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Intergenerational Mobility, Economic Shocks, and the Role of Human Capital

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Abstract

How do economic shocks at the time of labor market entry interact with the intergenerational persistence of disadvantage? While the importance of family background for future labor market success outweighs the impact of increased unemployment, negative economic shocks disproportionately harm those from disadvantaged backgrounds. As a result, a one standard deviation increase in unemployment causes a 11–15% decrease in intergenerational mobility. Mobility decreases as higher unemployment widens the pre-existing gap in college education by socioeconomic status, and we show that differences in human capital are a key factor which explain rates of both relative and absolute mobility.

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1 Introduction

In many countries, the dream of upward mobility appears to be fading, with ”sticky floors” prevailing as a significant barrier. This term describes the phenomenon where children born into poverty face substantial challenges in ascending the economic ladder, while those born into wealth enjoy a considerable advantage. On the one hand, the concept of a level playing field and equality of opportunity has gained increased importance in contemporary society. There is a growing emphasis that every individual should have the opportunity to achieve economic prosperity, irrespective of their parental economic background. However, in most countries, achieving this ideal remains a distant reality marked by varying levels of intergenerational mobility. The increase in relative upward mobility among cohorts born between 1955 and 1975 in OECD countries was followed by stagnation for individuals born after 1975 (OECD, 2018).

In this paper, we offer a novel perspective on the extent of intergenerational persistence in disadvantage by comparing it to the impacts of macroeconomic shocks on long-term labor market outcomes. This contrasts the relative importance of the micro-level economic condition of the family children grow up in and the state of the economy they face when they enter the labor market. Both growing up in a family with a low socioeconomic standard and facing adverse macroeconomic conditions after graduation are factors an individual cannot influence. No one chooses in which type of family they are born and no individual decision can shape the condition of the national economy at the time of labor market entry. Both factors, however, greatly shape the economic future of the individual (Oreopoulos, von Wachter and Heisz, 2012; Black and Devereux, 2011). In addition, we assess how intergenerational mobility is causally impacted by adverse economic shocks. While an extensive literature emphasizes the importance of family background for child outcomes (Black and Devereux, 2011; Björklund and Salvanes, 2011), less is known about the extent to which individual decisions and government policy can increase intergenerational mobility. We, therefore, study the role of children’s human capital in fostering intergenerational mobility and explaining the international variation in rates of intergenerational mobility.

We find that fixed family factors matter overwhelmingly more than economic conditions at young ages. At the same time, increased unemployment at the time of entering the labor market decreases intergenerational mobility, and human capital is key in explaining the strong intergenerational persistence in outcomes. We combine data from the Programme for the International Assessment of Adult Competencies (PIAAC) published by the OECD with unemployment time series data. The PIAAC data is a cross-country nationally representative dataset including individual-level data on both participants’ own education, skill, and labor market outcomes as well as their parents’ level of education. This makes it particularly well-suited for studying intergenerational mobility and the role of human capital. We use unemployment rate data to account for exogenous macroeconomic conditions. Leveraging the variation across cohorts and countries we measure the effect of unemployment rates at labor market entry on later labor market success. We categorize individuals according to their family background using parent's education data in PIAAC. We test the relative importance of those two factors by comparing individuals across countries and cohorts who differentially face unemployment rates at young ages and come from different socioeconomic backgrounds. While the relationship between family background and labor market outcomes can involve various pathways (genetically transferred abilities, individual's own education, etc.), we can causally estimate the influence of exogenous economic conditions on future labor market outcomes and intergenerational mobility. This is because individual decisions do not affect the national unemployment rate experienced by a person at a certain age, which is solely determined by their birth year.

From the PIAAC dataset, we include 21 countries for which we can find early unemployment time series. We restrict our sample to those aged 35-59 to both focus on long-term labor market effects for prime-age workers and avoid the influence of retirement. We use two different measures of intergenerational mobility, a relative and an absolute one. We define relative mobility as the difference in the adult earnings decile between those with low educated parents and those with high educated ones, while the fraction of individuals with low-educated parents who reach high-skilled occupations measures absolute mobility. While relative mobility compares the outcomes of individuals with low to those with high educated parents, absolute mobility measures the degree to which individuals with low-educated parents reach the top (high skilled occupations).

Given that family factors matter a lot, we provide an understanding of how much a child's own education and skill explain relative intergenerational mobility as well as how much differences in human capital accumulation across countries explain the variation in absolute intergenerational mobility from an international perspective. In other words, we decompose both of our measures of intergenerational mobility to understand the role of children's human capital investment as an engine for social mobility. To break down our measure of relative mobility, we employ the decomposition method outlined by Gelbach (2016) in both a pooled analysis and on a country-by-country basis to allow for rich cross-country comparisons. This decomposition method is similar to the usual Oaxaca-Blinder decomposition method but solves the issue of sequence sensitivity by employing the omitted variable bias formula. Additionally, we construct a variance decomposition to understand how much human capital differences in comparison to other country-specific factors explain the international variation in absolute mobility rates.

We present three sets of results. First, we show that the impact of intergenerational disadvantage is much stronger than the impact of broader economic conditions during early adulthood on later adulthood economic outcomes. A standard deviation increase in the average unemployment rate around the time of transitioning from education to the labor market decreases the long-run earnings by 2 percentiles. While macroeconomic conditions at this critical stage have the largest and most persistent effect on long-term earnings and career progression (Oreopoulos et al., 2012; Arellano-Bover, 2022), this effect is outweighed by the magnitude of intergenerational persistence in disadvantage. Adulthood earnings are on average 13 percentiles lower for children of low-educated parents compared to those of highly-educated parents, which is equivalent to the effect of a six standard deviation increase in the unemployment rate. The contrast is even more pronounced when using high-skilled occupation as the outcome variable. Low SES individuals are on average 31.4 percentage points less likely to move to the top (end up in high-skilled occupation), while a one standard deviation increase in unemployment only reduces the probability of being in a high-skilled occupation by 1.6 percentage points. In a heterogeneity analysis we find that the intergenerational persistence in disadvantage is lower for individuals with low educated parents in countries with more vocationally-oriented education systems. This suggests that education matters not just in quantity but also in different fields of study.

Second, we show that changes in unemployment at the time of entering the labor market lead to changes in rates of relative intergenerational mobility, where adverse macroeconomic shocks further widen the gap between those from low and high SES backgrounds. Indeed, while the average impact of unemployment on labor market outcomes is small in comparison to the importance of family background, those from low SES backgrounds are significantly more afflicted by increasing unemployment. A one standard deviation increase in unemployment causes a 11–15% decrease in relative intergenerational mobility. Education is a key factor in these patterns, as the effects of unemployment on education also differ by SES. High SES students increasingly invest in college education during times of high unemployment relative to those from low SES backgrounds. These differential changes in education by SES are a key mechanism behind why adverse economic shocks decrease rates of relative mobility.

Finally, we investigate how much both child education and skill development can break the ties to disadvantaged family backgrounds, given the variation in intergenerational mobility across different educational systems and the differential response of education to economic shocks by SES. We focus on a measure of human capital which combines the importance of both education and skills, as both matter for intergenerational mobility and labor market outcomes (Blanden, Gregg and Macmillan, 2007; Hanushek, Schwerdt, Wiederhold and Woessmann, 2015). We quantify the importance of education and skills in two ways. First, we decompose our relative measure of mobility into a part mediated by own education level, skill level and a remaining unexplained part. We find that 87% of the difference between low and high SES individuals in adult earnings is explained by differences in two factors: education, which explains 56%, and skill level, which explains 31%. Similar results are found for high skilled occupations. Second, we measure how much of the variation in absolute mobility across countries is caused by differences in human capital accumulation, measured as an index of both education and skills. We find that while average human capital investment of the different countries can explain 49% of the variation in absolute mobility across countries, roughly half of this variation remains unexplained, pointing towards a potentially important role in economic conditions and institutions across different countries.

Taken together, these findings paint a stark picture: the persistence in disadvantage across generations is stronger than the persistence in the effect of even major economic shocks. Most of the gaps between socioeconomic groups are explained by differences in human capital while adverse macroeconomic conditions further widen the education gaps between the different groups. This emphasizes the need for policy interventions focused on investments in human capital for those from underprivileged backgrounds as well as supporting the disadvantaged when entering the labor market in times of recession.

Our research bridges two distinct strands of literature: intergenerational mobility and the long-term effect of macroeconomic conditions at labor market entry. There exists an extensive literature on intergenerational mobility in both earnings and education (Black, Devereux and Salvanes, 2005; Holmlund, Lindahl and Plug, 2011; Black and Devereux, 2011; Björklund and Salvanes, 2011), which highlights the importance of changes over time (Chetty, Hendren, Kline, Saez and Turner, 2014b), variation across geographic region (Chetty, Hendren, Kline and Saez, 2014a), neighborhoods (Chetty and Hendren, 2018a,b), and multi-generational measures of mobility (Nybom and Stuhler, forthcoming). However, far less is known about the importance of factors which cause shifts in patterns of intergenerational mobility. While Pekkarinen, Uusitalo and Kerr (2009); Nybom and Stuhler (forthcoming) and Bütikofer, Dalla-Zuanna and Salvanes (2022) establish the causal impacts of education reforms and the discovery of oil on intergenerational mobility respectively, we leverage a general economic shock which affects all workers at the time of joining the labor market.

Building on these foundations, we measure the extent of intergenerational persistence in disadvantage and quantify the importance of the role of education. We show that adverse economic shocks, facing a recessions at the time of first entry into the labor market, has disproportionate effects by socioeconomic status. As such, we add new insights to the literature on the long-term consequences of adverse macroeconomic conditions (Kahn, 2010; Oreopoulos et al., 2012; Liu, Salvanes and Sørensen, 2016; Schwandt and von Wachter, 2019; Arellano-Bover, 2022). Our results emphasize the importance of education and skills, and demonstrate that education policy matters for intergenerational mobility (Biasi, 2023). At the same time, policymakers should also consider the importance of initial labor market outcomes when focusing on rates of intergenerational mobility, which also have important distributional consequences.

2 Data and Methodology

In the first part of this section, we discuss the sources of our data, and the criteria applied for sample restriction, provide an overview of our sample, and detail the methodology for constructing our key measures. Next, we describe our empirical strategy.

2.1 Data Overview and Sample Selection

We use data from the Programme for the International Assessment of Adult Competencies (PIAAC) provided by the Organisation for Economic Co-operation and Development (OECD) together with unemployment time series data gathered from different sources.

PIAAC The PIAAC data surveys individuals aged 16-65 years in 39 different countries, with thousands of participants in every country. We use the first cycle of PIAAC, which comprises three rounds of implementation. The data collection process took place between 2011 and 2012 for 25 of those countries, while the remaining countries participated in the second and third rounds in 2014-2015 and 2017, respectively. PIAAC includes a background questionnaire with data on parental educational background in three categories. Parents' education is defined as high if at least one parent has tertiary education, mid if the highest educated among both parents has an upper secondary or post-secondary non-tertiary degree, and low if neither of them has attained upper secondary education. We use these measures in our study of intergenerational mobility as a proxy for parental socioeconomic standards categorized into three groups: low, mid, and high SES. Additionally, the questionnaire collects rich data on the demographics of the individual such as immigration background, age, and gender. It also includes an assessment that measures cognitive skills divided into literacy, numeracy, and problem-solving in technology-rich environments. The literacy and numeracy segments evaluate individuals' abilities to comprehend and utilize information from written texts and quantitative data across various scenarios. Additionally, problem-solving in technology-rich environments evaluates individuals' competence in using ICT skills to effectively address a range of challenges and tasks.

Information about the respondents' own education level and labor market outcomes such as current occupation and income are also gathered in PIAAC. In the data, occupations are categorized using the International Standard Classification of Occupations (ISCO-08) in one and two-digit categories as well as four skill-level categories. We use the four skill-based categorization reporting the current or last occupation of the respondent, which is comprised of skilled occupations (e.g. civil engineers, pharmacists, commercial managers, etc.), semi-skilled white-collar occupations (e.g. customer services clerks, sales workers, etc.), semi-skilled blue-collar occupations (e.g. agricultural workers, drivers, etc.) and elementary occupations (e.g. cleaners, package deliverers, etc.). For earnings, we use the decile where the individual lies in his country when comparing monthly earnings including bonuses for wage and salary earners and self-employed. The education variable we employ includes five categories: lower secondary or less, upper secondary, post-secondary, non-tertiary, tertiary – professional degree, and tertiary - bachelor/master/research degree.

A major advantage of the PIAAC dataset is that it is nationally representative within participating countries. The sample of adults surveyed and assessed is reflective of the broader adult population in terms of key demographic characteristics such as age, gender, education level, and region. This method of representative sampling, coupled with the incorporation of provided survey weights which we use in our analysis throughout, enables us to conduct valid cross-country comparisons of intergenerational mobility.

Taken together, all those factors make the PIAAC dataset well-suited for measuring intergenerational mobility and ideal for providing valuable international insights on the drivers of intergenerational mobility across countries.

Unemployment Time Series We merge the PIAAC dataset with the unemployment time series around the age of joining the labor market for the different cohorts in each country. The main source of our unemployment data is the Main Economic Indicators database published by the OECD and retrieved from FRED, Federal Reserve Bank of St. Louis. For countries where early unemployment rate data was not available in this dataset, we supplemented it with unemployment time series from other sources (e.g. International Monetary Fund). For a full list of the sources of unemployment data by country see appendix table A.1.

Sample Restriction We restrict our sample to individuals aged 35–59 as in Arellano-Bover (2022). We drop those older than 59 to avoid retirement issues influencing our main outcome variables (earning decile and current occupation). Younger participants are still in education or starting work with low experience. We therefore focus on respondents older than 35 to capture the long-term persistent effects of bad economic conditions at market entry instead of immediate short-term effects upon labor market entry. Individuals who migrated to their current country of residence after the age of 15 are also dropped because they graduate with different degrees and face different labor market conditions in their home countries than the rest of their cohort in their current country of residence around the period of joining the labor market. We include only countries for which we can match unemployment data early enough for older cohorts. For this reason, we end up with 21 countries, five of which are excluded in some results due to lack of access to specific age data. The main results on intergenerational mobility are robust to the inclusion/exclusion of these countries (table **??**) and also the choice of younger age ranges.

2.2 Summary Statistics and Measurement of Key Variables

Sample Descriptive Statistics Table 1 shows descriptive statistics for our sample of nearly 60,000 participants across 21 countries. Most of the individuals in the sample have low or mid educated parents, which makes it a suitable sample for testing the extent of upward intergenerational mobility in those countries. Roughly 23% of our sample have high educated parents while 38% and 39% have mid and low educated parents, respectively.

The biggest fraction of our sample (approximately 39%) have obtained upper secondary education while almost 20% dropped out of formal education after lower secondary or before and nearly 24% have a university degree. In our paper we investigate the role different educational systems can affect the rate of intergenerational mobility comparing countries with more vocational education to those with more general education. About a third of our sample's qualifications are vocationally oriented. There is, however a big variation in that rate across countries. Appendix figure A.3 shows how in some countries the fraction of those with vocational education is as low as 11%, 14% and 21% in Italy, Spain and the US, while almost three quarters of the population has vocational education in Austria and Germany. If an individual's highest level of education is secondary school or post secondary non-tertiary, the participant is asked whether his degree was vocationally oriented or not. Following Hanushek, Schwerdt, Woessmann and Zhang (2017) and Hampf and Woessmann (2017) we add to those who responded yes to this question the ones who graduated with a tertiary professional degree which have a tertiary professional degree which is equivalent to level 5B in the International Standard Classification of Education (ISCED 5B).

In our main analysis we use the numeracy skill score for several reasons. The problem-solving in technology-rich environments assessment is missing for a third of our sample as the assessment did not take place in three of the main countries in our analysis and respondents who chose the paper format in all the other countries also did not undergo this assessment. The correlation between the literacy and numeracy score in our sample is 0.91. Therefore, following the existing literature (Hanushek et al., 2015), we focus on numeracy skills which are comparable across countries relative to other measures of skills. The scale of the score is from zero till 500 with 500 being the highest possible achievable score. The PIAAC data includes ten plausible values for each individual, which we average to have one measure of numeracy skill. The mean of this measure in our sample is 264.

The majority of our sample have no immigration background since more than 97% are native born. Men and women are equally represented in our sample where females comprise 51% of the participants. Since we focus on individuals between the age of 35 and 59, the average age is 45.5 years.

In constructing our measures of mobility we use two main labor market outcomes, occupation and earnings decile. Since our sample consists of prime age workers, the average decile is 6.2 and a large fraction of them are in skilled occupations. While approximately 39% are skilled, 17% are unemployed, and 43% are semi-skilled.

Measuring Unemployment To ensure that unemployment rates provide a consistent measure of economic conditions across different countries, we standardize unemployment rates on a country-by-country basis as in Arellano-Bover (2022). Specifically, for each country, we compute a standardized measure by subtracting the mean unemployment rate during the study period from each data point and then dividing by the standard deviation of unemployment in that country:

$$u^*_{ct} = \frac{u_{ct} - \overline{u}_c}{\sigma^u_c} \tag{1}$$

where u^*_{ct} represents the standardized unemployment rate for year t and country c, u_{ct} is the actual unemployment rate at that year and country, $\overline{u}_c$ and σ^u_c are the mean and the standard deviation of the unemployment rate for country c over all the years included, respectively. This approach generates a time series of standardized unemployment rates u^*_{ct}, expressed in units of standard deviations, which facilitates meaningful comparisons over time and across nations. Appendix figure A.2 shows plots of standardized unemployment rates across the 21 countries in our sample, revealing that there is sufficient variation in unemployment across years and countries to measure its effect on labor market outcomes.

We assign to each individual in the PIAAC dataset the average of the standardized unemployment rate in their country in the years when they were 18 to 25 years old. We choose this age bin following Arellano-Bover (2022), as it represents the age span, where the majority of participants in our sample finish formal education. We show the results for other ages as well in Table B.1 where the coefficient for family background remains robust in all specifications. Additionally, previous literature documents that unemployment is the most critical and has the biggest impact on long-term labor market outcomes during this phase. For example, Oreopoulos et al. (2012) show that the effect of unemployment on individuals earnings is much higher for labor market entrants compared to already employed ones. This result is also confirmed by Arellano-Bover (2022) who finds no statistically significant effect of unemployment between the ages of 26-30 and 31-35 on individuals' log-run skill development. We therefore use unemployment at graduation age to study the effect of exogenous economic shocks where their effect is the most critical.

Measuring Intergenerational Mobility We use two distinct measures of intergenerational mobility defining an absolute intergenerational mobility rate and a relative one. Our relative intergenerational mobility measure captures the difference in adult earnings decile of individuals coming from a low (mid) socioeconomic background compared to high socioeconomic background. We contrast this measure with the effect of external economic shocks proxied by a standard deviation increase in unemployment.

Our variance decomposition employs the absolute mobility measure. Because the average decile low SES individuals reach across countries shows limited variation, we use an alternative labor market outcome, occupation. We define a country's absolute intergenerational mobility as the share of individuals from low-educated families who end up in high-skilled occupations, reflecting bottom-to-top mobility as in Chetty et al. (2014a). They measure the fraction of people for whom the "American dream" came true by ending up in the top quintile despite being raised in a bottom quintile family. Our measure exhibits substantial variation across countries, as depicted in Figure 2. In the least mobile country, Turkey, only 13% of the people with low-educated parents make it to the top, in contrast to 66% of those with high educated parents. Similarly, Germany, Greece and Korea have rates below 20%. While three quarters of those with high educated parents have a high skilled occupation in Italy, barely 20% of those with low educated parents make it to the top. On the other side of the distribution, Denmark, Sweden, New Zealand, Canada and the Netherlands all have absolute mobility rates above 40%.

There exist considerable gaps between groups from different socioeconomic backgrounds in our sample. For example, the average decile of those with high educated parents is 6.9 while those with mid and low educated parents have an average decile of 6.2 and 5.6 , respectively. A quarter of the low SES individuals are unemployed and only 23% of them have a high skilled occupation while less than 9% of the high SES are unemployed and 60% of them have a high skilled occupation (Table A.2). Comparing the different cohorts in our sample we can see that over time the fraction of individuals with high and mid educated families grew (Panel A of Figure 1). Despite the downward trend, the fraction of those with low educated families remains the highest for all cohorts. Among those born in low educated families, the fraction attaining high education themselves is rising while that of mid education falls and low education remains on average constant. This suggests a rise in intergenerational education mobility overall for the cohorts and countries we study. However, the fact that the fraction of low educated individuals from low educated families remains constant and the highest fraction among high and mid educated low SES people throughout shows some persistence.

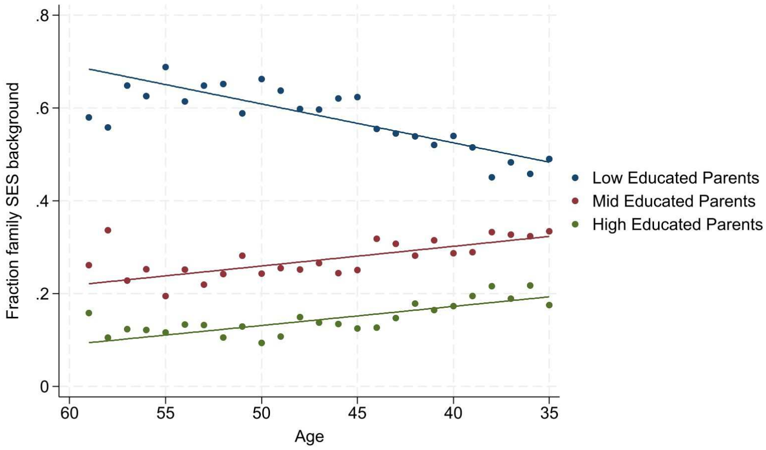
Panel C in Figure 1 illustrates our measure of absolute mobility over various cohorts. It reveals a strong persistence in socioeconomic status, where the proportion of high-skilled individuals remains relatively stable across all cohorts on average. Specifically, individuals with highly educated parents consistently have the highest proportion of skilled occupations, averaging around 60%, while those from low socioeconomic backgrounds consistently have the lowest proportion, never exceeding one-third. Additionally, there is a modest decrease in absolute mobility over time, indicated by the slight negative trend in the proportion of high-skilled individuals among those with low educated parents. Throughout the quarter-century under study, the threat of being stuck at the bottom persists across all cohorts.

	Observations	Mean	SD
Age	38,254	45.510	6.697
High Educated Family	59,088	0.227	0.419
Mid Educated Family	59,088	0.382	0.486
Low Educated Family	59,088	0.390	0.488
Lower secondary or less	59,064	0.196	0.397
Upper secondary	59,064	0.388	0.487
Post-secondary, non-tertiary	59,064	0.052	0.223
Tertiary – professional degree	59,064	0.125	0.330
Tertiary - bachelor/master/research degree	59,064	0.239	0.427
Vocational Education	59,088	0.323	0.468
Numeracy skill score	59,088	264.127	51.156
Skilled occupations	59,088	0.386	0.487
Semi-skilled white-collar occupations	59,088	0.254	0.435
Semi-skilled blue-collar occupations	59,088	0.179	0.383
Elementary occupations	59,088	0.065	0.247
NEET	59,063	0.169	0.375
Monthly earned income in deciles	43,295	6.159	2.852
Female	59,088	0.507	0.500
Native Born	59,088	0.973	0.162
Unemp. age 18-25	59,088	0.109	0.660

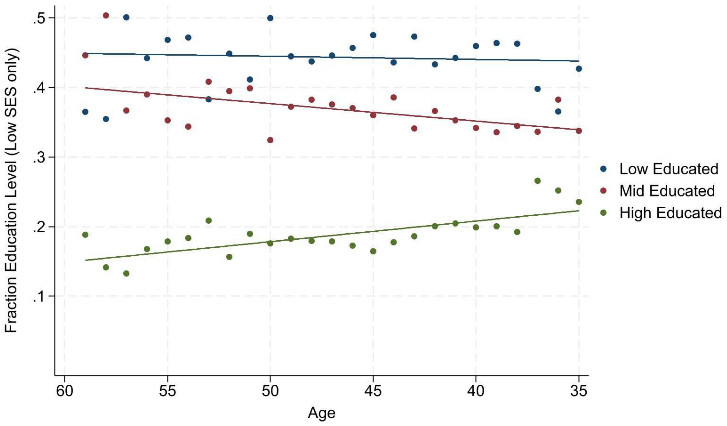
Table 1 Summary Statistics

Notes: This table presents summary statistics for our sample comprising individuals aged 35 to 59. Survey weights are used to calculate the means and standard deviations reported in columns 2 and 3. Family's education is the maximum among a respondent's two parents. It is defined as high if at least one parent has tertiary education, mid if the highest educated among both parents has an upper secondary or post-secondary non-tertiary degree, and low if neither of them has attained upper secondary education. Numeracy test score is calculated for each individual as the average of plausible values. It ranges from 0 to 500. NEET stands for not currently employed and did not participate in education or training in the last 12 months. Deciles of monthly earnings include bonuses for wage and salary earners and self-employed.

(a) Panel A



(b) Panel B



(c) Panel C

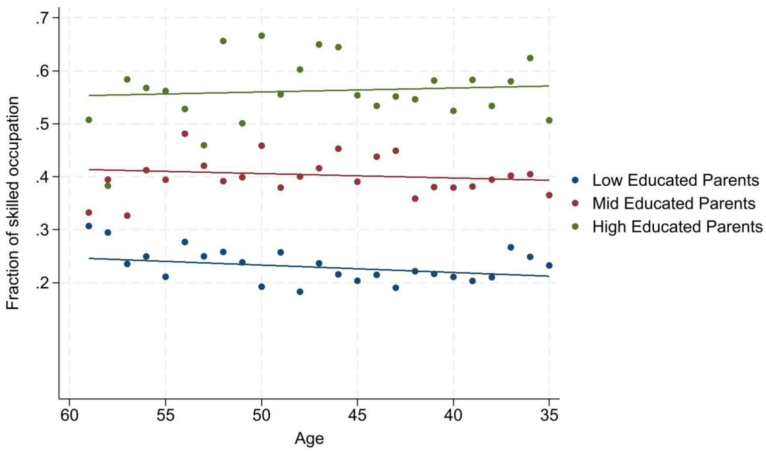


Figure 1 Trends in Intergenerational Mobility

Notes: This figure shows how several characteristics have evolved over time using cohort averages. Panel A plots the fraction of each SES group (individuals with low, mid and high educated parents) in each cohort. In panel B we restrict the sample to low SES individuals and plot the fraction of individuals who have low, mid, and high education themselves. Finally, panel C plots the fraction of individuals in high skilled occupations by SES. All figures are generated using survey weights to ensure national representativeness.

Figure 2 Intergenerational Mobility by Country

Notes: This figure shows the fraction of individuals with low-educated and high-educated families that end up in skilled occupations. The green bars are our measure of absolute mobility. Family's education is the maximum among a respondent's two parents. It is defined as high if at least one parent has tertiary education, mid if the highest educated among both parents has an upper secondary or post-secondary non-tertiary degree, and low if neither of them has attained upper secondary education. Survey weights are used to ensure national representativeness.

2.3 Empirical Strategy

Our empirical analysis includes three main parts: a baseline regression, a Gelbach decomposition and a variance decomposition.

Baseline Regression This part of our analysis contrasts the effect of exogenous economic conditions with fixed family factors. We measure initial labor market conditions using the standardized unemployment rate at the time of graduation and contrast this with the fixed determinant of originating from a family with either low or middle educational attainment. We identify the causal effect of graduation in bad economic conditions by leveraging the variation in unemployment rate across countries and cohorts using the following linear model:

$$y_{ic} = \beta_1 low\_SES_i + \beta_2 mid\_SES_i + \gamma u^{18-25}_{a(i)c} + \delta_c + \delta_{a(i)} + X_i'\lambda + \epsilon_{ic} \tag{2}$$

where y_{ic} is the outcome measure for individual i in country c and age cohort a. Our main labor market outcome measures are earnings decile and a dummy variable that equals one if the individual has a skilled occupation. low_SES_i and mid_SES_i are dummy variables that equal one if the education level of the individual's parents is low and middle, respectively. To compare this to exogenous economic conditions we use the standardized unemployment rate, $u^{18-25}_{a(i)c}$. For each individual we assign the average unemployment rate he faced in his country when he was between the ages of 18 and 25 after standardizing it by country as described in section 2.2. The age fixed effects, denoted as $\delta_{a(i)}$, account for age-related factors that impact labor market outcomes and are consistent across countries.

This ensures that our comparisons are based on individuals of the same age. On the other hand, the country fixed effects denoted as δ_c, capture variations in labor market outcomes across different countries that apply for all cohorts. These differences can stem from various factors, such as the distribution of occupations within each country (e.g., specialization in certain industries leading to more skilled or semi-skilled occupations). Our controls, X_i', include gender and immigration, where we include a dummy that equals one if the respondent is native-born and another for females. We cluster standard errors on the country-cohort level.

In this regression, β_1 captures how much lower the average outcome variable is for the individuals with a low socioeconomic background compared to those with a high socioeconomic background. Similarly, β_2 captures this penalty for individuals with parents who had a mid-level education. On the other hand, γ captures the effect of a one standard deviation higher unemployment rate during the period of transition from education to the labor market. This contrasts the exogenous effect of joining the labor market in bad economic conditions to the effect of being born in a low/mid educated family.

Both factors are exogenous to the individual in the sense that no decision by the individual can influence in which family they are born (the education of their parents) or what unemployment rate they face at a certain age since this is determined by the birth year of the individual and external macroeconomic conditions. β_1 and β_2 test the persistence of outcomes across generations and measure equality of opportunity. The more labor market outcomes in late adulthood are influenced by family background, the less equality of opportunity there is.

Many factors can explain the association between parents' education and adult labor market outcomes. It could be genetically transferred abilities, the individual's own education, the neighborhoods they grew up in or many other factors. One main channel often studied in the literature is the individual's own human capital (Björklund and Salvanes, 2011; Black et al., 2005). Children born to well educated parents are much more likely to get higher educational attainment, which in turn leads to better labor market outcomes. In addition to education, we also use skill as a measure of human capital. Next we, therefore, use decomposition methods that help us understand how much of the intergenerational mobility is mediated by education level and skill in two different ways.

Gelbach Decomposition Since human capital is a main mediator through which family background impacts children's outcomes in adulthood, we decompose the relative intergenerational persistence measure to quantify the contribution of the individual's own education and skill, first on the individual level. This decomposition quantifies to what extent educational interventions are important for equalizing opportunities for children from disadvantaged backgrounds.

For this decomposition we use the method developed by Gelbach (2016). Using the omitted variable bias formula, Gelbach (2016) decomposes the effect of adding more explanatory variables to the base specification on the change in the coefficient of interest in the full specification. This method has the same objective as the Oaxaca-Blinder decomposition. However, sequentially adding variables and seeing how the coefficient changes does not correctly identify the contribution of each added variable to the change in the coefficient if the added variables are correlated. This is important in our context given the correlation between education and skill measures. To avoid this sequence sensitivity, Gelbach (2016) develops a method that identifies what share of change in the coefficient of interest is attributed to each variable and in which direction the change goes. We use this method to understand what share of the association between child's labor market outcomes and family background is explained by both the level of education and the skill level of the child jointly as well as the share of each separately. Our base specification is therefore equation 2 (without unemployment) while our full specification, which decomposes the importance of child education and skill is:

$$y_{ic} = \beta_1 low\_SES_i + \beta_2 mid\_SES_i + \beta_3 skill_i + \sum_{e=1}^{5} E_{ei}\beta_{4e} + \delta_c + \delta_{a(i)} + X_i'\lambda + \epsilon_{ic} \tag{3}$$

This differs from the base regression only by $\beta_3 skill_i + \sum_{e=1}^{5} E_{ei}\beta_{4e}$, where $skill_i$ is the numeracy score level and E_{ei} are five dummy variables for the five education levels as explained in the data section 2.2. This method then allows us to measure how much each own education and skill accounts for the change in our coefficient of interest β_1 between equation (2) and (3). β_1 measures relative mobility by capturing the difference in labor outcome measures between the low and the high SES. In other words, this decomposition answers the question on how much of intergenerational persistence is due to differences in human capital among individuals from different socioeconomic family backgrounds. While education dummy variables only account for the broad level of education of the individual (e.g upper-secondary only or university degree), this may mask considerable heterogeneity among the actual amount of education people with the same degree in the same country and cohort could have. This could be due to differences in the quality of education across schools or regions in the same country or also differences in the grades they graduated with. The variable measuring numeracy skill from the PIAAC test score therefore goes a step further to account for the actual difference among the skills of those individuals. Adding numeracy skill accounts for differences in inherent ability as well as a combination of learned skills and experiences to provide a more comprehensive understanding of human capital.

Variance Decomposition We build upon the individual perspective in the decomposition as in Gelbach (2016), which focuses on understanding the drivers of relative mobility, to a cross-country perspective understanding the drivers of absolute mobility. In the Gelbach decomposition, we decompose the *difference* in the fraction of low SES individuals reaching high skilled positions compared to high SES individuals reaching high skilled positions within the same country (relative mobility within a country). In this variance decomposition exercise, however, we decompose the variation in the fraction of those from low SES families reaching the top across countries (absolute mobility across countries). While the Gelbach decomposition decomposes the difference between low and high SES individuals keeping the country-specific context constant, the variance decomposition zooms out to compare absolute mobility of the low SES across different countries. In this variance decomposition we examine whether differences in human capital across countries explain the variation in cross-country absolute mobility rates or whether other country-specific factors play a major role.

The cross-country variance decomposition exercise provides an understanding of how much of the variation in absolute mobility is explained by the variation in human capital. As the starting point for this exercise, equation (4) specifies absolute mobility at the individual-level as a function of child human capital, the additional impact of their home country, and an individual specific error term:

$$absolute\_mobility_{i,c} = \theta H_{i,c} + \delta_c + \omega_{i,c} \tag{4}$$

where $absolute\_mobility_{i,c}$ is an indicator for absolute mobility for individual i in country c, $H_{i,c}$ represents human capital, and δ_c measures the contribution of country-specific factors towards mobility.

$H_{i,c}$ can also be written as the contribution of the country average human capital and some individual-specific error term:

$$H_{i,c} = \overline{H_c} + \nu_{i,c} \tag{5}$$

Plugging equation (5) into equation (4) and rearranging gives:

$$absolute\_mobility_{i,c} = (\theta \overline{H_c} + \delta_c) + (\theta \nu_{i,c} + \omega_{i,c}) \tag{6}$$

Similar to equation (5) which defines individual human capital, $absolute\_mobility_{i,c}$ can also be written as the contribution of the country average mobility and some individual-specific error term:

$$absolute\_mobility_{i,c} = \overline{absolute\_mobility_c} + \zeta_{i,c} \tag{7}$$

A comparison of equations (6) and (7) provide the basis for the variance decomposition exercise, as the country average rates of absolute mobility is given by:

$$\overline{absolute\_mobility_c} = \theta \overline{H_c} + \delta_c \tag{8}$$

which allocates a component of absolute mobility explained by average levels of human capital and the return to education ($\theta \overline{H_c}$) and a component which is unexplained by human capital (δ_c).

We measure the variance of average mobility at the country level and decompose it into the relative contribution of the terms in equation (8) by:

$$Var(\overline{absolute\_mobility_c}) = \theta^2 Var(\overline{H_c}) + Var(\delta_c) + 2\theta Cov(\overline{H_c}, \delta_c) \tag{9}$$

The variance in average rates of absolute mobility across countries can be decomposed into a part explained by the variation in average human capital across countries ($\theta^2 Var(\overline{H_c})$). The variance decomposition exercises uses the cross-country variation in absolute mobility given in equation (9), where we define absolute mobility as the fraction of low SES reaching high skilled occupations, as depicted in figure A.1.

3 Exogenous Economic Conditions Versus Family Background

We test the relative importance of family background and macroeconomic conditions for labor market outcomes in adulthood. Our results in this section show that fixed family factors matter much more than external economic conditions around the years of joining the labor market, at least 6 times more. Table 2 shows our estimates of both factors, the relationship between adult income with family background, and the effect of economic conditions each separately in columns 1-2 and 4-5. Columns 3 and 6 contrast both in one regression showing estimates of β_1, β_2 and γ from equation 2. All coefficients are robust to the different variables added.

Across all specifications, both factors matter. However, coming from a lower SES family matters considerably more than exogenous economic conditions. The monthly earnings of those coming from a low (middle) socioeconomic background are on average 1.3 (0.65) deciles lower than those with highly educated parents, where the whole sample's average is 6.16. In contrast, a one standard deviation increase in the average unemployment rate an individual faces when joining the labor market reduces long-run earnings by 0.22 deciles. The socioeconomic background of an individual's parents matters more than a considerable deterioration in macroeconomic conditions, as a standard deviation change in unemployment could be as high as 6.4 percentage point increase as in Spain for example. The fact that family background still matters when children are 35-59 years old highlights the strong intergenerational persistence in socioeconomic standards.

Differences in earnings decile among individuals with different family backgrounds and facing different labor market conditions could stem from different occupational choices later in life. High unemployment upon graduation could cause graduates to settle for worse jobs which might hurt their career progression (Oreopoulos et al., 2012). Likewise, individuals with lower SES family may have less network connections which might prevent them from reaching skilled occupations. We provide evidence of those two effects in columns 4-6 of table 2, where the outcome is a dummy variable that equals one if the individual is in a skilled occupation as defined in section 2.1. As with earnings, family background matters more than macroeconomic conditions for the type of occupation the individual ends up in. While 40% of our whole sample are in a skilled occupation, those with a low (middle) SES background are 31.4 (16) percentage points less likely to be in a high-skill occupation than those from a high SES. In contrast, a one standard deviation increase in unemployment only reduces the probability of being in a high-skilled occupation by 1.6 percentage points. As with earnings, family background matters considerably more than the effect of a recession in the early years of one's career.

VARIABLES	(1) Earnings Decile	(2) Earnings Decile	(3) Earnings Decile	(4) High Skilled	(5) High Skilled	(6) High Skilled
Low Educated Family	-1.297***		-1.299***	-0.314***		-0.314***
	(0.070)		(0.070)	(0.012)		(0.012)
Mid Educated Family	-0.647***		-0.650***	-0.159***		-0.159***
	(0.067)		(0.067)	(0.010)		(0.010)
Unemp. age 18-25		-0.217***	-0.221***		-0.015*	-0.016**
		(0.042)	(0.042)		(0.008)	(0.008)
Observations	27,440	27,440	27,440	38,254	38,254	38,254
R-squared	0.192	0.170	0.193	0.112	0.065	0.112
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Avg. outcome	6.155	6.155	6.155	0.399	0.399	0.399

Clustered standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2 Exogenous Economic Conditions Versus Family Background

Notes: This table shows results of OLS regressions based on equation (2) with survey weights. In columns 1-3, the dependent variable is the earnings decile of the individual, and in columns 4-6 it is a dummy variable that equals one if the individual is in a skilled occupation according to the ISCO-08 classification as defined in section 2.1. Family's education is the maximum among a respondent's two parents. It is defined as high if at least one parent has tertiary education, mid if the highest educated among both parents has an upper secondary or post-secondary non-tertiary degree, and low if neither of them has attained upper secondary education. Unemployment is measured in country-specific standard deviations and averaged across the years where the individual was between 18-25 years old as explained in section 2.2. In all columns, we add controls for gender and immigration, cohort, and country fixed effects. Standard errors are clustered on the country-cohort level.

3.1 Robustness

In this section, we outline 3 different robustness checks for our baseline regression. We test the robustness of our results to measuring unemployment at different ages, adding more countries and adding country-specific quadratic age-trends.

Since some individuals might enter the labor market before the age of 18, we measure in a robustness check the effect of the unemployment rate when the individual is 16, 17, and 18 years old. We find that a one standard deviation increase in unemployment decreases earnings decile in the long run by 0.09 to 0.1 deciles (Table B.1). Family matters 13 times more in those specifications. Our chosen measure of macroeconomic conditions (averaging unemployment between the ages of 18 and 25) is therefore a conservative measure of economic shocks that are more persistent. Still, the effect is dwarfed by the intergenerational persistence of disadvantage.

Table 2 excludes 5 countries from our analysis (Austria, Canada, Germany, USA and New Zealand) since we only have age categories in 5-year bins for those countries but not continuous age data. As a robustness check, we impute the average of the unemployment rate for all the years where the individual could have been between 18 and 25 according to his age bin for those 5 countries. We use age bin fixed effects instead of precise age fixed effects. Since here we cannot capture specific yearly cohort effects and use imprecise estimates of the unemployment rate for 5 countries because we average across more years, the coefficient on unemployment is not statistically significant in table **??** but it is still negative. In contrast, family background coefficients remain negative and statistically significant at all conventional levels of confidence. In fact, adding those countries increases the family background coefficients sightly to 1.46 for low SES and 0.7 for mid compared to 1.3 and 0.65 respectively in our main specification

Additionally, we run a specification of equation (2) that includes country-specific quadratic age trends, $\delta_c a(i) + \delta_c a(i)^2$ following Arellano-Bover (2022) to account for non-linear country-specific variations in how age (or time) influences labor market outcomes. The age-earnings profile would look different in different countries for example. Those country-specific quadratic trends would also capture changes in the institutional framework. The results are provided in Table B.3. Earnings decile results are robust to adding those trends for both unemployment and family coefficients have almost the same magnitude. Only the unemployment coefficient's statistical significance drops since controlling for the age trends by country takes away much of the variation in unemployment trends. This also explains why we see no statistically significant effect of unemployment on high-skilled occupations in the last column of the table.

3.2 Heterogeneity: Gender and Vocational Education

While family background matters considerably more than exogenous economic conditions, here we ask whether everyone is equally affected. Specifically, we study heterogeneity by gender and assess the importance of the types of education systems in the different countries. The results suggest that relative mobility is slightly lower for women compared to men while the effect of macroeconomic conditions is similar for both. Repeating the analysis using the mother's and father's education separately we find that the gap in labor market outcomes between the high and the low SES is higher when we use the father's education compared to using the mother's. Countries with more vocationally-oriented education systems show a lower intergenerational persistence of disadvantage for individuals from a low SES family background.

Table 3 shows that the average earnings decile of men is 7 in our sample and 5.2 for women. Additionally, women from low SES have a 1.4 lower earnings decile on average compared to high SES ones while this penalty is 1.2 for men. Middle SES also have a bigger difference for women (0.7) compared to high SES where for men it is 0.5. For the effect of unemployment, the coefficient is very similar for both genders and close to the baseline coefficient; a standard deviation increase in the average unemployment rate during the transition to the labor market decreases the earnings decile in the long run by 0.22 to 0.23 deciles for both men and women.

In the baseline results, we use the highest among the father and mother's education as an indicator of family background. In table B.4 we repeat the analysis by each parent's education level separately. We find that the gaps between the high and the low SES are more pronounced when we use the father's education compared to using the mother's. This result also holds for both daughters and sons separately (Table B.5 and B.6).

It is expected to find that the relationship between family and labor market outcomes differs by the type of educational system available in each country. One aspect that varies significantly across countries concerning educational opportunities is the extent to which vocational versus general education is provided. As discussed in section 2, appendix figure A.3 shows this variation across countries where only 11% have vocational education in Italy in contrast to 73% in Germany. In table 4 we interact the family background dummy variables with a standardized measure of the intensity of vocational education in each country. Vocational education intensity variable is the fraction of individuals with vocational education in each country. Our vocational intensity measure therefore varies across countries and is standardized to have a mean of zero and a standard deviation of one. [1]

Our results in table 4 show that countries with more vocationally-oriented education systems show a lower intergenerational persistence of disadvantage for individuals from a low SES family background. While on average a low socioeconomic family background is associated with a 1.4 decile decrease in the earnings decile of an individual, in a country that has a one standard deviation higher intensity in vocational education this association is lower by 0.2 deciles, an effect which is statistically significant. For middle SES where the penalty is 0.7 deciles, higher vocational intensity countries do not seem to do better than lower ones as the interaction variable is not statistically significant. Those results suggest that vocational education works as an engine of social mobility for individuals with low-educated family backgrounds which is consistent with findings in the literature (Bennett, Foley, Green and Salvanes, 2024).

[1] In this specification, we use all 21 countries (including the 5 countries where we only have the age bin, not the specific age of individuals) because the five countries include ones that lie on both ends of the distribution of vocational intensity such as Germany and Austria with the highest intensities and the US, which is among the lowest. The relevant baseline comparison for this table is therefore the version of the baseline table where the five countries are included in the robustness section. **??**.

	Male			Female		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Earnings Decile	Earnings Decile	Earnings Decile	Earnings Decile	Earnings Decile	Earnings Decile
Low Educated Family	-1.191***		-1.194***	-1.371***		-1.370***
	(0.085)		(0.085)	(0.110)		(0.110)
Mid Educated Family	-0.544***		-0.549***	-0.738***		-0.738***
	(0.088)		(0.088)	(0.110)		(0.110)
Unemp. age 18-25		-0.227***	-0.234***		-0.226***	-0.224***
		(0.053)	(0.054)		(0.068)	(0.068)
Observations	14,318	14,318	14,318	13,122	13,122	13,122
R-squared	0.066	0.043	0.068	0.083	0.057	0.084
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Avg. decile	7.048	7.048	7.048	5.180	5.180	5.180

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3 Heterogeneity by Gender

Notes: This table shows results of OLS regressions based on equation (2) with survey weights. In columns 1-3, the sample is restricted to include only male individuals while the sample of columns 4-6 is restricted to females. The dependent variable in all columns is the earnings decile of the individual. Family's education is the maximum among a respondent's two parents. It is defined as high if at least one parent has tertiary education, mid if the highest educated among both parents has an upper secondary or post-secondary non-tertiary degree, and low if neither of them has attained upper secondary education. Unemployment is measured in country-specific standard deviations and averaged across the years where the individual was between 18-25 years old as explained in section 2.2. In all columns, we control for immigration background and add cohort and country fixed effects. Standard errors are clustered on the country-cohort level.

	(1)	(2)	(3)
VARIABLES	Earnings Decile	Earnings Decile	Earnings Decile
Low Educated Family	-1.394***		-1.396***
	(0.075)		(0.074)
Low x Voc	0.219***		0.215***
	(0.064)		(0.065)
Mid Educated Family	-0.693***		-0.694***
	(0.048)		(0.048)
Mid x Voc	0.010		0.009
	(0.038)		(0.039)
Unemp. age 18-25		-0.042	-0.047
		(0.067)	(0.066)
Observations	43,295	43,295	43,295
R-squared	0.159	0.129	0.159
Age Bin FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Avg. decile	6.168	6.168	6.168

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4 Heterogeneity by Education Type

Notes: This table shows results of OLS regressions based on equation (2) with survey weights. "Low x Voc" and "Mid x Voc" are family education dummies interacted with a measure of vocational education intensity that varies on the country level as described in section 3.2. The dependent variable in all columns is the earnings decile of the individual. Family's education is the maximum among a respondent's two parents. It is defined as high if at least one parent has tertiary education, mid if the highest educated among both parents has an upper secondary or post-secondary non-tertiary degree, and low if neither of them has attained upper secondary education. Unemployment is measured in country-specific standard deviations and averaged across the years where the individual was between 18-25 years old as explained in section 2.2. In all columns, we add controls for gender and immigration, cohort, and country fixed effects. Standard errors are clustered on the country-cohort level.

4 How do Economic Shocks When Joining the Labor Market Impact Intergenerational Mobility?

Given the strong importance of family background for labor market success, an important question is what factors lead to causal shifts in intergenerational mobility. Whether economic shocks increase or decrease rates of relative intergenerational mobility depends crucially on whether the impacts of unemployment on labor market outcomes differ across SES groups. Indeed, while the average impact of adverse economic conditions on labor market outcomes may be small in comparison to the importance of family background, this may mask considerable heterogeneity in the impacts of unemployment by socioeconomic status.

Table 5 shows that the effect of adverse economic conditions on long-term labor market outcomes is mainly driven by low SES, and that macroeconomic downturns further widen the gap between those from low and high SES backgrounds. Columns 2 and 4 of table 5 interact the unemployment rate with the variables capturing socioeconomic background to differentially estimate the effect of unemployment by socioeconomic group. The effect of unemployment is driven exclusively by those from low SES backgrounds, irrespective of whether occupation or earnings are used as an outcome measure. While the effect of unemployment for other groups is not statistically significant, a one standard deviation increase in unemployment reduces the earnings of a low SES individual by 2 percentiles and the probability of having a high-skill occupations by 3.5 percentage points. These correspond to a considerable portion of the difference in labor market outcomes between low and high SES children, where a one standard deviation increase in unemployment would decrease relative mobility by 11–15%. Table 5 reveals that while family background still matters considerably for labor market outcomes, adverse economic conditions at labor market entry further widen rates of relative mobility between low and high SES children and further increase the persistence of disadvantage.

VARIABLES	(1) Earnings Decile	(2) Earnings Decile	(3) High Skill	(4) High Skill
Low Educated Family	-1.299***	-1.289***	-0.314***	-0.312***
	(0.070)	(0.070)	(0.012)	(0.012)
Mid Educated Family	-0.650***	-0.647***	-0.159***	-0.159***
	(0.067)	(0.068)	(0.010)	(0.011)
Unemp. age 18-25	-0.221***	-0.104	-0.016**	0.007
	(0.042)	(0.083)	(0.008)	(0.017)
Low x Unemp. age 18-25		-0.188**		-0.035**
		(0.094)		(0.017)
Mid x Unemp. age 18-25		-0.034		-0.010
		(0.102)		(0.015)
Observations	27,440	27,440	38,254	38,254
R-squared	0.193	0.193	0.112	0.113
Age FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Avg. outcome	6.155	6.155	0.399	0.399

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5 The Effect of Unemployment by Family Background

Notes: This table shows results of OLS regressions based on equation (2) with survey weights in columns 1 and 3. Columns 2 and 4 add to equation (2) two interactions: "Low x Unemp. age 18-25" and "Mid x Unemp. age 18-25" are family education dummies interacted with the standardized average unemployment rate. In columns 1-2, the dependent variable is the earnings decile of the individual, and in columns 3-4 it is a dummy variable that equals one if the individual is in a skilled occupation according to the ISCO-08 classification as defined in section 2.1. Family's education is the maximum among a respondent's two parents. It is defined as high if at least one parent has tertiary education, mid if the highest educated among both parents has an upper secondary or post-secondary non-tertiary degree, and low if neither of them has attained upper secondary education. Unemployment is measured in country-specific standard deviations and averaged across the years where the individual was between 18-25 years old as explained in section 2.2. In all columns, we add controls for gender and immigration, cohort, and country fixed effects. Standard errors are clustered on the country-cohort level.

A remaining question is why those from high SES backgrounds are not affected in the same way by negative economic shocks. Table C.7 points to the importance of the ability of high SES students to pursue more education to avoid joining the market in times of recession. While on average, there is no impact of unemployment on education (column 1), there exist considerable differences across SES groups. Those from high SES families see changes in education which are countercyclical, that is, when unemployment increases at the time of entering university, high SES children increasingly pursue a university degree. In contrast, there is no overall change in the education choice of those from low SES families. Relative to the increase in education among high SES families, the SES gap in education widens as a result of increases in unemployment, and the differential education response by SES is a key mechanism behind why adverse economic shocks decrease rates of relative mobility.

5 Understanding the Drivers of Mobility

Building on the concerning persistence of intergenerational disadvantage documented in the prior section, we further examine the factors that drive this. Identifying these drivers is crucial to understanding potential interventions for promoting intergenerational mobility. To achieve this, we employ two decomposition methods: the Gelbach decomposition and the variance decomposition. The Gelbach decomposition examines the drivers of relative mobility, how much of the difference between the fraction of low and high SES children reaching the top (as well as the difference in the average earnings decile of the low and high SES) is due to both groups having different education and skill levels. On the other hand, the variance decomposition examines the drivers of absolute mobility, showing how much of the difference across countries in the fraction of low SES reaching the top is due to the low SES having more human capital or human capital being more important for reaching the top in this country.

5.1 Gelbach Decomposition

The results of the Gelbach decomposition show that the vast majority of the gap in relative mobility between low and high SES can be explained by the difference in their own human capital.

In table 6 we provide the decomposition results showing that education level and skill score explain a big part of the gap in labor market outcomes between individuals from a high and a low socioeconomic background. We focus on two labor market outcome measures as before, working in a skilled occupation and the earnings decile. The "base" coefficients in the lower panel of the table correspond to the coefficient on low_SES_i in our previous results, as in equation (2). The "full" coefficient corresponds to the coefficient on the same variable after adding education level dummy variables and the skill variable, as in equation (3).

As in table 2, there is a considerable gap between low- and high-SES families in skilled employment, where low SES children are 35 percentage points less likely to be in a high skilled occupation.[2] After controlling for child human capital measures, the importance of family background declines considerably, from 0.35 to 0.06. Indeed, differences in child human capital explain a significant share of the difference in relative mobility of low SES children, 82%, where two thirds of this difference is explained by the variation in education level and a fifth by skill level. This means that the difference in labor market outcomes between low and high SES children can be explained by lower levels of education and lower skills compared to high SES individuals.

Similarly, the difference in earnings between both groups drops by 1.27 deciles (87%) when we shut down the channel of human capital. Here skill plays a larger role, almost 31%, while education level explains 56.3%. While descriptive, these results highlight the importance of human capital as an engine for intergenerational mobility. However, using any of our labor market outcomes, a part of the gap still remains unexplained by human capital. This means that even when having the same level of education and skill, individuals with parents from lower education are on average still less likely to

[2]The coefficient is slightly different than that of table 2, where it equals 0.31, because for the Gelbach exercise, we include the five countries that were excluded in the previous tables due to lack of specific age data.

have a skilled occupation and have a lower average earnings decile. Yet investing in human capital of children from low socioeconomic backgrounds is a crucial driver of intergenerational mobility.

Appendix tables D.1 and D.2 report the same descriptive results separately for each country, while table 6 pools all countries together while using country fixed effects, which may mask a vast heterogeneity in levels of intergenerational persistence. Human capital might also play a relatively bigger or smaller role in intergenerational mobility due to differences in labor market structure, pay scales and institutional frameworks across countries. Human capital measures generally matter a lot in all countries where in some countries they explain almost all of the gap between high and low SES families (such as Denmark and Norway) and in some places they explain around 70%. While there does exist some cross-country variation in the importance of child human capital for equality of opportunity, child human capital is a crucial factor for intergenerational mobility in each country.

	(1) Earnings Decile	(2) High Skilled
Low Educated Family		
Total Explained	-1.2711***	-0.2855***
	(0.0206)	(0.0035)
Skill score	-0.4502***	-0.0684***
	(0.0135)	(0.0020)
Own Education	-0.8209***	-0.2171***
	(0.0179)	(0.0032)
Observations	43284	59064
Base coefficient	-1.458	-0.348
Full coefficient	-0.187	-0.062
% unexplained	12.8	17.9
% explained	87.2	82.1
Skill score	30.9	19.7
Own Education	56.3	62.4

Table 6 Decomposition using Gelbach (2016)

Notes: This table provides results of decomposing our measure of relative mobility into a part explained by education, another by skill score, and an unexplained part. We use the method proposed by Gelbach (2016) as described in section 2.3. Skill score is the score of the numeracy skill test provided in PIAAC. It is computed as the average of plausible values. Own education stands for education fixed effects in five categories of education level as described in section 2.1. Observations are weighted using survey weights.

5.2 Variance Decomposition: Explaining Bottom to Top Mobility

Across the countries in our sample, there exists substantial variation in rates of bottom to top mobility, defined as coming from a low-SES family and being employed in a high-skilled occupation. Why do some countries, such as Turkey, Greece, and Italy, have low rates of absolute mobility and other countries such as the Netherlands, Canada, and Sweden have high rates of absolute mobility (Figure 3)? We decompose the factors that determine the difference in rates of absolute mobility across countries. Specifically, we ask how much differences in human capital across countries explain the cross-country variation in rates of absolute mobility. Given the importance of both educational qualifications and skills seen for relative mobility, we construct a measure of overall index of human capital as the combined influence of schooling and skills. As in Carneiro, Cattan, Dearden, Van der Erve, Krutikova and Macmillan (2022), we regress an individual's earnings decile on education qualifications and skills:

$$y_i = \alpha_0 + \alpha_1 skill_i + \sum_{e=1}^{5} E_{ei}\alpha_{2e} + \epsilon_i \quad (10)$$

Our index of human capital H_i is then the predicted earnings decile of individual i, $\hat{y}_i$, based solely on an individual's schooling and skills from the previous equation:

$$H_i = \hat{y}_i \quad (11)$$

Figure 3 reveals considerable differences in rates of absolute mobility: low mobility countries have rates of absolute mobility of around 15% while high mobility countries mobility rates are around 45%.[3] There exists a strong positive relationship between absolute mobility and our index of human capital revealing that places which have a higher human capital index tend to have higher absolute mobility on average. There exists a strong correlation between average mobility rates and human capital across countries, and as such, we would expect cross-country differences in human capital to be an important driver of rates of absolute mobility across countries.

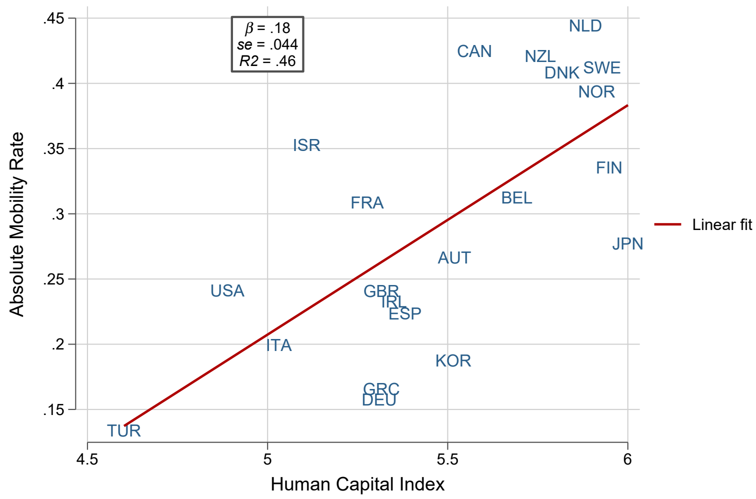


Figure 3 The Relationship Between Rates of Absolute Mobility and Human Capital Index

Notes: This figure plots the absolute mobility measure against the average human capital index for each country with a fitted regression line. Absolute mobility is measured as the fraction of individuals with low educated parents who end up in high skilled occupations (bottom-to-top intergenerational mobility). The human capital index is the national average of the predicted earnings calculated using education level and skill score as described in section 5.2. Survey weights are used to ensure national representativeness.

Table 7 presents a formal decomposition of the variance as detailed in Section 2.3. The exercise asks to what extent the cross-country variation in absolute mobility is explained by the variation in human capital across countries and what part remains unexplained by human capital. Cross-country

[3]Consistent with Figure 3, Figure E.1 shows a considerable variation in the distribution of both variables across all countries.

differences in human capital are a key factor explaining cross-country variation in rates of absolute mobility: nearly 50% of the variation in mobility is explained by variation in human capital. While human capital is clearly a key factor in why some countries have high and low rates of mobility, it is also not everything. The remaining 50% of variation in absolute mobility is unexplained by human capital, pointing to the importance of differences in labor market institutions and other country-specific factors across different countries. Yet, both decomposition exercises point to the importance of human capital in intergenerational mobility. Indeed, we show that human capital is key in explaining both relative mobility, comparing low and high-SES individuals, and absolute mobility, coming from a low-SES family and ending up in a high-skilled occupation.

	(1) Variance in Upward Mobility
Share Explained by:	
Human Capital Index	0.489
Country Fixed Effects	0.539
Covariance	-0.028
Number of Countries	21
Variance in Upward Mobility	0.010

Table 7 Decomposing the Importance of Human Capital for Cross-Country Variance in Absolute Mobility
This tables shows the results of the variance decomposition described in section 2.3. Absolute mobility is measured as the fraction of individuals with low-educated parents who end up in high skilled occupations (bottom-to-top intergenerational mobility). The human capital index is the national average of the predicted earnings calculated using education level and skill score as described in section 5.2. Survey weights are used in all computations to ensure national representativeness.

6 Conclusion

Our research sheds light on the relative importance of family background compared to external economic shocks. We have observed that while macroeconomic conditions during the transition from education to the labor market significantly impact long-term earnings and career progression, the enduring effect of intergenerational persistence in disadvantage is substantial. Additionally, adverse macroeconomic conditions disproportionately affect long-term earnings and career progression for individuals from lower socioeconomic backgrounds. Economic shocks further widen the gap between the different groups exacerbating existing inequalities. This underscores the importance of policies specifically designed to support individuals from low socioeconomic backgrounds entering the workforce during recessions.

Our analysis also highlights the role of human capital investments in breaking intergenerational persistence of disadvantage. We decompose relative mobility rates which compare late adulthood labor market outcomes of individuals from low versus those from high socioeconomic family backgrounds. We find that a significant portion of the gap in earnings and occupational outcomes between the different socioeconomic groups can be attributed to differences in education and skill levels.

Human capital investment emerges as a crucial lever for breaking the cycle of disadvantage, with education playing a pivotal role in enhancing equality of opportunity.

Moreover, our international comparisons underscore the role of human capital investment at a broader societal level, with variations in human capital investment levels across countries explaining a substantial portion of the differences in absolute mobility observed. These insights emphasize the urgent need for targeted policies aimed at leveling the playing field for individuals from low socioeconomic backgrounds and supporting such individuals during times of high unemployment.

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Appendix

A Data and Descriptives

Country	Start Year	End Year	Source
Austria	1968	2011	OECD
Belgium	1970	2011	OECD
Canada	1968	2011	OECD
Denmark	1969	2011	OECD
Finland	1968	2011	OECD (LFS)
France	1969	2012	OECD
Germany	1968	2011	OECD
Greece	1977	2014	OECD
Ireland	1971	2011	OECD (LFS)
Israel	1971	2014	ILO
Italy	1970	2011	OECD (LFS)
Japan	1968	2011	OECD
Korea	1969	2011	ILO
Netherlands	1970	2011	OECD
New Zealand	1971	2014	OECD
Norway	1972	2011	OECD
Spain	1972	2011	OECD (LFS)
Sweden	1968	2011	OECD (LFS)
Turkey	1980	2014	IMF
United Kingdom	1971	2011	OECD
United States	1968	2011	OECD

Table A.1 Unemployment Data Sources

Notes: This table shows the sources of our unemployment data for each country included in our dataset. "OECD" only refers to the Main Economic Indicators complete database published by the Organization for Economic Cooperation and Development. When "LFS" is indicated in brackets, it refers to the OECD's Labour Force Statistics Indicators database. IMF is the International Monetary Fund.

	(1) Low	(2) Mid	(3) High	(4) Total
Age	46.17	44.83	44.28	45.51
	(6.603)	(6.721)	(6.708)	(6.697)
Lower secondary or less	0.401	0.0826	0.0340	0.196
	(0.490)	(0.275)	(0.181)	(0.397)
Upper secondary	0.387	0.472	0.248	0.388
	(0.487)	(0.499)	(0.432)	(0.487)
Post-secondary, non-tertiary	0.0255	0.0766	0.0580	0.0524
	(0.158)	(0.266)	(0.234)	(0.223)
Tertiary – professional degree	0.0834	0.144	0.163	0.125
	(0.277)	(0.351)	(0.370)	(0.330)
Tertiary - bachelor/master/research degree	0.103	0.225	0.497	0.239
	(0.303)	(0.418)	(0.500)	(0.427)
Vocational Education	0.281	0.386	0.288	0.323
	(0.449)	(0.487)	(0.453)	(0.468)
Numeracy skill score	243.8	269.9	289.4	264.1
	(50.48)	(46.91)	(45.06)	(51.16)
Skilled occupations	0.234	0.413	0.603	0.386
	(0.424)	(0.492)	(0.489)	(0.487)
Semi-skilled white-collar occupations	0.260	0.271	0.215	0.254
	(0.439)	(0.444)	(0.411)	(0.435)
Semi-skilled blue-collar occupations	0.226	0.180	0.0965	0.179
	(0.419)	(0.384)	(0.295)	(0.383)
Elementary occupations	0.100	0.0529	0.0260	0.0653
	(0.300)	(0.224)	(0.159)	(0.247)
NEET	0.248	0.138	0.0868	0.169
	(0.432)	(0.345)	(0.282)	(0.375)
Monthly earned income in deciles	5.599	6.193	6.882	6.159
	(2.792)	(2.821)	(2.817)	(2.852)
Female	0.513	0.501	0.506	0.507
	(0.500)	(0.500)	(0.500)	(0.500)
Native Born	0.968	0.986	0.961	0.973
	(0.177)	(0.118)	(0.194)	(0.162)
Unemp. age 18-25	0.0467	0.137	0.170	0.109
	(0.703)	(0.642)	(0.601)	(0.660)
Observations	59088			

Table A.2 Summary Statistics by SES using weights

Notes: This table presents summary statistics using survey weights for our sample comprising individuals aged 35 to 59. Columns one, two, three, and four show means and standard deviations for individuals with low-educated families, mid-educated families, high-educated families, and the whole sample, respectively. Family's education is the maximum among a respondent's two parents. It is defined as high if at least one parent has tertiary education, mid if the highest educated among both parents has an upper secondary or post-secondary non-tertiary degree, and low if neither of them has attained upper secondary education. Numeracy test score is calculated for each individual as the average of plausible values. It ranges from 0 to 500. NEET stands for not currently employed and did not participate in education or training in the last 12 months. Deciles of monthly earnings include bonuses for wage and salary earners and self-employed. Standard deviations are reported in parentheses.

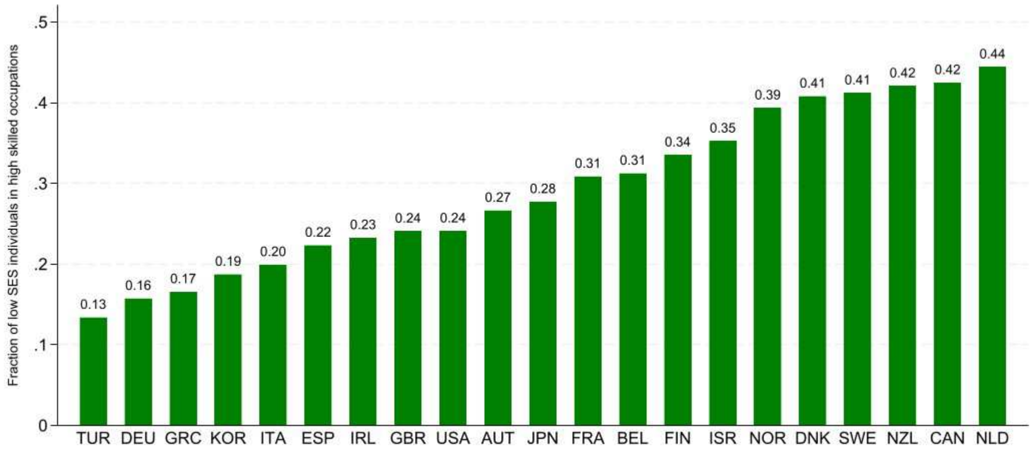

Figure A.1 Absolute Intergenerational Mobility by Country

Notes: This figure shows the fraction of individuals with low-educated families that end up in skilled occupations (our measure of absolute mobility).Family's education is the maximum among a respondent's two parents. It is defined as high if at least one parent has tertiary education, mid if the highest educated among both parents has an upper secondary or post-secondary non-tertiary degree, and low if neither of them has attained upper secondary education. Survey weights are used to ensure national representativeness.

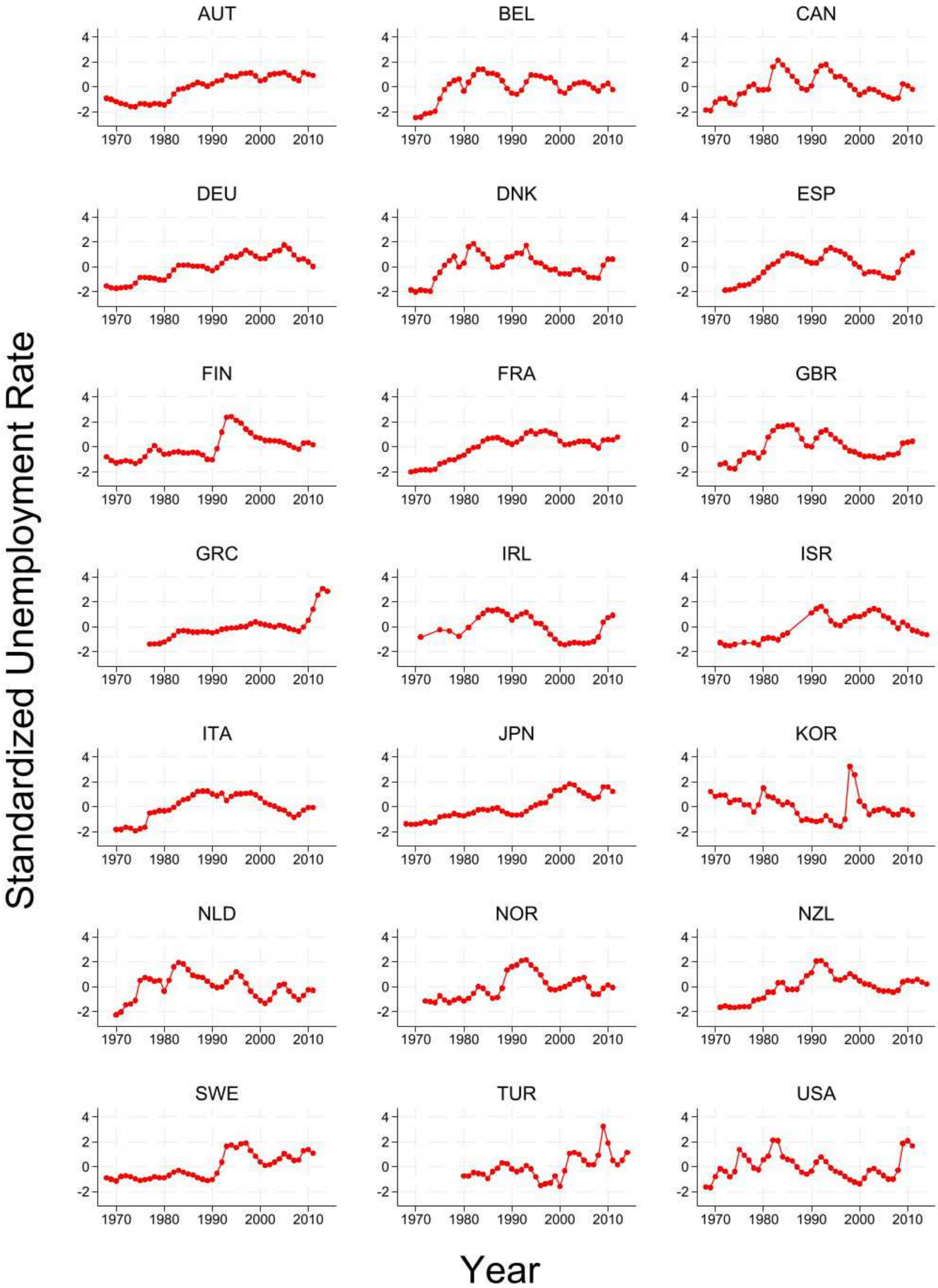

Figure A.2 Standardized Unemployment Rate by Country

Notes: This figure shows unemployment time series by country. The plotted unemployment rate is standardized to be measured country-specific standard deviations as explained in section 2.2.

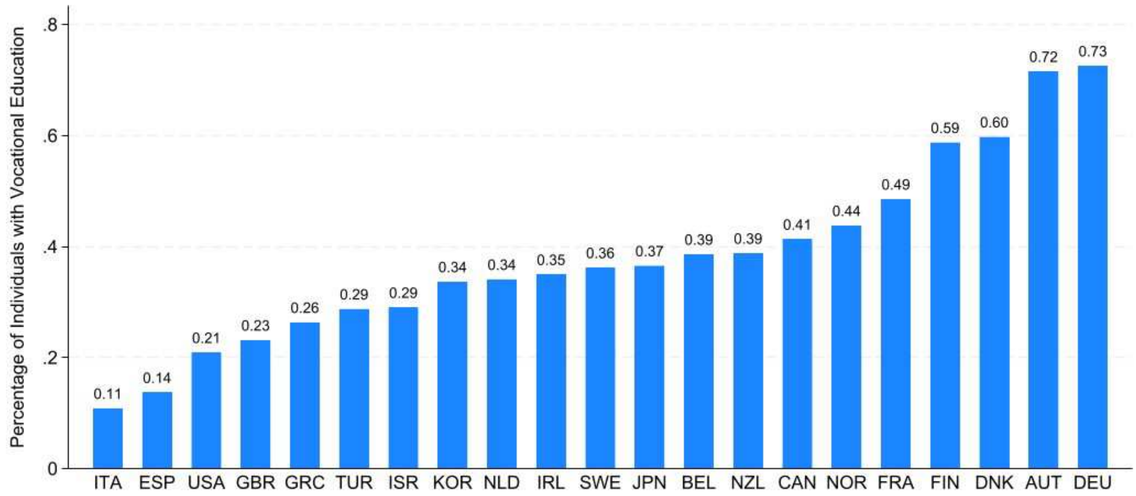

Figure A.3 Vocational Education Rate by Countries

Notes: This figure shows the fraction of individuals who have vocational education in every country. If an individual's highest level of education is secondary school or post secondary non-tertiary, the participant is asked whether his degree was vocationally oriented or not. Following Hanushek et al. (2017) and Hampf and Woessmann (2017) we add to those who responded yes to this question the ones who graduated with a tertiary professional degree which have a tertiary professional degree which is equivalent to level 5B in the International Standard Classification of Education (ISCED 5B). Survey weights are used to ensure national representativeness.

B Robustness and Heterogeneity

B.1 Unemployment Rate at Different Ages

VARIABLES	(1) Earnings Decile	(2) Earnings Decile	(3) Earnings Decile	(4) Earnings Decile
Low Educated Family	-1.296***	-1.293***	-1.297***	-1.299***
	(0.070)	(0.070)	(0.070)	(0.070)
Mid Educated Family	-0.648***	-0.647***	-0.648***	-0.650***
	(0.068)	(0.068)	(0.068)	(0.067)
Unemp. age 16	-0.090***			
	(0.035)			
Unemp. age 17		-0.096***		
		(0.034)		
Unemp. age 18			-0.099***	
			(0.035)	
Unemp. age 18-25				-0.221***
				(0.042)
Observations	27,440	27,064	27,285	27,440
R-squared	0.192	0.192	0.192	0.193
Age FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Avg. decile	6.155	6.155	6.155	6.155

Clustered standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B.1 Unemployment at Different Ages

Notes: This table shows results of OLS regressions based on equation (2) with survey weights but every column includes unemployment measured at a different age as indicated. "Unemp. age 16" means that every individual is assigned the standardized national unemployment rate they faced in their country of residence when they were 16 years old.Family's education is the maximum among a respondent's two parents. It is defined as high if at least one parent has tertiary education, mid if the highest educated among both parents has an upper secondary or post-secondary non-tertiary degree, and low if neither of them has attained upper secondary education. The dependent variable is the earnings decile of the individual. In all columns, we add controls for gender and immigration, cohort, and country fixed effects. Standard errors are clustered on the country-cohort level.

B.2 Full, imputing average for missing countries

Table B.2 includes five countries for whom we can only measure unemployment in 5 year bins (Germany, USA, Canada, Austria, New Zealand).

VARIABLES	(1) Earnings Decile	(2) Earnings Decile	(3) Earnings Decile	(4) High Skill	(5) High Skill	(6) High Skill
Low Educated Family	-1.459***		-1.460***	-0.348***		-0.348***
	(0.085)		(0.085)	(0.017)		(0.017)
Mid Educated Family	-0.699***		-0.699***	-0.186***		-0.186***
	(0.051)		(0.051)	(0.010)		(0.010)
Unemp. age 18-25		-0.042	-0.055		0.004	0.001
		(0.067)	(0.064)		(0.008)	(0.008)
Observations	43,295	43,295	43,295	59,088	59,088	59,088
R-squared	0.158	0.129	0.158	0.107	0.051	0.107
Age Bin FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Avg. outcome	6.168	6.168	6.168	0.428	0.428	0.428

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.2 Basline on Sample of 21 Countries

Notes: This table shows results of OLS regressions based on equation (2) with survey weights but includes 5 more countries than the baseline sample in table 2. In columns 1-3, the dependent variable is the earnings decile of the individual, and in columns 4-6 it is a dummy variable that equals one if the individual is in a skilled occupation according to the ISCO-08 classification as defined in section 2.1. Family's education is the maximum among a respondent's two parents. It is defined as high if at least one parent has tertiary education, mid if the highest educated among both parents has an upper secondary or post-secondary non-tertiary degree, and low if neither of them has attained upper secondary education. Unemployment is measured in country-specific standard deviations and averaged across the years where the individual could have between 18-25 years old approximated using 5-year age bins. In all columns, we add controls for gender and immigration, age bin, and country fixed effects. Standard errors are clustered on the country-cohort level.

B.3 Country-Specific Quadratic Age Trends

In a robustness check we run a specification of equation (2) that includes country-specific quadratic age trends, $\delta_c a(i) + \delta_c a(i)^2$ following Arellano-Bover (2022) to account for non-linear country-specific variations in how age (or time) influence labor market outcomes:

$$y_{ic} = \beta_1 low\_SES_i + \beta_2 mid\_SES_i + \gamma u^{18-25}_{a(i)c} + \delta_c + \delta_{a(i)} + \delta_c a(i) + \delta_c a(i)^2 + X_i' \lambda + \epsilon_{ic} \tag{12}$$

The age-earnings profile would look different in different countries for example. Those country-specific quadratic trends would also capture changes in the institutional framework. The results are provided in Table B.3. Earnings decile results are robust to adding those trends for both unemployment and family coefficients have almost the same magnitude. Only the unemployment coefficient's statistical significance drops since controlling for the age trends by country takes away much of the variation in unemployment trends. This also explains why we see no statistically significant effect of unemployment on high skilled occupations in the last column of the table.

VARIABLES	(1) Earnings Decile	(2) Earnings Decile	(3) High Skilled	(4) High Skilled
Low Educated Family	-1.299***	-1.306***	-0.314***	-0.318***
	(0.070)	(0.071)	(0.012)	(0.012)
Mid Educated Family	-0.650***	-0.655***	-0.159***	-0.161***
	(0.067)	(0.068)	(0.010)	(0.010)
Unemp. age 18-25	-0.221***	-0.195*	-0.016**	0.015
	(0.042)	(0.100)	(0.008)	(0.014)
Observations	27,440	27,440	38,254	38,254
R-squared	0.193	0.195	0.112	0.117
Age FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Country-specific quadratic age trends	No	Yes	No	Yes
Avg. outcome	6.155	6.155	0.399	0.399

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.3 Adding Country-Specific Quadratic Age Trends

Notes: This table shows results of OLS regressions based on equation (2) in columns 1 and 3 and equation (12) in columns 2 and 4. Survey weights are used in all specifications. In columns 1-2, the dependent variable is the earnings decile of the individual, and in columns 3-4 it is a dummy variable that equals one if the individual is in a skilled occupation according to the ISCO-08 classification as defined in section 2.1. Family's education is the maximum among a respondent's two parents. It is defined as high if at least one parent has tertiary education, mid if the highest educated among both parents has an upper secondary or post-secondary non-tertiary degree, and low if neither of them has attained upper secondary education. Unemployment is measured in country-specific standard deviations and averaged across the years where the individual was between 18-25 years old as explained in section 2.2. In all columns, we add controls for gender and immigration, cohort, and country fixed effects. Standard errors are clustered on the country-cohort level.

B.4 Mother/Father

VARIABLES	(1) Earnings Decile	(2) Earnings Decile	(3) High Skill	(4) High Skill
Low Educated Mother	-0.900***		-0.242***	
	(0.082)		(0.015)	
Mid Educated Mother	-0.226**		-0.081***	
	(0.093)		(0.014)	
Unemp. age 18-25	-0.222***	-0.218***	-0.016**	-0.015**
	(0.043)	(0.041)	(0.008)	(0.008)
Low Educated Father		-1.013***		-0.260***
		(0.073)		(0.011)
Mid Educated Father		-0.449***		-0.117***
		(0.078)		(0.011)
Observations	27,440	27,440	38,254	38,254
R-squared	0.182	0.185	0.091	0.100
Age FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Avg. outcome	6.155	6.155	0.399	0.399

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.4 Baseline using Mother and Father's Education Separetely

Notes: This table shows results of OLS regressions based on equation (2) with survey weights. In columns 1-2, the dependent variable is the earnings decile of the individual, and in columns 3-4 it is a dummy variable that equals one if the individual is in a skilled occupation according to the ISCO-08 classification as defined in section 2.1. Mother and father's education is defined as low if the parent's highest level of education is lower secondary or less (ISCED 1,2, 3C short or less). Mid education is upper secondary (ISCED 3A-B, C long) or post-secondary, non-tertiary (ISCED 4A-B-C). High education is tertiary education degrees including professional degrees (ISCED 5B) or bachelor/master/research degrees (ISCED 5A/6). Unemployment is measured in country-specific standard deviations and averaged across the years where the individual was between 18-25 years old as explained in section 2.2. In all columns, we add controls for gender and immigration, cohort, and country fixed effects. Standard errors are clustered on the country-cohort level.

VARIABLES	(1) Earnings Decile	(2) Earnings Decile	(3) High Skill	(4) High Skill
Low Educated Mother	-0.920***		-0.216***	
	(0.121)		(0.020)	
Mid Educated Mother	-0.281**		-0.069***	
	(0.131)		(0.021)	
Unemp. age 18-25	-0.225***	-0.227***	-0.013*	-0.014*
	(0.069)	(0.067)	(0.008)	(0.008)
Low Educated Father		-1.045***		-0.235***
		(0.110)		(0.015)
Mid Educated Father		-0.486***		-0.115***
		(0.119)		(0.014)
Observations	13,122	13,122	19,914	19,914
R-squared	0.069	0.075	0.090	0.099
Age FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Avg. outcome	5.180	5.180	0.370	0.370

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.5 Daughters

Notes: This table shows results of OLS regressions based on equation (2) with survey weights. The sample used here is restricted to female individuals only (daughters). In columns 1-2, the dependent variable is the earnings decile of the individual, and in columns 3-4 it is a dummy variable that equals one if the individual is in a skilled occupation according to the ISCO-08 classification as defined in section 2.1. Mother and father's education is defined as low if the parent's highest level of education is lower secondary or less (ISCED 1,2, 3C short or less). Mid education is upper secondary (ISCED 3A-B, C long) or post-secondary, non-tertiary (ISCED 4A-B-C). High education is tertiary education degrees including professional degrees (ISCED 5B) or bachelor/master/research degrees (ISCED 5A/6). Unemployment is measured in country-specific standard deviations and averaged across the years where the individual was between 18-25 years old as explained in section 2.2. In all columns, we add controls for immigration, cohort, and country fixed effects. Standard errors are clustered on the country-cohort level.

VARIABLES	(1) Earnings Decile	(2) Earnings Decile	(3) High Skill	(4) High Skill
Low Educated Mother	-0.839***		-0.265***	
	(0.106)		(0.021)	
Mid Educated Mother	-0.151		-0.086***	
	(0.115)		(0.022)	
Unemp. age 18-25	-0.235***	-0.228***	-0.019*	-0.017
	(0.054)	(0.053)	(0.011)	(0.010)
Low Educated Father		-0.940***		-0.285***
		(0.092)		(0.016)
Mid Educated Father		-0.387***		-0.117***
		(0.102)		(0.017)
Observations	14,318	14,318	18,340	18,340
R-squared	0.057	0.060	0.084	0.094
Age FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Avg. outcome	7.048	7.048	0.431	0.431

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.6 Sons

Notes: This table shows results of OLS regressions based on equation (2) with survey weights. The sample used here is restricted to male individuals only (sons). In columns 1-2, the dependent variable is the earnings decile of the individual, and in columns 3-4 it is a dummy variable that equals one if the individual is in a skilled occupation according to the ISCO-08 classification as defined in section 2.1. Mother and father's education is defined as low if the parent's highest level of education is lower secondary or less (ISCED 1,2, 3C short or less). Mid education is upper secondary (ISCED 3A-B, C long) or post-secondary, non-tertiary (ISCED 4A-B-C). High education is tertiary education degrees including professional degrees (ISCED 5B) or bachelor/master/research degrees (ISCED 5A/6). Unemployment is measured in country-specific standard deviations and averaged across the years where the individual was between 18-25 years old as explained in section 2.2. In all columns, we add controls for immigration, cohort, and country fixed effects. Standard errors are clustered on the country-cohort level.

C Impact of Economic Shocks on Education

VARIABLES	(1) University Degree	(2) University Degree
Low Educated Family	-0.404***	-0.410***
	(0.011)	(0.010)
Mid Educated Family	-0.264***	-0.269***
	(0.010)	(0.010)
Unemp. age 18	0.001	0.036***
	(0.005)	(0.010)
Low x Unemp. age 18		-0.040***
		(0.010)
Mid x Unemp. age 18		-0.035***
		(0.011)
Observations	37,974	37,974
R-squared	0.144	0.145
Age FE	Yes	Yes
Country FE	Yes	Yes
Controls	Yes	Yes
Avg. outcome	0.240	0.240

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.7 University Degrees

Notes: This table shows results of OLS regressions based on equation (2) with survey weights. Column 2 adds to equation (2) two interactions: "Low x Unemp. age 18" and "Mid x Unemp. age 18" are family education dummies interacted with the standardized unemployment rate. The dependent variable is a dummy variable that equals one if the individual has a university degree (Tertiary degree: bachelor/master/research degree ISCED 5A/6). Family's education is the maximum among a respondent's two parents. It is defined as high if at least one parent has tertiary education, mid if the highest educated among both parents has an upper secondary or post-secondary non-tertiary degree, and low if neither of them has attained upper secondary education. Unemployment is the national rate of unemployment in the country of residence when the individual was 18 years old measured in country-specific standard deviations. In all columns, we add controls for gender and immigration, cohort, and country fixed effects. Standard errors are clustered on the country-cohort level.

D Gelbach (2016) Decomposition

Since both labor market outcomes and family background are correlated with education and skill, the β_1 in equations 2 and 3 will not be identical. We will denote the one in the base regression equation 2 as β_1^{base} and the other as β_1^{full}. According to the omitted variable formula, the β_1^{base} would be a combination of the β_1^{full} and a bias:

$$\beta_1^{base} = \beta_1^{full} + \eta \tag{13}$$

where η is the difference between the base and the full coefficient due to controlling for both the skill and the education of the individual. According to the omitted variable formula, the bias, η is equal to a combination of the direct effect of the omitted variable on the outcome measure scaled by its effect on the variable of interest. In our case:

$$\beta_1^{base} - \beta_1^{full} = \eta = \tau^{skill}\beta_3 + \sum_{e=1}^{5} \tau_e^{educ}\beta_{4e} \tag{14}$$

where τ^{skill} and τ^{educ} are the coefficients from the auxiliary regressions of the omitted variables (education and skill) on our family background variable (here we focus on low_SES_i) and the controls.

β_3 and β_{4e} are the coefficients on skill and education category dummies from equation 3. Each of the two terms in the last equation specifies the part of the bias explained by each omitted variable: $\tau^{skill}\beta_3$ is the part explained by skill and $\sum_{e=1}^{5}\tau_e^{educ}\beta_{4e}$ is the part explained by education level. This method then allows us to measure how much each own education and skill accounts for the change in our coefficient of interest β_1. In other words, this decomposition answers the question on how much of intergenerational persistence is due to differences in education and skill among individuals from different socioeconomic family backgrounds. Education dummy variables only account for the broad level of education of the individual (e.g upper-secondary only or university degree) which masks some heterogeneity among the actual amount of education people with the same degree in the same country and cohort could have. This could be due to differences in the quality of education across schools and universities or regions in the same country or also differences in the grades they graduated with. The variable measuring numeracy skill from the PIAAC test score therefore goes a step further to account for the actual difference among the skills of those individuals. Adding it accounts for differences in inherent ability as well as a combination of learned skills and experiences. This can capture also differences in the quality of education among individuals with the same level of education.

	(1) AUT	(2) BEL	(3) CAN	(4) DEU	(5) DNK	(6) ESP	(7) FIN	(8) FRA	(9) GBR	(10) GRC	(11) IRL
Low Educated Family											
Total Explained	-0.9466***	-1.3050***	-0.9593***	-1.3384***	-0.8257***	-1.4879***	-1.1346***	-1.5795***	-1.3249***	-1.2244***	-1.6176***
	(0.0929)	(0.1025)	(0.0373)	(0.1157)	(0.0666)	(0.1339)	(0.1006)	(0.1046)	(0.0854)	(0.1564)	(0.1399)
Numeracy Score	-0.4155***	-0.4735***	-0.3304***	-0.5471***	-0.3065***	-0.2882***	-0.3043***	-0.6092***	-0.5053***	-0.0261	-0.4275***
	(0.0627)	(0.0670)	(0.0254)	(0.0773)	(0.0406)	(0.0691)	(0.0498)	(0.0679)	(0.0613)	(0.0842)	(0.0834)
Own Education	-0.5310***	-0.8316***	-0.6289***	-0.7913***	-0.5191***	-1.1997***	-0.8303***	-0.9703***	-0.8197***	-1.1984***	-1.1901***
	(0.0739)	(0.0910)	(0.0325)	(0.0945)	(0.0538)	(0.1248)	(0.0851)	(0.0885)	(0.0716)	(0.1607)	(0.1279)
Observations	1762	1693	8876	1962	2468	1439	2101	2352	2549	913	1138
Base coefficient	-0.989	-1.390	-0.957	-1.434	-0.916	-1.582	-0.746	-1.637	-1.477	-1.622	-1.868
Full coefficient	-0.043	-0.085	0.002	-0.096	-0.090	-0.094	0.388	-0.057	-0.153	-0.398	-0.250
% unexplained	4.3	6.1	-0.2	6.7	9.9	5.9	-52.0	3.5	10.3	24.5	13.4
% explained	95.7	93.9	100.2	93.3	90.1	94.1	152.0	96.5	89.7	75.5	86.6
Numeracy score	42.0	34.1	34.5	38.1	33.5	18.2	40.8	37.2	34.2	1.6	22.9
Own Education	53.7	59.8	65.7	55.2	56.7	75.8	111.2	59.3	55.5	73.9	63.7

	(1) ISR	(2) ITA	(3) JPN	(4) KOR	(5) NLD	(6) NOR	(7) NZL	(8) SWE	(9) TUR	(10) USA
Low Educated Family										
Total Explained	-1.3907***	-1.4670***	-0.7491***	-0.8799***	-0.9391***	-0.9475***	-0.7734***	-0.7752***	-2.2048***	-1.5542***
	(0.1418)	(0.1795)	(0.0720)	(0.0737)	(0.0777)	(0.0905)	(0.0748)	(0.0759)	(0.3178)	(0.1261)
Numeracy Score	-0.5830***	-0.3952***	-0.3491***	-0.2907***	-0.2496***	-0.4159***	-0.2973***	-0.3168***	-0.4599***	-0.6129***
	(0.1071)	(0.0866)	(0.0481)	(0.0456)	(0.0417)	(0.0600)	(0.0482)	(0.0500)	(0.1340)	(0.0906)
Own Education	-0.8077***	-1.0718***	-0.4000***	-0.5892***	-0.6895***	-0.5316***	-0.4761***	-0.4584***	-1.7450***	-0.9413***
	(0.1199)	(0.1603)	(0.0628)	(0.0655)	(0.0688)	(0.0684)	(0.0617)	(0.0635)	(0.2804)	(0.1070)
Observations	827	1398	2120	2606	1857	1497	1705	1643	835	1543
Base coefficient	-1.584	-1.688	-0.971	-1.008	-1.099	-1.043	-0.703	-0.774	-1.983	-1.947
Full coefficient	-0.193	-0.221	-0.222	-0.128	-0.160	-0.095	0.070	0.001	0.221	-0.393
% unexplained	12.2	13.1	22.8	12.7	14.5	9.1	-10.0	-0.1	-11.2	20.2
% explained	87.8	86.9	77.2	87.3	85.5	90.9	110.0	100.1	111.2	79.8
Numeracy score	36.8	23.4	36.0	28.8	22.7	39.9	42.3	40.9	23.2	31.5
Own Education	51.0	63.5	41.2	58.5	62.8	51.0	67.7	59.2	88.0	48.3

Table D.1 Gelbach Decomposition by Country for Earnings Deciles

Notes: This table provides results of decomposing our measure of relative mobility into a part explained by education, another by skill score, and an unexplained part for each country separately.The outcome variable here is the earnings decile of the individual. We use the method proposed by Gelbach (2016) as described in section 2.3. Skill score is the score of the numeracy skill test provided in PIAAC. It is computed as the average of plausible values. Own education stands for education fixed effects in five categories of education level as described in section 2.1. Observations are weighted using survey weights.

	(1) AUT	(2) BEL	(3) CAN	(4) DEU	(5) DNK	(6) ESP	(7) FIN	(8) FRA	(9) GBR	(10) GRC	(11) IRL
Low Educated Family											
Total Explained	-0.2262***	-0.3063***	-0.2123***	-0.3333***	-0.2318***	-0.3100***	-0.2565***	-0.3152***	-0.2910***	-0.3185***	-0.3130***
	(0.0174)	(0.0183)	(0.0066)	(0.0232)	(0.0151)	(0.0187)	(0.0207)	(0.0167)	(0.0143)	(0.0220)	(0.0206)
Numeracy Score	-0.0619***	-0.0506***	-0.0842***	-0.0858***	-0.0540***	-0.0321***	-0.0507***	-0.0928***	-0.0861***	-0.0133**	-0.0388***
	(0.0088)	(0.0093)	(0.0045)	(0.0113)	(0.0068)	(0.0080)	(0.0075)	(0.0096)	(0.0093)	(0.0059)	(0.0104)
Own Education	-0.1644***	-0.2556***	-0.1281***	-0.2474***	-0.1778***	-0.2779***	-0.2058***	-0.2223***	-0.2048***	-0.3052***	-0.2742***
	(0.0150)	(0.0176)	(0.0055)	(0.0206)	(0.0131)	(0.0182)	(0.0182)	(0.0145)	(0.0125)	(0.0218)	(0.0200)
Observations	2327	2213	11638	2451	2923	2472	2592	3125	3555	2078	1798
Base coefficient	-0.338	-0.430	-0.241	-0.403	-0.223	-0.394	-0.317	-0.355	-0.337	-0.455	-0.391
Full coefficient	-0.111	-0.124	-0.029	-0.070	0.009	-0.084	-0.061	-0.040	-0.046	-0.136	-0.078
% unexplained	33.0	28.8	11.9	17.3	-4.0	21.3	19.1	11.3	13.6	30.0	19.9
% explained	67.0	71.2	88.1	82.7	104.0	78.7	80.9	88.7	86.4	70.0	80.1
Numeracy score	18.3	11.8	34.9	21.3	24.2	8.2	16.0	26.1	25.6	2.9	9.9
Own Education	48.7	59.5	53.1	61.4	79.8	70.6	64.9	62.6	60.8	67.1	70.1

	(1) ISR	(2) ITA	(3) JPN	(4) KOR	(5) NLD	(6) NOR	(7) NZL	(8) SWE	(9) TUR	(10) USA
Low Educated Family										
Total Explained	-0.3494***	-0.4434***	-0.1958***	-0.1752***	-0.2379***	-0.2679***	-0.1788***	-0.2041***	-0.3766***	-0.3337***
	(0.0221)	(0.0286)	(0.0135)	(0.0111)	(0.0160)	(0.0215)	(0.0138)	(0.0167)	(0.0301)	(0.0209)
Numeracy Score	-0.1105***	-0.0406***	-0.0380***	-0.0332***	-0.0437***	-0.0760***	-0.0562***	-0.0477***	-0.0187**	-0.1033***
	(0.0149)	(0.0085)	(0.0068)	(0.0056)	(0.0075)	(0.0102)	(0.0077)	(0.0076)	(0.0074)	(0.0143)
Own Education	-0.2388***	-0.4028***	-0.1578***	-0.1419***	-0.1942***	-0.1919***	-0.1226***	-0.1564***	-0.3579***	-0.2304***
	(0.0191)	(0.0270)	(0.0128)	(0.0106)	(0.0148)	(0.0178)	(0.0116)	(0.0143)	(0.0296)	(0.0185)
Observations	1386	2285	2567	3530	2314	1695	2227	1839	1874	2175
Base coefficient	-0.443	-0.540	-0.227	-0.247	-0.286	-0.261	-0.179	-0.244	-0.530	-0.405
Full coefficient	-0.093	-0.096	-0.031	-0.072	-0.048	0.006	-0.000	-0.040	-0.153	-0.071
% unexplained	21.1	17.8	13.8	29.2	16.9	-2.5	0.1	16.3	28.9	17.6
% explained	78.9	82.2	86.2	70.8	83.1	102.5	99.9	83.7	71.1	82.4
Numeracy score	25.0	7.5	16.7	13.4	15.3	29.1	31.4	19.6	3.5	25.5
Own Education	54.0	74.7	69.5	57.4	67.8	73.4	68.5	64.1	67.6	56.9

Table D.2 Gelbach Decomposition by Country for High Skill Occupations

Notes: This table provides results of decomposing our measure of relative mobility into a part explained by education, another by skill score, and an unexplained part for each country separately. The outcome variable is a dummy variable that equals one if the individual is in a skilled occupation according to the ISCO-08 classification as defined in section 2.1. We use the method proposed by Gelbach (2016) as described in section 2.3. Skill score is the score of the numeracy skill test provided in PIAAC. It is computed as the average of plausible values. Own education stands for education fixed effects in five categories of education level as described in section 2.1. Observations are weighted using survey weights.

E Cross-Country Distribution of Absolute Mobility and Human Capital Index

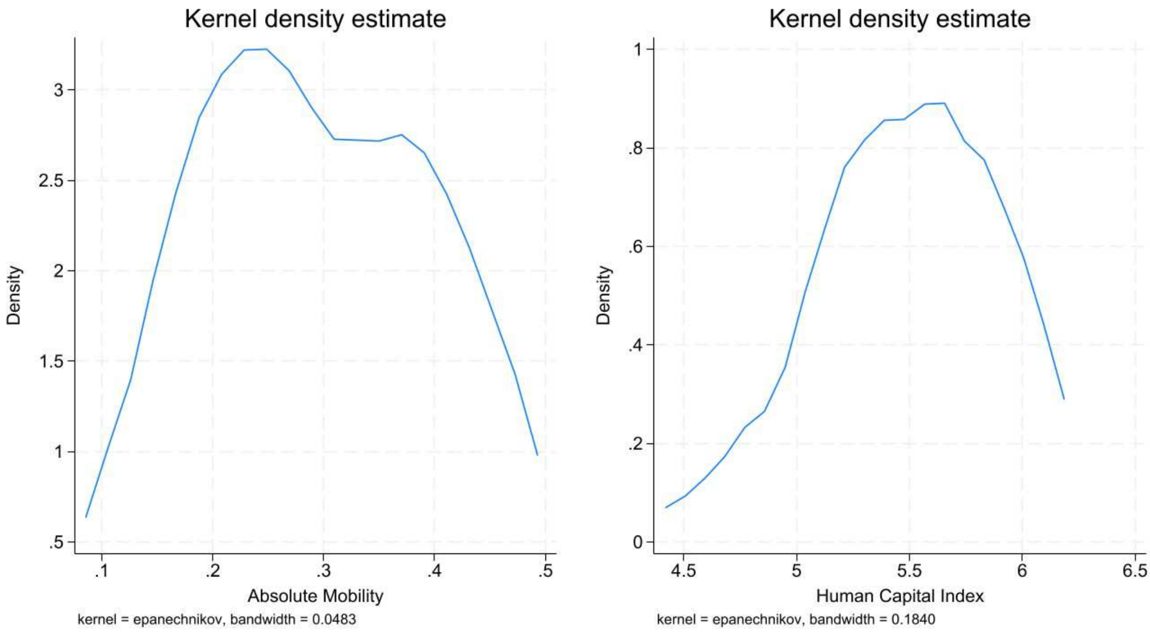

Figure E.1 Cross-Country Distribution of Absolute Mobility and Human Capital Index

Notes: This figure shows the distribution of our absolute mobility measure (on the left) and the average human capital index (on the right) at the country level. Absolute mobility is measured as the fraction of individuals with low educated parents who end up in high skilled occupations (bottom-to-top intergenerational mobility). The human capital index is the national average of the predicted earnings calculated using education level and skill score as described in section 5.2. Survey weights are used to ensure national representativeness.