)	0.48*** (0.02)	8.19*** (0.01)	52.8
Females	Benchmark sample n = 1522 | N = 548,234	0.22*** (0.06)	0.17*** (0.04)	0.42*** (0.02)	6.42*** (0.01)	53.28
	Without siblings n = 1509 | N = 545,152	0.22*** (0.06)	0.17*** (0.03)	0.41*** (0.02)	6.52*** (0.01)	53.32

Standard errors are in parentheses. *,**,*** stands for statistically significant at 10%, 5%, 1% levels, respectively. Probabilities obtained using an ordered logit and the share of individuals earning more than their fathers are expressed in %. Correlations have the associated significance level of the elasticities used to compute them. The share of individuals earning more than their fathers does not have an associated significance level. n stands for the number of observations used and N for the total population represented by those observations using survey weights

Table 25 Sensitivity of Intergenerational Mobility in Education to the Exclusion of Siblings

		Corr	Prob	Share
All individuals	Benchmark sample n = 2549 | N = 980,083	0.26***	44.35***(0.01)	84.47
	Without siblings n = 2519 | N = 973,655	0.26***	44.41***(0.01)	84.52
Males	Benchmark sample n = 1027 | N = 431,849	0.24***	36.93***(0.02)	82.54
	Without siblings n = 1010 | N = 428,503	0.24***	37.14***(0.02)	82.59
Females	Benchmark sample n = 1522 | N = 548,234	0.29***	49.98***(0.02)	85.99
	Without siblings n = 1509 | N = 545,152	0.29***	49.91***(0.02)	86.03

Standard errors are in parentheses. *,**,*** stands for statistically significant at 10%, 5%, 1% levels, respectively. Probabilities obtained using an ordered logit and the share of individuals with more education than their fathers are expressed in %. The share of individuals with more education than their fathers does not have an associated significance level. n stands for the number of observations used and N for the total population represented by those observations using survey weights

constant from year 1 to year 4 for results to be comparable. In other words, we have to guarantee that the same individuals remain in the different survey waves used to compute the average incomes. This allows us to make some inference about what might happen to our main estimates if we were able to keep the entire initial pseudo-parents sample, which would guarantee that the differences are mainly due to the number of years used to compute parental average income, instead of changes in the sample composition (Murray et al., 2018). According to Solon (1992), the larger the number of periods used to compute the parental average income, the more reduced the attenuation bias should

Table 26 Sensitivity of Intergenerational Mobility in Income to Attenuation Bias

	Number of periods	Elasticity	Correlation	Rank-rank slope	Prob	Share
All individuals n = 2549 N = 980,083	1 year	0.23*** (0.04)	0.17*** (0.03)	0.52*** (0.02)	8.13*** (0.01)	58.37
	4 years	0.28*** (0.04)	0.21*** (0.03)	0.64*** (0.02)	6.55*** (0.01)	48.73
Males n = 1027 N = 431,849	1 year	0.28*** (0.06)	0.22*** (0.05)	0.56*** (0.04)	8.69*** (0.02)	58.65
	4 years	0.33*** (0.06)	0.25*** (0.05)	0.67*** (0.03)	7.35*** (0.01)	49.41
Females n = 1522 N = 548,234	1 year	0.19*** (0.07)	0.13*** (0.05)	0.47*** (0.03)	7.70*** (0.01)	58.16
	4 years	0.24*** (0.06)	0.17*** (0.05)	0.59*** (0.02)	5.95*** (0.01)	48.19

Standard errors are in parentheses. *,**,*** stands for statistically significant at 10%, 5%, 1% levels, respectively. Probabilities obtained using an ordered logit and the share of individuals earning more than their fathers are expressed in %. Correlations have the associated significance level of the elasticities used to compute them. The share of individuals earning more than their fathers does not have an associated significance level. n stands for the number of observations used and N for the total population represented by those observations using survey weights

be regarding the intergenerational income elasticity. The same can be considered for the rank-rank slope as shown in Chetty et al. (2014). Results are presented in Table 26.[30]

See Table 26

Regarding the intergenerational income elasticity, when we increase the time on which parental individual income is averaged to four years, we obtain an estimate that is 22% higher (from about 0.23 to 0.28). Mazumder (2005) simulates by how much intergenerational elasticity is attenuated when considering several periods on which they average parental income. The author shows that when four years are used, the estimates may be downward biased by about 31.3%. Our evidence suggests that attenuation bias plays a considerable role in our estimates. If we perform the same exercise as Mazumder (2005) on our benchmark estimates using the corresponding attenuation factor for a single year (0.526), the intergenerational income elasticity in Table 3 should be approximately 0.49 instead of 0.26. For men this would compute an elasticity of 0.57 instead of 0.3 and for girls 0.42 instead of 0.22. This attenuation bias would change the benchmark correlations as well: for children, males, and females, they would be equal to 0.38 instead of 0.20, 0.46 instead of 0.24, and 0.32 instead of 0.17, respectively.[31]

Nybom and Stuhler (2017) and Murray et al. (2018) find the rank-rank specification to be more robust to attenuation bias than the log–log specification. Our estimates for the elasticity and rank slope may have also increased more than in some works (23% from 0.52 to 0.64 in our case), which use family income as a measure for parental income. This is the case of Chetty et al. (2014), who consider that in this context using individual measures of economic status, such as individual income, may lead to larger differences when

[30] For children, we could use longitudinal samples to also address the attenuation bias, but these do not contain retrospective information on parents. Besides, we cannot link longitudinal to the cross-sectional waves where that information would be available.

[31] We cannot state that, in opposition to our previous finding, results for Portugal would now be part of the most persistent countries in the literature, since the studies used for comparison can also suffer from attenuation bias: if this is true, the relative positions of the countries should remain the same.

comparing estimates for different period averages because individual income fluctuates more across years. Income measured on a single year should also be noisy for the measures not directly influenced by the attenuation bias: we have a pattern of mobility declining for the remaining measures. Concerning the bottom to top income level probability, there is a fall of 19% (from 8.13 to 6.55%), and in the case of the share of individuals earning more than their fathers this measure falls 17% (from 58.37 to 48.73%). Gender patterns are similar to the findings for the benchmark sample.

Appendix 3: The Relationship between Relative Mobility in Income and Education

As pointed out by Narayan et al. (2018), mobility in education and mobility in income should be related. The authors argue that this relationship is likely to be positive because income persistence is verified due to the endowments that are inherited and to the investments parents make in children, namely their education. Restuccia and Urrutia (2004) and Marrero and Rodriguez (2013) find that education is an important factor for economic persistence. Hence, we can formalize their relationship as follows.

Theorem A1

Assuming that the logged current income of parents, y_{it}^{p}, is orthogonal with respect to the age of children, A_{it}^{c}, and its squared, $A_{it}^{c\,2}$, the responsiveness of intergenerational relative mobility in income (β_1) to marginal changes in intergenerational relative mobility in education (∂_1) is given by considering the model defined by

$$\frac{d\beta_1}{d\partial_1} = \varrho^{c}\varrho^{p} Var\left(Ed_{it}^{p}\right)\left[Var\left(y_{it}^{p}\right)\right]^{-1} \geq 0$$

$$\begin{cases} y_{it}^{c} = \varrho^{c} Ed_{it}^{c} + \chi'^{c} W_{it}^{c} + u_{it}^{c} \\ y_{it}^{p} = \varrho^{p} Ed_{it}^{p} + \chi'^{p} W_{it}^{p} + u_{it}^{p} \\ y_{it}^{c} = \beta_0 + \beta_1 y_{it}^{p} + \gamma_1^{c} A_{it}^{c} + \gamma_2^{c} A_{it}^{c\,2} + \alpha_{it} \\ Ed_{i}^{c} = \partial_0 + \partial_1 Ed_{i}^{p} + \pi_i \end{cases}$$

where the first two equations reflect, for children and for parents, respectively, the Mincer (1974) wage equations, which measure the change in logged current income (y_{it}) due to an additional year of current maximum education attained (Ed_{it}), reflected by ϱ, after controlling for other factors (W_{it}); the third regression corresponds to the standard equation used to estimate the intergenerational income elasticity; the last expression estimates the relationship between the maximum years of education attained of parents and children; and u_{it}, α_{it} and π_i are the error terms. The proof of this theorem is presented below.

Proof of Theorem A1

We have that $\beta_1 = \frac{Cov(y_{it}^{c}, y_{it}^{p})}{Var(y_{it}^{p})}$, which, for the Mincer-type equation implies[32]:

$$\beta_1 = \frac{Cov\left(\varrho^{c} Ed_{i}^{c} + \chi'^{c} W_{i}^{c} + u_{i}^{c}, \varrho^{p} Ed_{i}^{p} + \chi'^{p} W_{i}^{p} + u_{i}^{p}\right)}{Var\left(\varrho^{p} Ed_{i}^{p} + \chi'^{p} W_{i}^{p} + u_{i}^{p}\right)}$$

$$= \frac{\varrho^{c}\varrho^{p} Cov\left(Ed_{i}^{c}, Ed_{i}^{p}\right) + Cov\left(\chi'^{c} W_{i}^{c} + u_{i}^{c}, \varrho^{p} Ed_{i}^{p}\right) + Cov\left(\varrho^{c} Ed_{i}^{c} + \chi'^{c} W_{i}^{c} + u_{i}^{c}, \chi'^{p} W_{i}^{p} + u_{i}^{p}\right)}{Var\left(\varrho^{p} Ed_{i}^{p} + \chi'^{p} W_{i}^{p} + u_{i}^{p}\right)} =$$

[32] We will omit the subscript t for simplicity.

$$= \frac{\varrho^c\varrho^p\partial_1 Var\left(Ed_i^p\right) + Cov\left(\chi'^c W_i^c + u_i^c, \varrho^p Ed_i^p\right) + Cov\left(\varrho^c Ed_i^c + \chi'^c W_i^c + u_i^c, \chi'^p W_i^p + u_i^p\right)}{Var\left(\varrho^p Ed_i^p + \chi'^p W_i^p + u_i^p\right)}$$

$$= \frac{\varrho^c\varrho^p\partial_1 Var\left(Ed_i^p\right) + Cov\left(\chi'^c W_i^c + u_i^c, \varrho^p Ed_i^p\right) + Cov\left(\varrho^c Ed_i^c + \chi'^c W_i^c + u_i^c, \chi'^p W_i^p + u_i^p\right)}{(\varrho^p)^2 Var\left(Ed_i^p\right) + Var\left(\chi'^p W_i^p\right) + Var\left(u_i^p\right) + 2\varrho^p Cov\left(Ed_i^p, \chi'^p W_i^p\right)}$$

$$= \frac{\varrho^c\varrho^p\partial_1 + \frac{Cov\left(\chi'^c W_i^c + u_i^c, \varrho^p Ed_i^p\right) + Cov\left(\varrho^c Ed_i^c + \chi'^c W_i^c + u_i^c, \chi'^p W_i^p + u_i^p\right)}{Var\left(Ed_i^p\right)}}{(\varrho^p)^2 + \frac{Var\left(\chi'^p W_i^p\right)}{Var\left(Ed_i^p\right)} + \frac{Var\left(u_i^p\right)}{Var\left(Ed_i^p\right)} + 2\varrho^p \frac{Cov\left(Ed_i^p, \chi'^p W_i^p\right)}{Var\left(Ed_i^p\right)}}$$

We are now able to uncover how mobility in income responds to changes in mobility in education:

$$\begin{aligned}
\frac{d\beta_1}{d\partial_1} &= \frac{\varrho^c\varrho^p}{(\varrho^p)^2 + \frac{Var\left(\chi'^p W_i^p\right)}{Var\left(Ed_i^p\right)} + \frac{Var\left(u_i^p\right)}{Var\left(Ed_i^p\right)} + 2\varrho^p \frac{Cov\left(Ed_i^p, \chi'^p W_i^p\right)}{Var\left(Ed_i^p\right)}} \\
&= \frac{1}{\frac{\varrho^p}{\varrho^c} + \frac{1}{\varrho^c\varrho^p}\frac{Var\left(\chi'^p W_i^p + u_i^p\right)}{Var\left(Ed_i^p\right)} + 2\frac{Cov\left(Ed_i^p, \chi'^p W_i^p\right)}{Var\left(Ed_i^p\right)}} \\
&= \frac{1}{\frac{\varrho^p}{\varrho^c} + \frac{1}{\varrho^c\varrho^p}\frac{Var\left(\chi'^p W_i^p + u_i^p\right)}{Var\left(Ed_i^p\right)} + \frac{2}{\varrho^c}\frac{Cov\left(Ed_i^p, \chi'^p W_i^p\right)}{Var\left(Ed_i^p\right)}} \\
&= \frac{1}{\frac{\varrho^p}{\varrho^c} + \frac{1}{\varrho^c\varrho^p}\frac{Var\left(y_i^p - \varrho^p Ed_i^p\right)}{Var\left(Ed_i^p\right)} + \frac{2}{\varrho^c}\frac{Cov\left(Ed_i^p, \chi'^p W_i^p\right)}{Var\left(Ed_i^p\right)}} \\
&= \frac{1}{\frac{\varrho^p}{\varrho^c} + \frac{1}{\varrho^c\varrho^p}\frac{Var\left(y_i^p\right) + (\varrho^p)^2 Var\left(Ed_i^p\right) - 2\varrho^p Cov\left(\hat{y}_{it}^p, Ed_i^p\right)}{Var\left(Ed_i^p\right)} + \frac{2}{\varrho^c}\frac{Cov\left(Ed_i^p, \chi'^p W_i^p\right)}{Var\left(Ed_i^p\right)}} \\
&= \frac{1}{\frac{2\varrho^p}{\varrho^c} + \frac{1}{\varrho^c\varrho^p}\frac{Var\left(y_i^p\right)}{Var\left(Ed_i^p\right)} + \frac{2}{\varrho^c}\left[\frac{Cov\left(Ed_i^p, \chi'^p W_i^p\right) - Cov\left(y_i^p, Ed_i^p\right)}{Var\left(Ed_i^p\right)}\right]} \\
&= \frac{1}{\frac{2\varrho^p}{\varrho^c} + \frac{1}{\varrho^c\varrho^p}\frac{Var\left(y_i^p\right)}{Var\left(Ed_i^p\right)} + \frac{2}{\varrho^c}\left[\frac{Cov\left(Ed_i^p, \chi'^p W_i^p - y_i^p\right)}{Var\left(Ed_i^p\right)}\right]} \\
&= \frac{1}{\frac{2\varrho^p}{\varrho^c} + \frac{1}{\varrho^c\varrho^p}\frac{Var\left(y_i^p\right)}{Var\left(Ed_i^p\right)} + \frac{2}{\varrho^c}\left[\frac{Cov\left(Ed_i^p, -\varrho^p Ed_i^p - u_i^p\right)}{Var\left(Ed_i^p\right)}\right]} = \frac{1}{\frac{2\varrho^p}{\varrho^c} + \frac{1}{\varrho^c\varrho^p}\frac{Var\left(y_i^p\right)}{Var\left(Ed_i^p\right)} + \frac{2}{\varrho^c}\left[\frac{Cov\left(Ed_i^p, -\varrho^p Ed_i^p\right)}{Var\left(Ed_i^p\right)}\right]} \\
&= \frac{1}{\frac{2\varrho^p}{\varrho^c} + \frac{1}{\varrho^c\varrho^p}\frac{Var\left(y_i^p\right)}{Var\left(Ed_i^p\right)} - \frac{2\varrho^p}{\varrho^c}\left[\frac{Cov\left(Ed_i^p, Ed_i^p\right)}{Var\left(Ed_i^p\right)}\right]} \\
&= \frac{1}{\frac{2\varrho^p}{\varrho^c} + \frac{1}{\varrho^c\varrho^p}\frac{Var\left(y_i^p\right)}{Var\left(Ed_i^p\right)} - \frac{2\varrho^p}{\varrho^c}\left[\frac{Var\left(Ed_i^p\right)}{Var\left(Ed_i^p\right)}\right]} = \frac{1}{\frac{2\varrho^p}{\varrho^c} + \frac{1}{\varrho^c\varrho^p}\frac{Var\left(y_i^p\right)}{Var\left(Ed_i^p\right)} - \frac{2\varrho^p}{\varrho^c}} \\
&= \frac{1}{\frac{1}{\varrho^c\varrho^p}\frac{Var\left(y_i^p\right)}{Var\left(Ed_i^p\right)}} = \varrho^c\varrho^p\frac{Var\left(Ed_i^p\right)}{Var\left(y_i^p\right)}.
\end{aligned}$$

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Data Availability Data is available upon request.

Declarations

Conflict of interest The authors declare that they do not have competing interests that may influence the work reported in this paper.

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