THE UNIVERSITY OF CHICAGO
STONE CENTER FOR RESEARCH ON WEALTH INEQUALITY AND MOBILITY
Harris School of Public Policy

SSRN Working Paper Series

Parental Investments and Socio-Economic Gradients in Learning across European Countries

Pedro Carneiro
University College London
Hugo Reis
Bank of Portugal
Alessandro Toppeta
Stockholm University

07/11/2024

24-05

1307 East 60th Street
Chicago, IL 60637
linkedin.com/in/ucstonecenter
twitter.com/UCStoneCenter

Parental Investments and Socio-Economic Gradients in Learning across European Countries*

Pedro Carneiro Hugo Reis Alessandro Toppeta

July 11, 2024

Abstract

There is a widespread belief that strong public investments in children contribute to a levelled playing field and promote social mobility. Generous maternity leave, affordable daycare, extensive social safety nets, excellent universal health care, and high-quality public schools, are all notable features of Nordic countries. However, we document that gaps in learning outcomes between children of rich and poor parents remain as high in Nordic countries as elsewhere in Europe, using the PISA and PIAAC data. One explanation we uncover for this paradox is that parental investment by poor and rich parents, which is as unequal in Nordic countries as in the rest of Europe, is important to explain these learning gaps, despite public investments aimed at levelling the playing field.

JEL codes: I24, J24, J62, D63

Keywords: Intergenerational Transmission, Inequality, Education, Human Capital.

*__Carneiro__: University College London, Institute for Fiscal Studies, Centre for Microdata Methods and Practice (e-mail: p.carneiro@ucl.ac.uk); __Reis__: Bank of Portugal, Universidade Catolica Portuguesa/Catolica Lisbon School of Business and Economics (e-mail: hfreis@bportugal.pt); __Toppeta__: SOFI, Stockholm University (e-mail: alessandro.toppeta@sofi.su.se). Carneiro gratefully acknowledges the support of the ERC through grant ERC-2015-CoG-682349. Hugo Reis and Alessandro Toppeta acknowledge the financial support of Fundacao para a Ciencia e Tecnologia through the project number PTDC/EGE-ECO/6055/2020. We would like to thank Miles Corak, Steven Durlauf, Ruben Enikolopov, Matthew Lindquist, Jeff Smith, Jan Stuhler, Michela Tincani, Matthew Wiswall and participants to the SEEK Workshop on Social Mobility and Economic Performance (ZEW Mannheim), CESifo Workshop on Opportunities, Mobility, and Well-Being (Munich), 6th IZA Economics of Education Workshop (Bonn), Bank of Portugal, ARC European Commission, Conference on New Research and Policy Perspectives on Inequality and Poverty (Montreal), SOLE (Portland), 2nd DEM workshop University of Luxembourg, Equality of Opportunity and Intergenerational Mobility (UniBa/LSE). The analyses, opinions and conclusions expressed herein are the sole responsibility of the authors and do not necessarily reflect the opinions of Banco de Portugal or the Eurosystem.

1 Introduction

Across the world, in rich and poor countries, there are large socio-economic status (SES) gradients in human capital, measured by schooling or test scores. These gradients in learning outcomes emerge early and persist (Carneiro and Heckman, 2002; Schady et al., 2015), and account for a large fraction of the intergenerational transmission of income (e.g., Bolt et al. (2021)).[1] As expected, SES gradients in test scores vary widely across countries, as documented, for example, from the Program for International Student Assessment (PISA), which collects measures of knowledge of math, reading and science, as well as their SES, for 15-year-old adolescents in multiple countries (e.g., OECD (2018)).

In this paper, we show that, surprisingly, SES gradients in PISA scores are not particularly high or low in countries known for low levels of intra and intergenerational income inequality, namely the Nordic countries (Denmark, Finland, Iceland, Norway and Sweden). Over the past 20 years, these countries have SES gradients in math, reading and science scores, similar to other countries in Europe (especially in the most recent period). This is surprising since Nordic countries are known for promoting policies, especially protective of poor families and children, through generous maternity leave, affordable daycare, extensive social safety nets, excellent universal health care, and high-quality public schools. Such policies are thought to contribute to a more level playing field, and foster social mobility.

It is plausible that differential parental investments in children by poor and rich parents drive SES gradients in learning, despite the equalizing effects of substantial public investments in Nordic countries, as argued in Landerso and Heckman (2017) and Heckman and Landerso (2022) when comparing Denmark and the United States (US). This is also reminiscent of recent arguments in the United Kingdom (UK) and elsewhere that strong public schools are not enough to induce a significant change in social mobility because of family behaviors (see, for example, Goldthorpe (2016), and for an older reference with the same flavor, Coleman and Others (1966)).

In support of this idea, we show that SES gradients in the quality of the home learning environment - henceforth referred to as parental investments and measured by the child's access to adequate study conditions, technology, books and art - are as high in Nordic countries as elsewhere in Europe. Furthermore, in any given year, the cross-country correlation between SES gradients in learning and SES gradients in parental investments is between 0.70 and 0.80.

[1] Neal and Johnson (1996) and Carneiro et al. (2005) also document that test scores account for the bulk of racial gaps in earnings, while Cameron and Heckman (2001) show that they can fully explain racial gaps in schooling in the United States.

We realize this is an association, which could be potentially driven by a third factor strongly correlated with both gradients. Nevertheless, it is remarkable how strong this correlation is. Furthermore, because PISA has been administered every 3 years for more than 20 years, we are able to construct a panel. We see that there is not only a strong cross-sectional correlation between SES gradients in parental investments and SES gradients in learning, but also that (within country) changes in the SES gradients in parental investment are strongly related to (within country) changes in SES gradients in the learning. This indicates that the cross-sectional correlation cannot be solely due to a time-invariant country effect. In fact, changes SES gradients in parental investments account for more than 50% of the within-country (across time) variation in SES gradients in test scores. None of the other country characteristics we examine is as strong a predictor of SES gradients in learning, either in the cross section or in the panel.[2]

It is *not* known to what extent the patterns we document (and those in Landerso and Heckman (2017) and Heckman and Landerso (2022)) have been in place for decades, or whether they are a recent phenomenon. To investigate this question, we use data from the Programme for the International Assessment of Adult Competencies (PIAAC), which measures skills in adulthood (while the PISA measures skills in adolescence). Since the PIAAC surveys adults from all age groups, we are able to look at SES gradients in skills over a much wider array of cohorts, although data is available for a more limited set of countries.

We show that recent cohorts from the PIAAC (corresponding to those tested in the PISA, so born in 1987 or later) have similar patterns to those we document for the PISA. (Nordic countries do not have particularly high or low SES gradients in test scores.) On the other hand, the same is not true for older cohorts. The cross-country correlation between SES gradients in adult skills and measures of intergenerational mobility (or IGE, for those born in 1960s from Corak (2013)) is 0.85 for the older cohorts (born between 1957 and 1966) for whom Nordic countries have low IGE and low SES gradients in skills, but 0.13 for the younger cohorts (born 1987 or later).[3]

In addition, we notice that the SES gradients in PISA scores appear to have widened

[2]We consider variables that are plausible predictors of intergenerational transmission and for which we were able to assemble at least a partial panel between 2003 and 2018 (e.g., GDP per capita, returns to schooling, difference between top and bottom rates of income tax, government expenditure in education, and school segregation).

[3]This may also be partly because the data used to measure the IGE in these countries includes primarily older cohorts born in the 1960s. Since those taking the PISA have only recently joined the labor market, it is possible that future measures of the IGE, more relevant to the cohorts of individuals taking the PISA, are more correlated with SES gaps in PISA scores. Some evidence is emerging that the IGE is rising in Nordic countries relative to the IGE elsewhere (Brandén et al., 2023; Ahrsjö et al., 2023).

in Nordic countries over the last two decades. The PIAAC data suggest that these trends seem to have started several decades ago, with Nordic countries becoming more similar to other countries in Europe in terms of skill-inequality by family background. We recognize that with a single cross section one cannot distinguish age and cohort effects. In principle, the age at the time people take the PIAAC test could matter for how well one performs on that test. However, we believe that it is more likely that these differences are due to cohort effects given the design of the test.

Finally, the last wave of PISA is for 2022, and tests adolescents right after a period of serious learning disruption induced by the COVID-19 pandemic. Relative to 2018, SES gradients in test scores are a little higher in 2022 for several countries, but flat or even declining for many others. More importantly, we do not notice any dramatic shift relative to past trends. Before and after COVID, there are large SES gradients in learning, that vary substantially across Europe. These gradients are not related to the IGE or school closures during 2020 (a proxy for public investment during COVID-19), but they show a strong association with SES gradients in parental investments in children.

Our main contribution is to document differences across countries and over time in SES gaps in learning, and more important, their determinants. We are able to relate measures of SES gradients in test scores and SES gradients in investments in children, which are comparable across a wide variety of countries and over several years.

We focus on learning outcomes to investigate the intergenerational transmission of inequality, while paying particular attention to measurement and comparability of its estimates across countries and over time. On the other hand, the literature has mostly focused on income or years of schooling, as proxies for economic status, to document the geography and the trends in the intergenerational transmission of inequality. For example, Chetty et al. (2014) popularize this analysis by documenting the geography of the intergenerational transmission of income in the United States for the 1980-1982 birth cohort. Hertz et al. (2008) and Narayan et al. (2018) document the intergenerational transmission of years of schooling across countries and over time.[4] We expand the focus from income and years of schooling to learning because the former could conceal a part of the picture, since the transmission of inequality starts much earlier in the life cycle with the formation of human capital (Carneiro and Heckman, 2003; Cunha and Heckman, 2007).

To do this, we use data from PISA and PIAAC and focus on European countries to

[4] Alesina et al. (2021), Neidhofer et al. (2018), Deutscher and Mazumder (2020), Acciari et al. (2022), Bell et al. (2023), Corak (2020), and Card et al. (2022) have documented the geography of intergenerational mobility of income or years of schooling in Africa, Latin America, Australia, Italy, England, Canada and United States. Hanushek et al. (2022) show that the socio-economic gradients in test score have failed to close in the United States over 50 years using multiple datasets.

examine a more uniform institutional setting. These international assessments enable us to estimate comparable measures of intergenerational transmission of inequality across countries and over time, based on the design of these tests. Our main measure of SES gradients in learning compares the test scores (math) between 15-year-old students, whose mothers have completed high school or above, with students, whose mothers have not completed high school. Importantly, we show that our main results are robust to other measures of SES and are not driven by changes in the composition of mothers' education and migrant population.[5]

On the other hand, estimates of the intergenerational transmission of income across countries come from different datasets and cohorts (Blanden, 2013; Corak, 2013; Stuhler, 2018), which can raise concerns of comparability. For example, Grawe (2006) has shown that 40 percent of the variation in the estimates of the intergenerational transmission of income across countries can be attributed to the estimation methodology, lifecycle bias and different datasets.

Although our main results focus on SES gradients in math, we also document that these are strongly correlated with SES gradients in reading, science, non-cognitive skills, and students' aspirations. Studying SES gradients in other traits contributes to a growing interest in documenting intergenerational mobility across multiple dimensions, such as wealth (Charles and Hurst, 2003), health (Halliday et al., 2020), attitudes (Dohmen et al., 2011) and non-cognitive development (Attanasio et al., 2022).

When studying the determinants of learning mobility, the closest papers to ours are Landerso and Heckman (2017) and Heckman and Landerso (2022). Our documentation of SES gradients in parental investments across countries is new, as is the evidence that changes in SES gradients in parental investments are correlated with changes in SES gradients in test scores across countries. We provide suggestive evidence that social norms towards education can constrain how both poor and rich parents invest in their children, even in the presence of equalizing policies.

We also present new evidence that the relationship between SES gradients in test scores and the IGE in income may have changed substantially over time, using PIAAC data. Relative to PISA reports (OECD, 2018), we combine all available periods, relate intergenerational mobility in learning to other measures of mobility and inequality, and study the determinants of mobility and its evolution over time. Notably, we show that the main patterns we observe for the SES gradients in math scores and SES gradients in

[5]Results are robust to other measures of SES, such as: using father's education, an indicator for whether mothers completed higher education, an indicator for whether mothers have at least the median education within the country and the rank of the SES index of economic, social and cultural status (ESCS) developed by the PISA team.

parental investment hold for the SES gradients in other dimensions of success, highlighting the importance of thinking about success as multi-dimensional.

We ask whether the positive cross-country relationship between IGE and cross-sectional inequality - known as the Great Gatsby curve (Corak, 2013) - holds when we measure the intergenerational transmission of learning for 15-year-old students, before they enter the labor market.[6] We do *not* find evidence of a Gatsby curve, with the results being robust to different datasets and different measures of inequality coming from PISA and the World Bank (Carneiro and Toppeta, 2022; Cardim and Carneiro, 2021; Blanden et al., 2023).

In a recent paper, Blanden et al. (2023) document that SES gradients in PISA scores are not related to country-level inequality (there is no Gatsby Curve in learning mobility), a result similar to the one documented in this paper. However, Blanden et al. (2023) also demonstrate that SES gradients in years of schooling are correlated with the levels of inequality in a country. Although Blanden et al. (2023) suggest a reasonable interpretation of these patterns (see, for example, Doepke and Zilibotti (2017, 2019)) , our paper points out an alternative explanation for this result. The cohorts used to investigate the Gatsby Curve in PISA scores are *younger* than those used for the Great Gatsby curve in years of schooling.[7] We document that younger PIAAC cohorts (the same ones taking PISA in 2003) show no correlation between SES gradients in test scores and either inequality or the IGE, while older cohorts born in 1960s show a strong correlation between SES gradients in test scores and either inequality or the IGE.

Our findings illustrate that the potential for public policy to level up opportunities in childhood may be more limited than widely believed. Especially for recent cohorts, disparities in parental investments in children are associated with large disparities in children's learning, even in countries with widespread availability of generous and high-quality health, education and anti-poverty services. Commenting on the apparent failure of UK education policy to promote social mobility, Goldthorpe (2016) argues that the increased competition for scarce high-end jobs (paired with loss aversion) induced richer

[6] Durlauf et al. (2022) review the literature on the Great Gatsby curve and discuss various explanations, such as credit constraints (Becker and Tomes, 1979; Becker, 1991; Solon, 1999), sorting and segregation (Durlauf and Seshadri, 2018), political economy of public good provision (Alesina et al., 2018), and aspirations (La Ferrara, 2019).

[7] Recently, some other concerns have been raised regarding the existence of a Great Gatsby curve to start with. For example, Mogstad and Torsvik (2023) highlight that the Gatsby curve can be driven by 3 groups of countries, removing the extremes, namely Scandinavian and Latin American countries, would then lead to a change in the sign of the Gatsby curve. Karlson and Landersø (2021) also argue that heterogeneity in intergenerational educational mobility may simply reflect that these economies are, at the time of comparison, at different stages in a development process towards a highly educated modern society. In sociology, DiPrete (2020) observes that income mobility is typically measured with before-tax/transfer income, while inequality is measured with after-tax/transfer income; when inequality is measured before taxes and transfers, the relationship between inequality and mobility is more modest.

families to invest even more in their children, in an effort to prevent them from falling down the social ladder. He argues for a more comprehensive bundle of policies to address social mobility, even suggesting that public education may not be the most adequate tool.

The results of this paper, and also those in Landerso and Heckman (2017) and Heckman and Landerso (2022), suggest that such measures may not be enough to make a significant dent in intergenerational inequalities, and perhaps even more innovative policies may be needed, for example, by addressing directly the SES disparities in family investments. One difficulty, of course, is that interfering with behaviors taking place within very private family settings is challenging. Alternatively, policies could attempt to open up bottlenecks on the path to success, such as expanding enrollment at elite universities, which are conducive to top jobs, to the extent that test scores are a good predictor for admission to these institutions (Fishkin, 2014; Durlauf et al., 2024).

This paper is organized as follows. Section 2 discusses the data and the measures of intergenerational mobility in learning outcomes (i.e., SES gradients in test scores). Section 3 describes the geography and trends in the intergenerational transmission of learning in Europe over the last two decades. In Section 4, we compare intergenerational transmission of learning and some of its possible determinants, exploring the role of parental investments. In Section 5, we extend the analysis to the 2022-PISA wave after COVID-19 and discuss possible implications for the future. Section 6 concludes.

2 Intergenerational transmission of learning

2.1 PISA data

We use individual-level data from the PISA tests, administered every 3 years from 2000 to 2022 by the Organisation for Economic Co-operation and Development (OECD). These data contain information on 15-year-old students' learning outcomes in reading, mathematics and science. Learning outcomes are measured via tests, meant to determine students' preparation in important courses as well as for their adult life. Our analysis focuses on math scores for 24 European nations that have taken the tests six waves in a row, but we also present a complete analysis for reading and science in the Appendix, which we refer to in the main text.

For the PISA test, typically, each country selects between 4,500 and 10,000 students through a two-stage stratified sampling technique. A random sample of at least 150 schools, enrolling 15-year-old students, is drawn first. Then, 35 students within each school are randomly selected to take part in the test. Each student answers a randomly

selected subset of questions from a pool of questions.

PISA test scores are explicitly designed to allow comparisons across countries and over time. To make test scores comparable, they are not presented as point estimates, but as "plausible values". These values are computed by drawing random plausible values for each student from a probability distribution of test scores estimated based on the student's answers (OECD, 2011). To ensure comparability, we use plausible values and survey weights throughout the analysis. First, using the plausible values accounts for the latent nature of test scores and produces a more precise representation of the associated uncertainty. Second, the inclusion of survey weights, as provided by PISA, allows for the estimation of population-level parameters, ensuring the representativeness of the findings within the target population. We therefore estimate the regression models iteratively, employing different plausible values for the dependent variable in each iteration and survey weights, to effectively tackle the intricate nature of the PISA data (see, for example, Jerrim et al. (2017)).

Every wave of the PISA data also includes a student, parent and school questionnaire. These questionnaires provide a wide range of information on students' and parents' characteristics, such as parents' education, educational investment in their children, and home resources. We use this information to measure parents' socio-economic status, which for the bulk of the paper, will be an indicator for whether the mother completed at least upper secondary schooling, as discussed in detail in Section 2.2.

We finally check to what extent the data on parental SES in the PISA conforms with data available from other sources. Appendix Figure A1 presents a validation of the measures collected in the PISA dataset against external data sources from the World Bank Database. Panel A of Appendix Figure A1 demonstrates a strong and close to 0.90 correlation between the proportion of mothers with at least upper secondary education (average over 7 PISA waves) and the proportion of females (aged 25+) with at least upper secondary education (World Bank database). Similarly, Panel B of Appendix Figure A1 presents the correlation between the standard deviation of the PISA index of economic, social and cultural status (ESCS) and the Gini coefficient from the World Bank, which is also reasonably high, reaching almost 0.60.[8]

[8]The Educational, Social, and Cultural Status (ESCS) index in PISA is a composite measure that captures the socio-economic background of students participating in the assessment. It combines information on various indicators, such as parental education, occupation, and possessions (like owning a car, among other variables), to provide a summary measure of a student's social and cultural capital.

2.2 Measuring intergenerational transmission of learning

In this section, we discuss the measures of intergenerational transmission of learning (i.e., SES gradients in test scores/intergenerational mobility in learning) that we use throughout the paper. Each measure has its own advantages and disadvantages. To aid in interpretation, we begin with the association between the child's test score and the mother's education, using an indicator for whether the mother has completed at least upper secondary schooling (Appendix Table A1 describes the ISCED levels).

For each student i in country c, cohort t and subject k, we estimate:

$$R(Y_{itc}^k) = \alpha_{tc}^k + \beta_{tc}^k HS_{itc}^P + \epsilon_{itc}^k \quad (1)$$

where $R(Y_{itc}^k)$ is the test score percentile rank, computed at European level, for subject k, for student i, at time t, living in country c. HS_{itc}^p is an indicator variable taking value 1 if student i's mother has completed at least upper secondary education, and 0 otherwise. Throughout the analysis, we use the survey weights and plausible values provided by the OECD to account for the complexities of the PISA test and assure comparability of test scores over time and across countries (see Section 2.1).

β_{tc}^k measures the association between the mother's education (at least upper secondary education) and her child's rank in the distribution of math scores, for cohort t in country c. This represents a measure of *relative mobility*, which we also call SES gradient in learning. This captures the difference in learning ranks between children whose mothers have different levels of schooling. Therefore, higher values of this parameter correspond to lower mobility (more persistence in the transmission of learning outcomes).

α_{tc}^k is the average learning rank for students whose mothers do not have a high school degree for cohort t in country c. This is a measure of *upward mobility* (higher values correspond to more mobility).

Both are important measures of intergenerational mobility in learning (SES gradients in learning): the former is a measure of relative inequality between children of more and less advantaged families, while the latter is a measure of how well children of disadvantaged families perform.

In the paper, we present estimates for the math percentile rank, computed at the European level, and mother's education as we consider it easier to interpret and more comparable. But we also show that the estimates are robust to: alternate measures of rank, definitions of parental socio-economic background, changes in composition and other measures of children's success (see Section 3).

Estimates of intergenerational transmission of learning are presented from 2003 be-

cause PISA begins to collect data on parental investment only from 2003 onwards. Mobility measures for 2000 are available in Appendix Table A.2. We finally present estimates for the 2022 wave (after COVID-19) in Section 5.

3 Intergenerational transmission of learning across Europe and over time

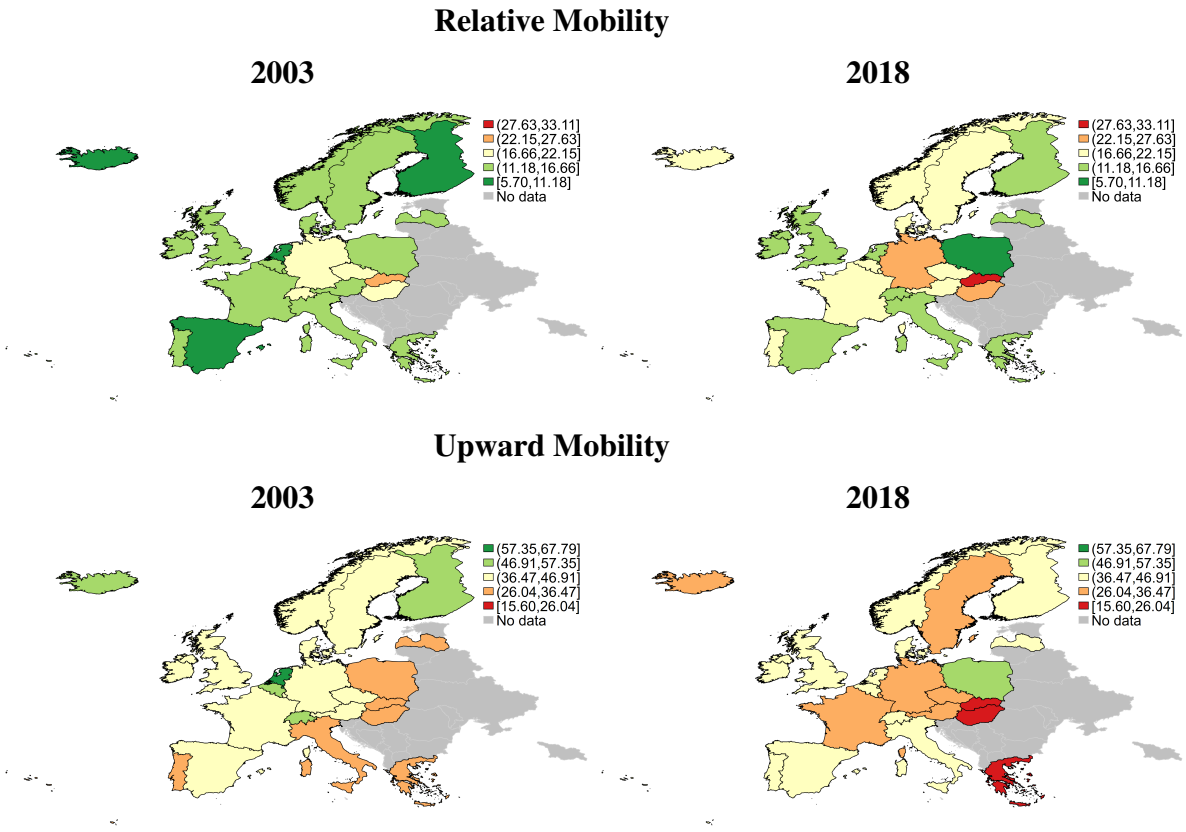
In our main analysis, we use the student i's math test score (rank), $R(Y_{itc}^{math})$, and start with the estimates of relative (β_{tc}^{math}) and upward (α_{tc}^{math}) mobility for different European countries and different cohorts, based on equation (1). Figure 1 presents a heat map of these measures for 2003 and 2018 PISA waves. Green areas represent countries with higher levels of mobility (low β_{tc}^{math} in the case of relative mobility, and high α_{tc}^{math} in the case of upward mobility), while red areas define countries with less mobility.

Take for example Germany, which is one of the countries with the highest SES gradients in learning in our sample (even though it is not a country with particularly high or low IGE, as documented in Corak (2013)). In 2003, the relative mobility, β_{tc}^{math}, was equal to 22, while the corresponding value for 2018 was 26. This means that, in Germany in 2003, children whose mothers completed upper secondary education were 22 percentiles above children whose mothers did not complete upper secondary education in the European distribution of PISA scores in math. This difference rose to 26 percentiles in 2018, which means that learning mobility decreased in Germany during this period. In 2003, the upward mobility, α_{tc}^{math}, was equal to 39, while the corresponding value for 2018 was 31. On average, children whose mothers did not complete upper secondary education scored in 39^{th} percentile of the PISA distribution in 2003, while in 2018 their performance decreased to the 31^{st} percentile (see Appendix Table A.2).

Together with Hungary and Slovakia, Germany is one of the three countries with lower relative learning mobility in Europe in 2003. Even though low-SES German students perform much worse than their high-SES counterparts, they perform much better than low-SES students in several other countries, such as Hungary, Slovakia, Poland, Italy, Greece, or Portugal. The countries with the lowest SES gradients in learning in 2003 are the Netherlands, Iceland, Spain and Finland. The Netherlands and Finland are also the two countries where students from low-SES backgrounds perform best across Europe.

By 2018, most (but not all) countries have lower levels of relative and upward mobility than in 2003. The countries with the lowest levels of relative mobility are still Germany, Hungary and Slovakia, and as in 2003, students of low-SES status perform much better

Figure 1: Heat map of intergenerational mobilities in learning (math score)



Note. The heat maps present the estimates of intergenerational mobility in learning for each country and cohort (the estimates are based on equation (1), regression of the rank math score on dummy equal to 1 if mother has at least upper secondary). The relative mobility measure is β_{tc}^{math} from equation (1). The upward mobility (α_{tc}^{math}) is the average rank of test score of children whose mothers do not have upper secondary. The rank is computed at the European level. Green areas are the most mobile and red areas are the least mobile. The intervals are the same for each year.

in Germany than in either Hungary and Slovakia (which, together with Greece, are the countries with the lowest performance of low-SES students in 2018). In this year, Poland is by far the country with the highest levels of relative and upward learning mobility among those in our sample.

There is however substantial stability between 2003 and 2018 in the relative position of countries in the sample. Appendix Figure A2 shows that the correlation in the estimates of relative mobility across countries between 2003 and 2018 is 0.7 (it is 0.8 between 2003 and 2009, and 0.93 between 2009 and 2018), while for upward mobility this correlation between 2003 and 2018 is 0.51 (0.65 for 2003 to 2009, and 0.94 for 2009 to 2018).

It is interesting that some of the larger deviations from this stability occur in Nordic countries. Sweden, Finland and Iceland (together with Slovakia and the Netherlands) are among the 5 countries where intergenerational mobility in learning decreased the most between 2003 and 2018 (Appendix Figure A3). In addition, we observe that, across cohorts,

SES gradients in test scores in the USA are similar to those in Europe (see Appendix Figure A4 for the estimates of learning mobility in the United States). Consistent with the arguments in Landerso and Heckman (2017) and Heckman and Landerso (2022), there is little difference between SES gradients in PISA scores between the USA and Denmark.

Robustness: We document that the estimates are robust to: alternate measures of rank, definitions of parental socio-economic background, changes in composition of migrant population and mother's education, and other measures of children's success.

First, Appendix Table A3 shows that our results are robust to alternate measures of rank. The correlation between the two measures (rank at the European vs rank at the country level) is high - 0.99 for β^k_{tc} and 0.67 for α^k_{tc}.[9] This is because there is a good overlap in the test score distributions across different countries (Appendix Tables A4 and A5). Second, the results are robust to using alternate definitions of parental socio-economic background, such as: (i) an indicator for whether the father has completed upper secondary education, (ii) an indicator for whether the mother has higher education, (iii) an indicator for whether the mother has at least the median education within the country and (iv) the rank of the index of economic, social and cultural status (ESCS) constructed by the PISA. Appendix Table A3 shows the correlations between the main measure of intergenerational mobility in learning presented in this section and the other measures using alternate definitions of parental socio-economic background, which are usually above 0.60. Third, Section 4.5 presents SES gradients in other dimensions of children's success, such as reading, science, educational aspiration, occupational aspiration and being on time to school.

We also document that these patterns are robust to considering only the native population (Appendix Figure A5) and notice that the correlation between the main measure and the one computed restricting the sample to the native population is 0.91, statistically significant. In addition, there is no correlation between the proportion of migrant students in the country and our estimates of mobility (Appendix Table A6).

Finally, we notice that the proportion of children, whose mothers have less than upper secondary schooling, varies substantially across countries, and even across time. For example, in 2003, 63% of children in Portugal and 22% of children in Finland come from families whose mothers have less than an upper secondary education. By 2018 these proportions are 47% and 7% respectively. This means that the composition of children

[9]The European rank is constructed by ordering each plausible value of the test scores in ascending order within Europe, using the weights provided by PISA. The advantage of using a European rather than a country-level rank is that the effect of mother's education on test score is more comparable, as we are using the same distribution of test scores.

in the lower-SES group potentially varies across countries and over time, affecting the interpretation of our findings. We however document that there is no clear correlation between the proportion of mothers with low levels of education and our estimates of mobility (Appendix Table A7).

4 Correlates: intergenerational transmission of learning

What drives differences across countries, and changes over time, in SES gradients in learning? This is an important, but difficult question to answer. Even if we identify important correlates of cross-country variation in SES gradients in learning, it is difficult to establish that they are causal drivers.

It turns out, however, that it is difficult to identify important correlates of SES gradients in learning to start with. Surprisingly, there are not many variables strongly correlated with SES gradients in learning. We explore this for relative mobility in Sections 4.1-4.3 and then turn to upward mobility and SES gradients in other traits in Sections 4.4 and 4.5.

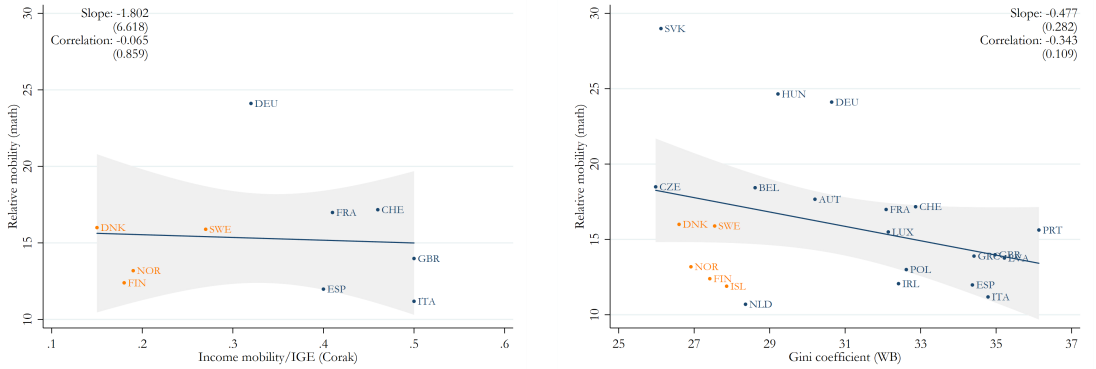
4.1 Intergenerational transmission of learning and inequality

We begin by asking if there is a relationship between SES gradients in learning and inter and intra-generational inequality. There are several reasons why one might observe such relationship. To the extent that human capital is an important determinant of earnings, it is perhaps natural to ask whether there is a relationship relating SES gradients in learning to inequality across countries.

First, we document that surprisingly SES gradients in PISA scores are *not* correlated with estimates of the intergenerational mobility in income across countries (left panel of Figure 2). The estimates of income mobility come from Corak (2013), who compiles a dataset of IGE estimates from published studies, adjusting them for methodological comparability. These estimates are for the cohort of children born during the early to mid-1960s, with their adult outcomes measured in the mid to late 1990s (Corak, 2013). As a robustness, we also reproduce the left panel of Figure 2 by using estimates of inequality of opportunity, available for a larger set of countries, and reach a similar conclusion (Appendix Figure B1).

Second, we ask if there is a positive cross-country relationship between relative mobility in learning and inequality in the society, known as the Great Gatsby curve (Corak, 2013), which has been widely discussed in the academic and popular press. It is observed not only across countries, but also within (Chetty et al., 2014; Corak, 2020). It has how-

Figure 2: Correlation between relative mobility (math), IGE (Corak, 2013), and Gini coefficient



Note. The Left Figure presents the correlation between relative mobility (math - averaged over PISA years) and income mobility measure from Corak (2013). Corak (2013)'s estimates of income mobility are measured as the elasticity between paternal earnings and a son's adult earnings, using data on a cohort of children born during the early to mid 1960s and measuring their adult outcomes in the mid to late 1990s. These IGE estimates are derived from published studies, adjusted for methodological comparability in Corak (2013). The Right Figure present the correlation between the relative mobility (math) and Gini coefficient from the World Bank (averaged over all PISA years). The estimates of upward and relative mobility are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

ever also been subject of controversy (Mogstad and Torsvik, 2023). We document that SES gradients in PISA scores are, if anything, negatively correlated with income inequality (right panel of Figure 2). As a whole, Nordic countries, which have the lowest income inequality in Europe, do not have smaller SES gradients in PISA scores than countries with high income inequality, such as Great Britain, Poland, Latvia or Portugal.

We show that even when we use other measures of inequality or learning mobility this correlation is often zero, but never positive. We find no evidence for the Great Gatsby curve when we reproduce the right panel of Figure 2 by: (i) linking the SES gradients in learning from each PISA wave to the Gini coefficient (World Bank) (Appendix Figure B2), (ii) computing the standard deviation of the ESCS index, built by PISA, to measure inequality in ESCS in any of the PISA cohorts (Appendix Figure B3) and (iii) using data from other international assessments, such as the Trends in International Mathematics and Science Study (TIMSS) and Progress in International Reading Literacy Study (PIRLS) studies, to measure learning (Appendix Figure B4 and Cardim and Carneiro (2021)).[10]

These findings hint towards the emergence of a poverty trap in education. Relative to other countries, rich parents in Nordic countries are not particularly impaired (e.g., by the progressivity of the tax system) when it comes to invest productively in their children. Furthermore, relative to other countries, poor parents in Nordic countries are not espe-

[10]Appendix Figure B5 shows that there is a strong cross-country correlation between SES gradients in learning measured in the TIMSS/PIRLS and PISA.

cially helped by the strong welfare state when it concerns their children's learning.[11] We turn to this next by first exploring when these patterns have emerged in Section 4.2 and then by exploring other possible correlates of relative mobility in learning in Section 4.3.

4.2 Using PIAAC to study older cohorts

These surprising results lead us to undertake further analysis measuring literacy and numeracy using comparable assessments across countries, but this time in a population of adults: the Programme for the International Assessment of Adult Competencies (PIAAC), also collected by the OECD. There are differences and similarities between the PIAAC and PISA, extensively discussed in many documents (e.g., Gal and Tout (2014)), the most obvious of which is that PISA measures skills in adolescence, and PIAAC measures skills in adulthood.

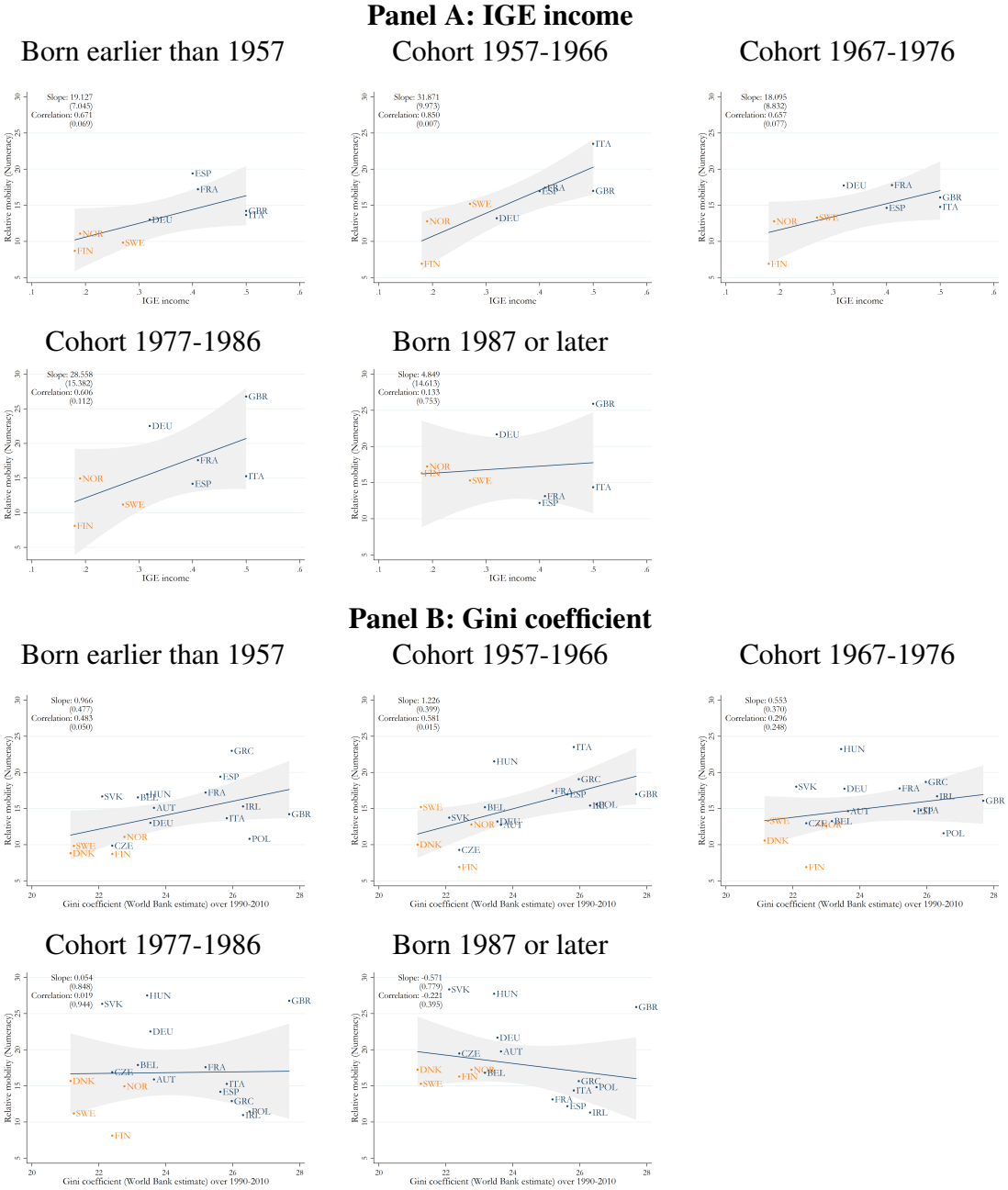
One important feature of the PIAAC sample (2012) is that its youngest respondents born in 1987 or later belong to the same cohorts that took the PISA test in 2003. In fact, when we compare SES gradients in learning for the same cohorts taking PISA and PIAAC (measuring SES using an indicator for whether the mother completed at least upper secondary schooling), the correlation between the two measures is about 0.7, statistically significant (Appendix Figure B6).

We therefore divide the PIAAC sample into different cohorts (or age groups), and estimate, for each cohort the (cross-country) correlation between SES gradients in test scores and the IGE estimates compiled by Corak (2013) for the cohort born in 1960, and the correlation between SES gradients in test scores and inequality (Gini coefficient from the World Bank, averaged over 1990-2010). The results, reported in Figure 3, are quite striking. They show that, for younger cohorts (the ones also surveyed in the initial waves of the PISA), there is no correlation between SES gradients in test scores and the IGE, or between SES gradients in test scores and inequality.

On the other hand, both these correlations are positive and large for older cohorts. It is possible that this is due to an age effect. Perhaps the age at the time one takes the PIAAC test really matters for how well one performs on that test. We believe, however, that it is more likely that these differences are due to cohort effects, given the design of the PIAAC test. For these older cohorts (but not for the younger cohorts), SES gradients in learning are the lowest in Nordic countries (as well as the Czech Republic and Poland), which are

[11] It is possible that, as argued in Landerso and Heckman (2017) and Heckman and Landerso (2022), higher SES parents in Nordic countries are just much better at accessing all the public benefits offered in their countries, so that the generous provision of these benefits does not equalize SES gradients (what they call the Matthew Principle).

Figure 3: PIAAC - correlation between mobility in numeracy, IGE (Corak, 2013), Gini coefficient



Note. The figures present the correlation between mobility in numeracy and IGE income (Corak (2013)'s sample) in Panel A and the correlation between mobility in numeracy and Gini coefficient (averaged over 1990-2010) in Panel B. Corak (2013)'s estimates of income mobility are measured as the elasticity between paternal earnings and a son's adult earnings, using data on a cohort of children born during the early to mid 1960s and measuring their adult outcomes in the mid to late 1990s. These IGE estimates are derived from published studies, adjusted for methodological comparability in Corak (2013). The mobility measure is the β_{tc}^{k} from regressing the rank of numeracy skill on a dummy equal to 1 if the mother has at least upper secondary. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

also the countries with the lowest IGE and lowest levels of inequality.

We do not know what changed, although one thing to notice is that the older cohorts in the PIAAC Nordic countries are the ones with the lowest SES gradients in test scores. It is only in recent cohorts of the PIAAC that the relative position of Nordic countries changes. Furthermore, as discussed above, for several Nordic countries SES gradients in PISA scores appear to increase between 2003 and 2018. The top 5 countries in Europe experiencing the largest increases in these gradients are Sweden, Iceland and Finland, together with the Netherlands and Slovakia.

In sum, some of the Nordic countries appear to be on a trend to higher skill-inequality by family background, making them more similar to other countries in Europe, and this trend seems to have started several cohorts ago (Appendix Figure B7). At this point, we can only speculate about the sources of these changes. We turn to some descriptive results that may help illuminate this issue in Section 4.3.

4.3 Public and private investments in children

In this section, we look at other potential correlates of SES gradients in PISA scores. Since we have constructed a panel database of SES gradients in tests scores across countries, it is possible to examine not only cross-sectional correlations, but also to study whether changes in particular variables are correlated with changes in SES gradients in test scores across different cohorts in each country.

4.3.1 Cross-sectional analysis

Here we start by looking at cross-sectional associations. We consider different sets of variables that can contribute to differences in learning outcomes across SES groups: *socio-economic variables* (returns to secondary school from the OECD, country GDP per capita from the World Bank database); *institutional variables* (the progressivity of the tax system, proxied by the difference between the top and lowest tax rates on personal income, and spending in public education from the World Bank database) and *education system variables* (age at which academic tracking starts from Eurydice and school level segregation, which we measure from the PISA data as the R-squared from regressing the ESCS index on school fixed effects).

A final variable concerns parental investments in children, in particular, the SES gradients in parental investments. To measure parental investment in children, we estimate a factor model with categorical items using data from the students' questionnaire, which includes information on home educational resources, such as the child's access to adequate

study conditions, technology, books and art. The factor model, described in detail in Appendix B.5.1, allows us to set the scaling assumption to obtain a comparable measure of parental investment across countries and over time.

We therefore measure the socio-economic gradient in parental investment by estimating a specification similar to equation (1), where we regress the rank of parental investment at European level on an indicator variable equal to 1 if the mother has completed at least upper secondary. It is important to highlight that this measure of parental investment mostly captures material investment. We note that material investment has been shown to be important for cognitive outcomes, while time investment is important for non-cognitive outcomes (Attanasio et al., 2020). Additionally, we investigate a plausible concern about whether the SES gradients in parental investment capture the same information as the ESCS index built by PISA, a proxy of family socio-economic background, and notice three things.

First, the ESCS is measured by combining information about parental education, occupation and possessions, such as cars, while parental investment is measured by combining information on home environmental inputs, such as possession of a desk, study space, literature. Second, Appendix Figure B8 shows a lack of correlation between inequality in ESCS and SES gradients in parental investments, hinting that inequality in the ESCS and SES gradients in parental investment are measuring two different factors. Third, PISA also collects some information on parental time investment from Portugal, Italy, Germany, and Belgium in 2012, 2015 and 2018. We notice that, for this subset of countries, SES gradients in parental investment (Appendix B.5.1) and SES gradients in time investment are positively correlated (0.3 for the three waves pooled together, while the correlation for 2018 is 0.7).[12]

We begin by showing the correlation between each of these variables (averaged over all PISA years) and relative mobility in math scores (averaged over all PISA years) in Table 1. The variables most correlated with relative mobility are: the age at which academic tracking starts, school segregation, and the SES gradients in parental investments. If we regress SES gradients in PISA scores on all variables considered in Table 1, the school age tracking and SES gradients in parental investment survive and remain statistically significant (Column (8)).

School tracking age has been documented to be relevant to explain learning mobility

[12]We construct a measure for the SES gradients in time investment by combining information on frequency of the following activities between the parents and the children: parents discuss how well my child is doing at school, parents eat <the main meal> with my child around, parents spend time just talking to my child, parents help child with his/her reading and writing, parents discuss political or social issues with child, parents go to a bookstore or library with child, parents talk with child about what he/she is reading.

Table 1: Correlates of relative mobility in learning (SES gradient in test scores)

	Relative mobility (math)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log GDP per capita	-1.901							-1.528
	(1.432)							(1.379)
Returns to secondary school		0.285*						0.012
		(0.137)						(0.102)
Difference between top and lowest tax rates on personal income			-0.051					0.048
			(0.072)					(0.053)
Government expenditure on education (% of GDP)				-0.498				0.979
				(0.569)				(0.563)
School tracking age					-0.987***			-1.074**
					(0.319)			(0.456)
School segregation						38.118***		1.775
						(10.741)		(15.890)
SES gradient in parental investment							0.841***	0.532**
							(0.128)	(0.202)
Observations	24	22	23	23	23	23	24	20
R^2	0.090	0.193	0.034	0.020	0.369	0.352	0.570	0.741

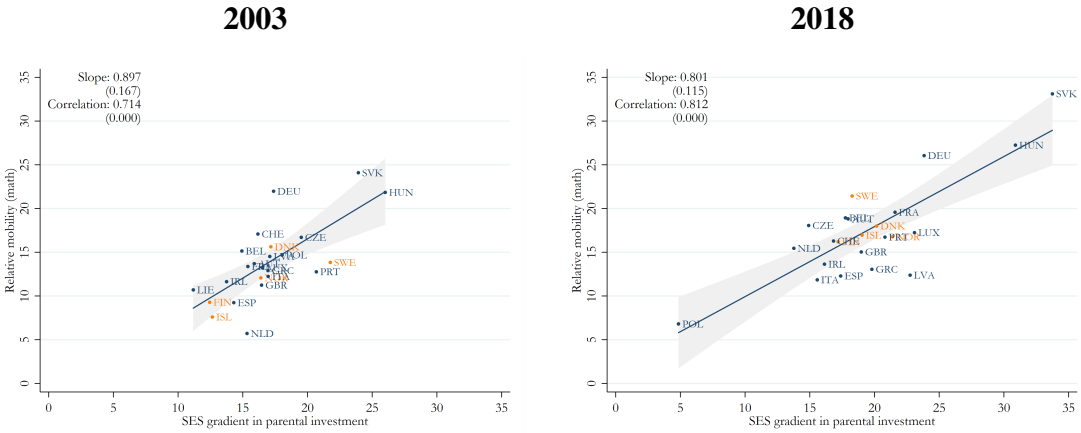
Note. The table shows the estimates from relative mobility in math (averaged over all PISA years) and country-level variables (averaged over all PISA years). We consider different sets of variables. Some are socio-economic variables: the returns to secondary school from the OECD, country GDP. Some are institutional variables, such as the progressivity of the tax system, proxied by the difference between top and lowest tax rates on personal income, and spending in public education. Some are related to the education system, such as the age in which academic tracking starts, from Eurydice and school level segregation, which we measure from the PISA data as the R-squared from regressing the ESCS index on school fixed effects. The estimates of upward and relative mobility are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. Details on how the SES gradients in parental investment is computed are available in Appendix B.5.1. Robust standard errors (*** p<0.01, ** p<0.05, * p<0.1).

(Pekkarinen et al., 2009; Pekkala Kerr et al., 2013; Ferreira and Gignoux, 2013), a finding we confirm in our study. Systems, where the placement of students into academic tracks starts early, such as in the case of Germany, would provide fewer chances for disadvantaged students to escape the least academic tracks, leading to larger SES gradients in test scores. In addition, a stronger sorting of students to schools based on SES (a higher level of SES segregation in schools) could lead to lower social mobility, especially if high-SES schools are also better schools (because they are better equipped, have better teachers, or because students have higher achieving peers).

The fact that there is a strong relationship between SES gradients in learning and SES gradients in parental investments is also not surprising, especially if the parental investment index we construct is a powerful predictor of an individual's test scores. What is perhaps noteworthy is the strength of this association. Figure 4 plots SES gradients in learning and SES gradients in parental investment for two PISA cohorts: 2003 and 2018. The correlation between these two variables is 0.71 in 2003 and 0.81 in 2018, both of which are strikingly high values. We also notice that the relationship between SES gradients in learning and SES gradients in parental investment is robust to excluding one country at a time (Appendix Table B1) and using the other measures of relative mobility described in the Appendix (Appendix Table B2).

Interestingly, Nordic countries, highlighted in orange in Figure 4, do not have particularly high or low SES gradients in parental investments. While in 2003, Finland and

Figure 4: Correlation between relative mobility (math) and SES gradients in parental investment.



Note. The figures present the correlation between relative mobility in learning (math) and SES gradients in parental investment. The estimates of relative mobility are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. Details on how the SES gradients in parental investment is computed are available in Appendix B.5.1. The rank is computed at the European level. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

Iceland had values for these gradients that were among the lowest in Europe (which was not the case for Denmark, Norway, or Sweden); by 2018, their values are indistinguishable from the typical European country, even though the quantity and quality of public services available to disadvantaged children may be especially high in these countries. On top of that, more advantaged parents are still able to invest more in their children than less advantaged parents, and the degree to which they do so is as high in Nordic countries as anywhere else. Therefore, it is perhaps not surprising that SES gradients in PISA scores are not especially low in Nordic countries.

We finally attempt to search for potential predictors of SES gradients in parental investment, at least in the cross section. Two variables, related to social norms and attitudes towards education, are correlated with SES gradients in parental investment: (i) confidence in the education system from the 2017 European Value Study (EVS), and (ii) perception that success depends strongly on parental wealth from the 2009 International Social Survey Programme (ISSP) on social inequality. The left panel of Appendix Figure B9 shows that a higher confidence in the education system is negatively correlated with larger socio-economic gradients in parental investment, while the right panel of Appendix Figure B9 shows that a stronger belief in the importance of a wealthy background is positively correlated with larger socio-economic gradients in parental investment.

4.3.2 Panel analysis

The cross-sectional associations, reported in the previous section, are interesting but they are also difficult to interpret because they may be driven primarily by third factors. Although we are not able to convincingly estimate the causal impact of these variables on social mobility in learning, we can nevertheless examine if changes over time/across cohorts in at least some of these variables are correlated with changes over time/across cohorts in SES gradients in PISA scores. This is possible because we observe multiple cohorts of children taking the PISA in multiple countries, between 2003 and 2018.

We therefore estimate the following model:

$$\beta_{tc}^{math} = X_{tc}\gamma + \tau_t + \theta_c + \epsilon_{tc} \tag{2}$$

where β_{tc}^{math} is the relative mobility in math for country c and cohort t, and X_{tc} is a country- and time-varying variable of interest. We include the year fixed effects, τ_t, and country fixed effects, θ_c, and ϵ_{tc} is the residual (we cluster standard errors at the country level).

The parameter of interest is γ and the estimates for all variables are available in Table 2. Here we would like to focus on the three main predictors of relative mobility (SES gradients in test scores): tracking age, school segregation, and SES gradients in investments. We cannot really use tracking age in this model because there are little to no changes in this variable across countries during the period we study. Therefore, we present results only for the other two variables.

Columns (5) and (6) of Table 2 document that changes in how segregated schools are across cohorts are not correlated with changes in SES gradients in PISA scores, but changes in SES gradients in parental investments are strongly related to changes in SES gradients in PISA scores. If we regress SES gradients in PISA scores on all the country- and time-varying variables, X_{tc}, considered in Table 2, the SES gradients in parental investment survive and remain statistically significant with a similar magnitude (Column (7)).

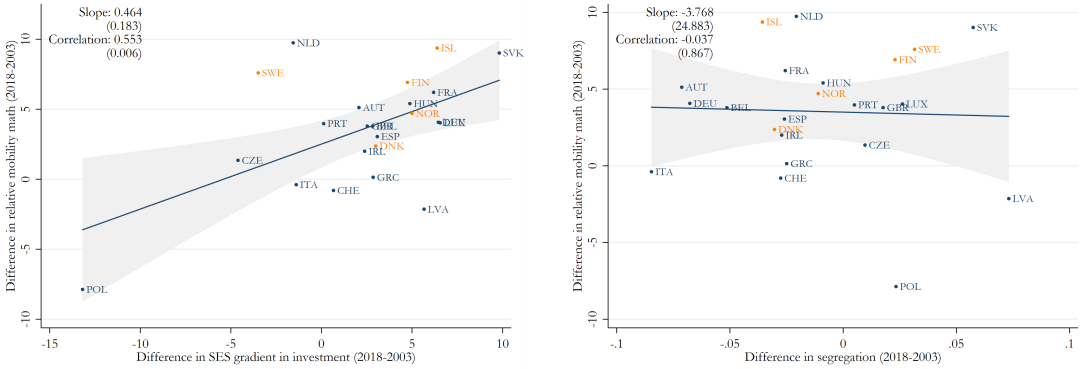
Figure 5 shows graphically the relationship between SES gradients in PISA scores and SES gradients in parental investment by plotting changes in SES gradients in PISA scores between 2003 and 2018 against changes in SES gradients in investment (left panel) and changes in segregation (right panel) during the same period. Strikingly, the countries, that have experienced the largest increase in the gradients in parental investments between more and less advantaged families, are Nordic countries: Norway, Finland, Iceland and Denmark. These results are, however, not driven by changes in inequality in these coun-

Table 2: Panel regressions: relative mobility in learning (SES gradient in test scores)

	Relative mobility (math)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log GDP per capita	-1.477						-5.149
	(4.119)						(5.433)
Returns to secondary school		0.106*					0.051
		(0.053)					(0.086)
Difference between top and lowest tax rates on personal income			0.028				0.083
			(0.066)				(0.110)
Government expenditure on education (% of GDP)				-0.342			-0.354
				(0.565)			(0.563)
School segregation					7.840		2.549
					(11.276)		(15.906)
SES gradient in parental investment						0.564***	0.631***
						(0.129)	(0.189)
Observations	160	118	137	117	159	142	74
R^2	0.802	0.841	0.808	0.819	0.802	0.881	0.916
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. The Table presents the panel estimates of relative mobility on economic variables with year and country fixed effects (equation (2)). The estimates of upward and relative mobility are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. Clustered standard errors at the country level (*** p<0.01, ** p<0.05, * p<0.1).

Figure 5: Correlation: changes in relative mobility, SES gradients in investment and segregation between 2003 and 2018.



Note. The figure presents the correlation between the changes in relative mobility (math), changes in the socio-economic gradients in parental investment, and changes in segregation between 2003 and 2018. The estimates of relative mobility are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. Details on how the SES gradients in parental investment is computed are available in Appendix B.5.1. The rank is computed at the European level. Segregation is measured in the PISA data as the R-squared from regressing the ESCS index on school fixed effects. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

tries. We indeed show that there is no strong correlation between inequality in ESCS and SES gradients in parental investments (Appendix Figure B8). Additionally, as we show in Section 4.1, income inequality is also not correlated with SES gradients in the PISA scores. We, finally, document that the relationship between SES gradients in learning and SES gradients in parental investment in the panel is generally robust to excluding one country at a time (Appendix Table B3) and using the other measures of relative mobility described in the Appendix (Appendix Table B4).

There could be several potential drivers of SES gradients in PISA scores. For example, the provision of public standardized education services, and the degree of inequality in school quality between schools attended by poor and rich students could in theory play a big role. In practice, we do not find evidence that this is the case. Although we see that the degree to which students segregate into schools based on their SES is associated with SES gradients in learning in the cross section, we do not find such relationship when we look at the panel.

It is therefore interesting that the main driver of the differences in SES gradients in PISA scores across countries seems to be differences in SES gradients in parental investment in children. Although we cannot rule out that whatever factors driving differences in SES gradients in parental investments across countries or time also have an independent effect on SES gradients in PISA scores, it is interesting to think about what these factors may be.

In sum, our results suggest that the roots of inequality in child outcomes lie in the family, despite equalizing policies, such as those observed in Nordic countries, aimed at levelling the playing field.

4.4 Upward mobility

There are many measures of social mobility, and one that has become very prominent is upward mobility (e.g., Chetty et al. (2014); Deutscher and Mazumder (2023)). Upward mobility measures the average outcomes of individuals coming from a disadvantaged background. In our setting in particular, this corresponds to the average rank in the PISA score distribution for individuals whose mothers have less than upper secondary schooling. It is of substantial interest if one is particularly worried about the outcomes of the most disadvantaged groups in a given country.

This is a very different measure from the one we focused on so far, and it may vary across countries for different reasons. For example, a country with an excellent education system can make sure the poor have good learning levels, without changing the gradients between learning levels of poor and rich students. In fact, it is remarkable how large the differences across countries in this measure are.

For example, in 2003, low-SES students in the Netherlands or Finland perform well above the 55^{th} percentile of the distribution of PISA across all countries, while in Greece, Hungary or Slovakia such students perform below the 30^{th} percentile. By 2018 the test scores of low-SES students decreased substantially across the board. They score in the 44^{th} and 38^{th} percentiles in the Netherlands and Finland respectively, and in the 25^{th}, 21^{st}

and 16^{th} percentiles in Greece, Hungary and Slovakia. It is also striking that the average student, whose mother has less than an upper secondary education, in countries, such as Finland or Iceland, has higher PISA scores than the average students, whose mothers have completed at least upper secondary, in countries, such as Italy or Portugal.

Upward mobility and the average PISA score of students in a country are obviously correlated, but far from perfectly (Appendix Figure C1): these patterns are not just explained by average differences across countries. For this reason, when we explore the correlates of learning mobility, we do not observe the same patterns as the ones noted by Woessmann (2016). In addition, perhaps unsurprisingly, the ranking of countries with regard to upward mobility is not exactly the same as the ranking using relative mobility, but there is a strong correlation of 0.60 in 2003 and 0.80 in 2018 (Appendix Figure C2).

Regarding the correlates of upward mobility, they work as the correlates of relative mobility. There is no correlation with inequality across countries or over time, and in the cross section, school segregation, age at first tracking, and upward mobility in parental investments have the strongest correlations with upward mobility in learning. In the panel, once we control for country and cohort fixed effects, only changes in the SES gradients in parental investment remain an important predictor of changes in upward mobility within country and over time (Appendix Table C1).

4.5 SES gradients in other traits

PISA has rich information on child outcomes, which we can use to examine SES gradients in skills and traits more broadly. There are three groups of variables. First, there are the well-known PISA scores, not only in math, but also in reading and science. Second, there are measures of occupational and educational aspirations for each child. Third, there are measures of self-efficacy and being on time to school. We describe these measures below and refer to Appendix C.3 for further details.

It is important, to the extent possible, to look beyond SES gradients in one academic subject, as human capital is multi-dimensional (see, for example, Heckman et al. (2006) and Deming (2023)). To measure students' educational and occupational aspirations, we follow La Ferrara (2019), defining occupational aspiration with a dummy equal to 1 for students, who expect to have a white collar job, and educational aspiration with a dummy equal to 1 for students, who expect to study at university. Self-efficacy captures the extent to which individuals believe in their own ability to engage in certain activities and perform specific tasks, especially when facing adverse circumstances (Bandura, 1977, 1991). To measure non-cognitive skills, we look at the probability of being on time to school (Cunha

and Heckman, 2007; Borghans et al., 2008).

We measure relative and upward mobility in these other traits by estimating equation (1), where the outcome is now one of the traits we describe above. Similarly, upward mobility is the average trait for the children whose mothers have not completed upper secondary education. Relative mobility is the difference in a certain trait between children whose mothers have completed at least upper secondary and mothers that have not.

We begin by showing how correlated (within a given year) measures of mobility using different traits are. Table 3 shows the matrix of correlations for relative mobility measures in 2018 (the remaining years, and correlations for upward mobility measures, are available in Appendix Tables C2 and C3).

As expected, it makes very little difference to measure SES gradients in math, reading or science. SES gradients in aspirations have strong positive correlations with SES gradients in test scores, but which are substantially away from 1, suggesting that these are quite different traits. Still positive, but less correlated with SES gradients in test scores, are SES gradients in being on time to school. Similar patterns are also found for the SES gradients in self-efficacy, which is available for 2003 and 2012 (Appendix Figure C3).

Table 3: Correlation among SES gradients (2018)

	Relative mobility in					
	Math	Read	Science	Educational aspiration	Occupational aspiration	Being on time to school
Math	1					
Read	0.962***	1				
Science	0.963***	0.980***	1			
Educational aspiration	0.473**	0.367*	0.345	1		
Occupational aspiration	0.541***	0.386*	0.361*	0.766***	1	
Being on time to school	0.536***	0.565***	0.571***	-0.047	-0.015	1

Note. The table presents the correlation among different measures of relative mobility for 2018. Each measure has been estimated by regressing the outcome of interest on dummy equal to 1 if mother has at least upper secondary (equation (1)). (*** p<0.01, ** p<0.05, * p<0.1).

Interestingly, Nordic countries experience low mobility - not only in learning outcomes - but also in these other traits. More importantly, we still uncover a strong relationship between SES gradients in these other traits and the SES gradients in parental investment, while we do not find a correlation between SES gradients in these other traits and inequality (Appendix Table C4).

5 SES gradients in learning before and after COVID-19

This final section uses the recently released PISA data from the 2022 wave and compares SES gradients in test scores in 2018 and 2022 (i.e., before and after the COVID-19 pandemic). Although it could be tempting to attribute any changes to the experience of students during the pandemic, there are longer-term trends in these gradients that should be considered first. This section focuses on the SES gradients in test scores, while other studies have documented a decrease in the average scores and in the share of students who are able to reach a minimum competence (see for example European Commission (2024)).

From the 2022 data, we still observe that SES gradients in test scores are as high for the Nordic countries as for the remainder of the countries in the sample (Appendix Figure D1). Appendix Figure D2 shows that there is a strong correlation between SES gradients in math scores in 2018 and 2022, and that the level of these gradients has not changed significantly between these two years. This can also be observed in Appendix Figure D3, presenting the trends in upward and relative mobility across several countries, with the 2022-PISA wave. Although it is true that there are several countries for which the SES gradient in PISA scores reached its highest value in the 2022 wave, there are also many others where this is not the case. More importantly, there is no obvious change in the evolution of these gradients over time. For most if not all countries, the 2022 data seems to follow a trend, rather than exhibiting a break from the past. Such patterns are also observed when we examine the evolution in SES gradients in parental investments between 2018 and 2022, as shown in Appendix Figure D4.

We also continue to see a strong correlation between SES gradients in parental investment and SES gradients in test scores, while we find no correlation between school closures during COVID-19 and SES gradients in test scores. In fact, comparing Appendix Figure D5 with Figure 4, we see that, if anything, the relationship between SES gradients in parental investment and SES gradients in test scores becomes stronger (correlation: 0.89). On the other hand, Appendix Figure D6 documents a lack of correlation between the number of fully-closed school days in lower secondary education in 2020 (a proxy for public investment) from OECD (2021) and SES gradients in test scores after COVID-19 (correlation: 0.07). It is possible that the COVID-induced disruption in learning, and more generally, in economic and social environments, experienced by children and their families, has not produced substantial changes in the patterns studied in this paper.

6 Conclusion

Standardized international tests show significant differences in student knowledge across countries, even within Europe. Not only that, there are also staggering differences in the magnitude of SES gradients in test scores across countries, in the test performance of the most disadvantaged students in each country, and how these vary over time.

Take the case of PISA, which is the main data source for our paper. In 2003, the gradients in PISA scores between children, whose mothers have or have not completed at least upper secondary education, are (to give just a few examples) 5 percentile ranks in the Netherlands, 11 in Great Britain, 16 in Denmark, and 22 in Germany. Fast forward to 2018, and these values are respectively, 16, 15, 18 and 26. A similar picture is found for upward mobility, where we observe a dramatic and worrisome decline of the average performance of disadvantaged students.

It is interesting that in Nordic countries, with generous and universal social benefits, SES gradients in learning are not particularly low, when compared to other European countries. This is especially true for the most recent cohorts of PISA, and generalizes the findings by Landerso and Heckman (2017) and Heckman and Landerso (2022), comparing Denmark and the USA. In fact, there is no correlation between the SES gradients in PISA scores and inter and intra-generational income inequality, neither in the cross section nor the time series. Data from the PIAAC suggests that this may have *not* been the case in the past.

Finally, when investigating the main correlates of SES gradients in PISA scores, we find them to be correlated with the level of SES segregation in schools, the age at which tracking first starts in the education system, and the SES gradients in parental investments. Of these, only the latter shows a cross-sectional association that persists even when we consider the entire panel and account for country and time fixed effects.

These findings underscore the importance of family behaviors in driving SES gradients in learning, which appear to be far more important than the role of social policies. If other countries were to import the same type of education and social policies as Nordic countries, it is not clear that they would experience substantial reductions in SES gradients in learning. These findings also suggest alternative policies, such as opening up bottlenecks along the path to success, to break the intergenerational transmission of inequality (Fishkin, 2014; Durlauf et al., 2024). For example, to the extent that test scores are a good predictor of enrolment in elite universities, which are conducive to top jobs, easing bottlenecks at these institutions could expand access to opportunities and mitigate inequalities.

References

Acciari, P., A. Polo, and G. L. Violante (2022). And yet, it moves: Intergenerational mobility in Italy. *American Economic Journal: Applied Economics 14*(3), 118–163.

Ahrsjö, U., R. Karadakic, and J. K. Rasmussen (2023). Intergenerational mobility trends and the changing role of female labor. *arXiv preprint arXiv:2302.14440*.

Alesina, A., S. Hohmann, S. Michalopoulos, and E. Papaioannou (2021). Intergenerational mobility in Africa. *Econometrica 89*(1), 1–35.

Alesina, A., S. Stantcheva, and E. Teso (2018). Intergenerational mobility and preferences for redistribution. *American Economic Review 108*(2), 521–54.

Attanasio, O., S. Cattan, E. Fitzsimons, C. Meghir, and M. Rubio-Codina (2020). Estimating the production function for human capital: results from a randomized controlled trial in Colombia. *American Economic Review 110*(1), 48–85.

Attanasio, O., Á. de Paula, and A. Toppeta (2022). Intergenerational mobility in socio-emotional skills. *Working Paper*.

Bandura, A. (1977). Self-efficacy: toward a unifying theory of behavioral change. *Psychological review 84*(2), 191.

Bandura, A. (1991). Social cognitive theory of self-regulation. *Organizational behavior and human decision processes 50*, 248–287.

Becker, G. (1991). *A Treatise on the Family*. Harvard Univ Press.

Becker, G. S. and N. Tomes (1979). An equilibrium theory of the distribution of income and intergenerational mobility. *Journal of Political Economy 87*(6), 1153–1189.

Bell, B., J. Blundell, and S. Machin (2023). Where is the land of hope and glory? The geography of intergenerational mobility in England and Wales. *The Scandinavian Journal of Economics 125*(1), 73–106.

Blanden, J. (2013). Cross-country rankings in intergenerational mobility: A comparison of approaches from economics and sociology. *Journal of Economic Surveys 27*(1), 38–73.

Blanden, J., M. Doepke, and J. Stuhler (2023). Chapter 6 - Educational inequality. Volume 6 of *Handbook of the Economics of Education*. Elsevier.

Bolt, U., E. French, J. H. Maccuish, and C. O'Dea (2021). The intergenerational elasticity of earnings: exploring the mechanisms. *CEPR Discussion Paper No. DP15975*.

Borghans, L., A. L. Duckworth, J. J. Heckman, and B. Ter Weel (2008). The economics and psychology of personality traits. *Journal of Human Resources 43*(4), 972–1059.

Brandén, G., M. Nybom, and K. Vosters (2023). *Like Mother, Like Child? The Rise of Women's Intergenerational Income Persistence in Sweden and the United States*. IZA-Institute of Labor Economics.

Cameron, S. V. and J. J. Heckman (2001). The dynamics of educational attainment for black, hispanic, and white males. *Journal of Political Economy 109*(3), 455–499.

Card, D., C. Domnisoru, and L. Taylor (2022). The intergenerational transmission of human capital: Evidence from the Golden Age of upward mobility. *Journal of Labor Economics 40*(S1), S39–S95.

Cardim, J. and P. Carneiro (2021). Chapter 4: Educational mobility in Europe. *PhD Dissertation: Essays in Economics of Education and Development, NOVASBE*.

Carneiro, P. and J. Heckman (2003). Human capital policy. *IZA discussion paper 821*.

Carneiro, P., J. Heckman, and D. Masterov (2005). Labor market discrimination and racial differences in pre-market factors. *Journal of Law and Economics 48*(1), 1–39.

Carneiro, P. and J. J. Heckman (2002). The evidence on credit constraints in post-secondary schooling. *The Economic Journal 112*(482), 705–734.

Carneiro, P. and A. Toppeta (2022). Socioeconomic gradients in test scores across Latin American and the Caribbean. *CAF working paper*.

Charles, K. and E. Hurst (2003). The correlation of wealth across generations. *Journal of Political Economy*, 1155–1182.

Chetty, R., N. Hendren, P. Kline, and E. Saez (2014). Where is the land of opportunity? The geography of intergenerational mobility in the United States. *The Quarterly Journal of Economics 129*, 1553–1623.

Coleman, J. and Others (1966). Equality of educational opportunity. Technical report.

Corak, M. (2013, September). Income inequality, equality of opportunity, and intergenerational mobility. *Journal of Economic Perspectives 27*(3), 79–102.

Corak, M. (2020). The Canadian geography of intergenerational income mobility. *The Economic Journal 130*(631), 2134–2174.

Cunha, F. and J. Heckman (2007). The technology of skill formation. *American Economic Review 97*(2), 31–47.

Deming, D. J. (2023). Chapter 6 - Multidimensional human capital and the wage structure. Volume 7 of *Handbook of the Economics of Education*, pp. 469–504. Elsevier.

Deutscher, N. and B. Mazumder (2020). Intergenerational mobility across Australia and the stability of regional estimates. *Labour Economics 66*, 101861.

Deutscher, N. and B. Mazumder (2023). Measuring intergenerational income mobility: A synthesis of approaches. *Journal of Economic Literature* (Forthcoming).

DiPrete, T. A. (2020). The impact of inequality on intergenerational mobility. *Annual Review of Sociology 46*(1), 379–398.

Doepke, M. and F. Zilibotti (2017). Parenting with style: Altruism and paternalism in intergenerational preference transmission. *Econometrica 85*(5), 1331–1371.

Doepke, M. and F. Zilibotti (2019). *Love, money, and parenting: How economics explains the way we raise our kids*. Princeton University Press.

Dohmen, T., A. Falk, D. Huffman, and U. Sunde (2011). The intergenerational transmission of risk and trust attitudes. *The Review of Economic Studies 79(2)*, 645–677.

Durlauf, S. N., G. Kim, D. Lee, and X. Song (2024). The evolution of black-white differences in occupational mobility across post-Civil War America. *National Bureau of Economic Research working paper*.

Durlauf, S. N., A. Kourtellos, and C. M. Tan (2022). The Great Gatsby Curve. *Annual Review of Economics 14*(1), 571–605.

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

European Commission (2024). *The twin challenge of equity and excellence in basic skills in the EU - An EU comparative analysis of the PISA 2022 results*. Publications Office of the European Union.

Ferreira, F. H. G. and J. Gignoux (2013, 02). The measurement of educational inequality: Achievement and opportunity. *The World Bank Economic Review 28*(2), 210–246.

Fishkin, J. (2014). *Bottlenecks: A new theory of equal opportunity*. Oxford University Press.

Gal, I. and D. Tout (2014). Comparison of PIAAC and PISA frameworks for numeracy and mathematical literacy. *OECD*.

Goldthorpe, J. (2016). Social class mobility in modern britain: changing structure, constant process. *Journal of the British Academy 4*, 89–111.

Grawe, N. D. (2006). Lifecycle bias in estimates of intergenerational earnings persistence. *Labour Economics 13*(5), 551–570.

Halliday, T. J., B. Mazumder, and A. Wong (2020). The intergenerational transmission of health in the United States: A latent variables analysis. *Health economics 29*(3), 367–381.

Hanushek, E. A., J. D. Light, P. E. Peterson, L. M. Talpey, and L. Woessmann (2022). Long-run trends in the US SES-Achievement gap. *Education Finance and Policy 17*(4), 608–640.

Heckman, J. J. and R. Landerso (2022). Lessons from Denmark about inequality and social mobility. *Labour Economics 77*, 101999.

Heckman, J. J., J. Stixrud, and S. Urzua (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics 24*(3), 411–482.

Hertz, T., T. Jayasundera, P. Piraino, S. Selcuk, N. Smith, and A. Verashchagina (2008). The inheritance of educational inequality: International comparisons and fifty-year trends. *The B.E. Journal of Economic Analysis and Policy 7*(2).

Jerrim, J., L. A. Lopez-Agudo, O. D. Marcenaro-Gutierrez, and N. Shure (2017). What happens when econometrics and psychometrics collide? An example using the PISA data. *Economics of Education Review 61*, 51–58.

Karlson, K. B. and R. Landersø (2021). The making and unmaking of opportunity: educational mobility in 20th-century denmark. *The Scandinavian Journal of Economics*.

La Ferrara, E. (2019). Presidential address: Aspirations, social norms, and development. *Journal of the European Economic Association 17*(6), 1687–1722.

Landerso, R. and J. J. Heckman (2017). The Scandinavian fantasy: The sources of intergenerational mobility in Denmark and the US. *The Scandinavian Journal of Economics 119*(1), 178–230.

Mogstad, M. and G. Torsvik (2023). Family background, neighborhoods, and intergenerational mobility. *Handbook of the Economics of the Family 1*(1), 327–387.

Narayan, der Weide, A. Cojocaru, S. Redaelli, C. Lakner, D. G. Mahler, R. Ramasubbaiah, and S. Thewissen (2018). Fair progress? Economic mobility across generations around the world. *World Bank Publications*.

Neal, D. A. and W. R. Johnson (1996). The role of premarket factors in black-white wage differences. *Journal of Political Economy 104*(5), 869–895.

Neidhofer, G., J. Serrano, and L. Gasparini (2018). Educational inequality and intergenerational mobility in Latin America: A new database. *Journal of Development Economics 134*(C), 329–349.

OECD (2011). PISA 2009. *Technical report. OECD Publishing, Paris*.

OECD (2018). PISA 2018 results (volume II): Where all students can succeed. *Technical report. OECD Publishing, Paris*.

OECD (2021). The state of global education: 18 months into the pandemic. *Technical report. OECD Publishing, Paris*.

Pekkala Kerr, S., T. Pekkarinen, and R. Uusitalo (2013). School tracking and development of cognitive skills. *Journal of Labor Economics 31*(3), 577 – 602.

Pekkarinen, T., R. Uusitalo, and S. Kerr (2009). School tracking and intergenerational income mobility: Evidence from the Finnish comprehensive school reform. *Journal of Public Economics 93*(7), 965–973.

Roemer, J. (1998). *Equality of Opportunity*. Harvard University Press.

Schady, N., J. Behrman, M. C. Araujo, R. Azuero, R. Bernal, D. Bravo, F. Lopez-Boo, K. Macours, D. Marshall, C. Paxson, et al. (2015). Wealth gradients in early childhood cognitive development in five Latin American countries. *Journal of Human Resources 50*(2), 446–463.

Solon, G. (1999). Intergenerational mobility in the labor market. *Handbook of Labor Economics vol. 3, Part A*, 1761–1800.

Stuhler, J. (2018). A review of intergenerational mobility and its drivers. *Joint Research Centre (Seville site)* (JRC112247).

Woessmann, L. (2016). The importance of school systems: Evidence from international differences in student achievement. *Journal of Economic Perspectives 30*(3), 3–32.

Appendices to "Parental Investments and Socio-Economic Gradients in Learning across European Countries"

A Descriptive evidence

A.1 Data validation of mother's education and ESCS index

Answers on parental education were coded by PISA into internationally-comparable educational qualifications, following the international Standard Classification of Education (ISCED), presented in Appendix Table A1.

Table A1: International Standard Classification of Education (ISCED) levels

Level	ISCED
0	None
1	ISCED 1 (primary education)
2	ISCED 2 (lower secondary)
3	ISCED Level 3B or 3C (vocational/pre-vocational upper secondary)
4	ISCED 3A (upper secondary) and/or ISCED 4 (non-tertiary post-secondary)
5	ISCED 5B (vocational tertiary)
6	ISCED 5A, 6 (theoretically oriented tertiary and post-graduate)

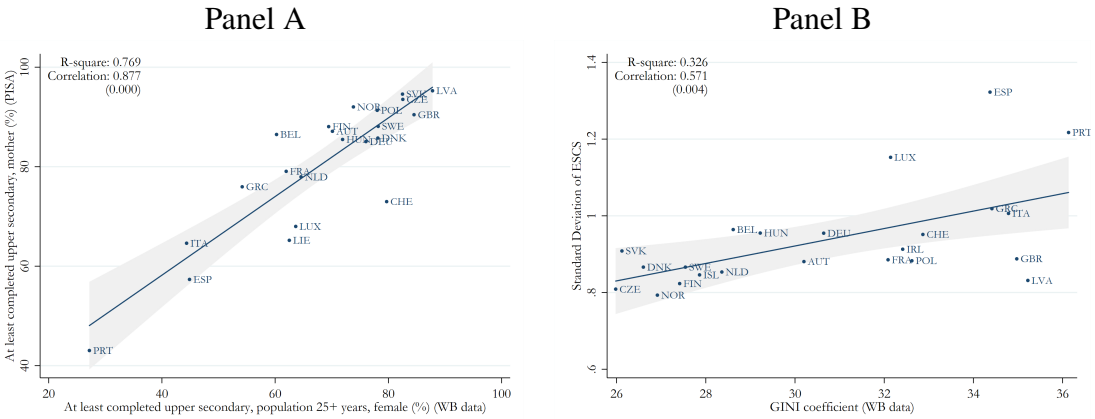
Note. The table presents the International Standard Classification of Education (ISCED) classification. PISA codes the answers on parental education into internationally-comparable educational qualifications, following the international Standard Classification of Education (ISCED).

Panel A of Appendix Figure A1 presents the correlation between the proportion of mothers with at least upper secondary education (average over 7 PISA waves) and the proportion of females (aged 25+) with at least upper secondary education (World Bank database).

We note that the proportion of mothers with at least upper secondary education is higher than proportion of females (aged 25+) with at least upper secondary education from the World Bank. This is because in PISA we have mothers, while in the World Bank we have female population. The correlation between the two is however high - close to 0.90.

Panel B of Appendix Figure A1 presents the correlation between the standard deviation of the PISA index of economic, social and cultural status (ESCS) and the Gini coefficient from the World Bank.

Figure A1: Correlation between PISA and the World Bank data



Note. Panel A presents the correlation between the proportion of mother with at least upper secondary education in PISA and the proportion of females (aged 25+) with at least upper secondary education in the World Bank database. Panel B presents the correlation between the standard deviation of the ESCS index in PISA and the Gini coefficient from the World Bank. In each panel, we compute each statistics at the country level for each wave and then link it to the respective wave of the World Bank database. The figures present the correlation between the averages computed over the 7 PISA waves. Confidence interval at 95% level in gray. The notes in the figures report the R-squared and the correlation between variables with the p-value in parenthesis.

A.2 Descriptive statistics on leaning mobility

Table A2: Descriptive statistics on leaning mobility

cnt	Upward	Relative	Upward	Relative	Upward	Relative	Upward	Relative	Upward	Relative	Upward	Relative	Upward	Relative
	2000		2003		2006		2009		2012		2015		2018	
AUT	49.17	10.53	41.04	13.69	38.60	17.58	32.25	19.95	34.43	20.64	31.07	22.45	34.65	18.82
BEL	44.90	20.18	49.75	15.14	44.27	18.47	42.71	17.31	39.07	20.08	38.10	18.89	37.84	18.93
CHE	50.35	18.68	47.77	17.08	50.50	15.50	49.05	16.91	47.13	17.40	44.05	18.32	43.11	16.28
CZE	35.89	16.19	41.33	16.70	31.39	25.14	31.39	18.56	32.71	18.99	35.77	15.78	35.53	18.06
DEU	30.11	25.76	38.68	21.98	38.47	20.77	41.39	20.28	30.74	29.18	33.13	24.76	30.90	26.05
DNK	43.94	16.67	43.01	15.62	44.61	14.00	39.11	15.99	36.80	16.81	43.30	14.90	37.71	17.99
ESP	39.56	14.11	41.81	9.24	40.82	11.31	39.94	11.57	38.57	12.81	39.55	12.52	37.18	12.28
FIN	57.59	7.53	56.37	9.28	58.85	9.51	51.42	13.85	44.44	13.99	39.91	16.39	38.42	16.19
FRA	49.58	12.12	45.65	13.37	40.21	16.34	37.43	18.99	35.01	19.56	34.80	18.94	33.48	19.58
GBR	50.32	13.91	44.25	11.24	41.80	11.55	35.88	16.07	37.80	14.50	36.54	15.55	39.25	15.03
GRC	29.12	15.22	26.23	12.91	29.40	14.91	30.76	13.35	25.46	14.20	26.03	13.62	25.11	13.05
HUN	29.80	22.15	29.23	21.84	30.12	22.57	25.66	27.37	23.74	24.51	21.46	26.87	21.38	27.25
IRL	46.91	9.89	42.81	11.63	42.76	12.98	39.37	11.37	42.27	11.02	40.44	13.90	38.83	13.64
ISL	51.71	9.64	50.45	7.59	45.30	12.68	43.51	13.59	40.71	10.92	38.24	11.87	35.58	16.96
ITA	34.50	9.13	33.42	12.23	34.44	10.76	39.79	10.23	38.47	11.81	40.16	12.28	38.76	11.84
LIE	52.11	14.64	55.19	10.70	51.23	13.43	48.41	20.14	49.79	14.83				
LUX	32.58	10.75	40.89	13.21	40.79	13.76	36.82	17.88	35.84	18.41	35.34	17.21	34.18	17.24
LVA	28.72	14.36	31.47	14.52	33.03	15.58	36.67	9.17	33.34	15.67	31.95	14.66	38.17	12.38
NLD	67.79	8.02	60.15	5.71	53.66	10.41	48.61	13.28	51.18	9.12	44.57	12.88	44.17	15.45
NOR	46.24	7.60	38.70	12.07	37.26	13.49	38.70	13.06	35.98	13.68	38.08	15.62	36.54	16.77
POL	38.71	6.80	33.65	14.68	34.57	17.49	32.94	18.26	36.98	20.24	47.33	6.73	50.01	6.80
PRT	35.28	11.88	35.92	12.76	36.80	14.89	39.72	18.57	40.18	17.68	40.94	16.86	39.87	16.73
SVK			27.84	24.09	24.14	27.49	22.74	28.40	15.60	32.11	17.85	28.76	16.36	33.11
SWE	47.35	9.50	42.66	13.83	41.81	13.38	35.18	17.42	32.87	14.30	31.55	21.36	33.69	21.43

Note. The table presents the estimates of relative and upward mobility. The estimates are based on equation (1), regression of the rank math score on dummy equal to 1 if mother has at least completed upper secondary. The rank is computed at the European level. Higher values of relative mobility correspond to lower mobility.

A.3 Robustness to alternate measures

Appendix Table A3 shows that the correlation between the alternate measures is relatively high, providing confidence that the main results are robust to different definitions

of intergenerational transmission of learning.

Reading test score - we estimate the mobility equation (1) by using the rank of the reading test score.

Rank at country level - We estimate the mobility equation (1) by using the rank of the test score at the country level. The country rank is constructed by ordering the each plausible value of the test scores in ascending order within each country, using the weights provided by PISA. By defining within-country ranks, the estimated social mobility parameter compares the positions in the country's outcome distribution of children at different points of the country's SES distribution. The disadvantage of this measure is the difficulty in comparing estimates across countries, since the distribution of test scores may vary considerably from country to country. So the same variation in rank can represent widely different changes in test scores depending on which country we consider. We note that constructing a European rank may be problematic if the test score distributions do not overlap across countries. Appendix Tables A4 and A5, however, show a good overlap of the test score distribution across countries.

Alternate measures of parental socio-economic status.

Father's education - We compute the main measure of relative mobility in math from equation (1) when using the father's education dummy, instead of the mother's ($\beta_{tc}^{math-father}$).

Mother's higher education - We define an indicator variable taking value 1 if i's mother has completed higher education (HE_{itc}^{P}), and 0 otherwise (Appendix Table A1). For each student i, country c, cohort t and subject k, we estimate:

$$R(Y_{itc}^{k}) = \alpha_{tc}^{k-uni} + \beta_{tc}^{k-uni} HE_{itc}^{P} + \epsilon_{itc}^{k} \tag{3}$$

Rank of ESCS - We analyse a rank-rank measure, where we regress the rank of the math test score on the rank of the socio-economic and cultural status (ESCS), which can be considered as a proxy of permanent income. For each student i, country c, cohort t and subject k, we estimate:

$$R(Y_{itc}^{k}) = \mu_{tc}^{k} + \rho_{tc}^{k} R(Y_{itc}^{P}) + \epsilon_{itc}^{k} \tag{4}$$

where $R(Y)_{itc}^{k}$ is test score (rank) for subject k for student i at time t living in country c and $R(Y)_{itc}^{p}$ is i's the index of socio-economic and cultural status (rank). The index of socio-economic and cultural status (ESCS) is derived from three factors: highest parental occupation, highest parental education, and an Item response Theory (IRT) scale based on student reports on home possessions. PISA has constructed the index in 2015, making

it comparable over the waves. ESCS components and the ESCS model has changed over cycles and with that, ESCS scores are not comparable across cycles directly. To enable a trend study, in PISA 2015 the ESCS was computed for the current cycle and also recomputed for the earlier cycles using a similar methodology. Some example of changes over the different waves are the following. The mapping of ISCED levels to years of schooling was updated in 2009 and 2015 for some countries, taking into account changes in countries' learning systems. Indicators of home possession (HOMEPOS) have been dropped or added in all PISA cycles (except in PISA 2012) taking into account social, technical and economic changes in participating societies. Moreover, the method for HOMEPOS estimation has changed in PISA 2009, PISA 2012 and PISA 2015. Since PISA 2012 parental occupation is coded into HISEI using the current international standard classification of occupations, ISCO-08. Previous cycles used ISCO-88. For the effects of ISCO-08 compared to ISCO-88 on ESCS and performance please see PISA 2012 Technical Report, pp. 372 (OECD, 2014).

Above median education - We use a different definition of socio-economic status by defining the indicator variable taking value 1 if i's mother has at least the median education within the country (ME^P_{itc}), and 0 otherwise. For each student i, country c, cohort t and subject k, we estimate:

$$R(Y^k_{itc}) = \alpha^{k-med}_{tc} + \beta^{k-med}_{tc} ME^P_{itc} + \epsilon^k_{itc} \tag{5}$$

where β^{k-med}_{tc} is difference in math rank between children whose mothers have below and at least the median education within the country and α^{k-med}_{tc} is the children's average rank when the mother has below the median education within the country.

Table A3: Correlation among alternate learning mobility measures

	Relative mobility						
	β_tc^{math}	$\beta_tc^{math-father}$	β_tc^{math-c}	β_tc^{read}	$\beta_tc^{math-uni}$	$\beta_tc^{math-med}$	ρ_tc^{math}
β_tc^{math}	1						
$\beta_tc^{math-father}$	0.942***	1					
β_tc^{math-c}	0.992***	0.928***	1				
β_tc^{read}	0.973***	0.941***	0.957***	1			
$\beta_tc^{math-uni}$	0.337	0.405*	0.342	0.292	1		
$\beta_tc^{math-med}$	0.714***	0.784***	0.701***	0.678***	0.739***	1	
ρ_tc^{math}	0.763***	0.753***	0.711***	0.772***	0.376*	0.661***	1

	Upward mobility						
	α_tc^{math}	$\alpha_tc^{math-father}$	α_tc^{math-c}	α_tc^{read}	$\alpha_tc^{math-uni}$	$\alpha_tc^{math-med}$	μ_tc^{math}
α_tc^{math}	1.000						
$\alpha_tc^{math-father}$	0.967***	1.000					
α_tc^{math-c}	0.670***	0.652***	1.000				
α_tc^{read}	0.888***	0.911***	0.774***	1.000			
$\alpha_tc^{math-uni}$	0.686***	0.621***	0.007	0.399*	1.000		
$\alpha_tc^{math-med}$	0.852***	0.866***	0.248	0.668***	0.861***	1.000	
μ_tc^{math}	0.737***	0.706***	0.362*	0.644***	0.625***	0.632***	1.000

Note. The table presents the correlation among different measures of learning mobility (averaged across PISA waves). "β_{tc}^{math}" is the main measure of relative mobility in math from equation (1), $\beta_{tc}^{math-father}$ is the main measure of relative mobility in math from equation (1) when using the father's education dummy instead of the mother's, β_{tc}^{read} is the main measure of relative mobility in reading from equation (1), β_{tc}^{math-c} is relative mobility in math from equation (1) when rank is computed within the country, $\beta_{tc}^{math-uni}$ is relative mobility in math from equation (3), $\beta_{tc}^{math-med}$ is relative mobility in math from equation (5), ρ_{tc}^{math} is relative mobility from equation (4) using the rank of the parents' ESCS. α_{tc}^{math} is the main measure of upward mobility in math from equation (1), $\alpha_{tc}^{math-father}$ is the main measure of upward mobility in math from equation (1) when using the father's education dummy instead of the mother's, α_{tc}^{read} is the main measure of upward mobility in reading from equation (1), α_{tc}^{math-c} is upward mobility in math from equation (1) when rank is computed within the country, $\alpha_{tc}^{math-uni}$ is upward mobility in math from equation (3), $\alpha_{tc}^{math-med}$ is upward mobility in math from equation (5), μ_{tc}^{math} is upward mobility from equation (4) using the rank of the parents' ESCS. (*** p<0.01, ** p<0.05, * p<0.1).

A.4 Descriptive statistics on test scores

Table A4: Test score statistics, 2003

Country Name	Reading							Mathematics						
	Min	P25	P50	P75	Max	Mean	N	Min	P25	P50	P75	Max	Mean	N
AUT	16.62	423.47	498.69	565.05	786.68	490.69	4597	205.42	439.37	506.22	571.43	790.92	505.61	4597
BEL	31.54	439.93	521.61	587.04	792.17	506.99	8796	114.3	456.22	537.14	611.17	834.06	529.29	8796
CHE	96.51	438.52	505.98	565.28	787.34	499.12	8420	164.42	460.76	529.66	594.98	839.12	526.55	8420
CZE	160.17	427.78	494.53	555.26	800.9	488.54	6320	199.41	449.4	516.77	584.41	857.83	516.46	6320
DEU	69.23	418.51	503.62	571.75	782.91	491.36	4660	147.31	432.17	509.16	578.31	801.06	502.99	4660
DNK	86.67	437.75	498.47	553.38	760.64	492.32	4218	157.36	453.17	516.08	578.24	777.16	514.29	4218
ESP	7.39	420.5	486.99	548.19	756.96	480.54	10791	115.42	426.19	487.1	546.44	787.38	485.11	10791
FIN	152.82	493.63	549.2	598.78	803.6	543.46	5796	223.15	488.24	543.73	602.63	837.64	544.29	5796
FRA	119.61	436.03	504.99	565.43	757.01	496.19	4300	189.7	449.06	514.24	575.25	782.94	510.8	4300
GBR	106.88	445.47	511.87	573.58	809.24	507.01	9535	146.8	444.1	509.78	572.6	808.9	508.26	9535
GRC	-17.89	406.34	479.84	545.95	780.09	472.27	4627	77.85	382.36	446.11	507.87	768.66	444.91	4627
HUN	129.4	422.03	486.57	546.47	752.47	481.87	4765	153.86	426.09	489.97	555.88	794.66	490.01	4765
IRL	150.09	460.18	520.64	576.9	754.22	515.48	3880	203.47	444.99	503.47	561.88	789.53	502.84	3880
ISL	53.3	430.74	498.6	560.3	789.42	491.75	3350	187.09	454.23	518.21	578.44	806.62	515.11	3350
ITA	-8.97	411.36	483.43	547	873.68	475.66	11639	68.09	400.47	466.07	530.24	817.56	465.66	11639
LIE	250.65	467.06	529.87	588.42	725.95	525.08	332	222.67	469.86	539.2	608.6	799.88	535.8	332
LUX	57.92	415.74	488.15	551.42	742.46	479.42	3923	180.11	430.24	495.23	557.17	793.86	493.21	3923
LVA	119.81	430.95	494.94	554.26	782.02	490.56	4627	140.22	423.52	484.06	543.53	811.51	483.37	4627
NLD	204.49	454.11	516.93	576.14	759.73	513.12	3992	213.24	470.95	539.62	608.32	802.41	537.82	3992
NOR	47.28	434.25	507.11	570.56	813.38	499.74	4064	179.75	432.87	495.26	559.99	814.57	495.19	4064
POL	106.47	436.43	500.46	562.63	799.43	496.61	4383	136.97	428.2	489.67	552.81	776.63	490.24	4383
PRT	126.46	417.62	485.57	543.81	753.32	477.57	4608	170.06	405.97	467.18	526.14	751.77	466.02	4608
SVK	54.77	407.86	472.68	535.3	751.61	469.16	7346	115.78	435.55	498.33	564.59	825.27	498.18	7346
SWE	34.53	453.14	520.57	581.58	803.7	514.27	4624	117.85	446.08	509.6	575.57	799.64	509.05	4624

Note. The table presents the descriptive statistics on the reading and math test scores in 2003.

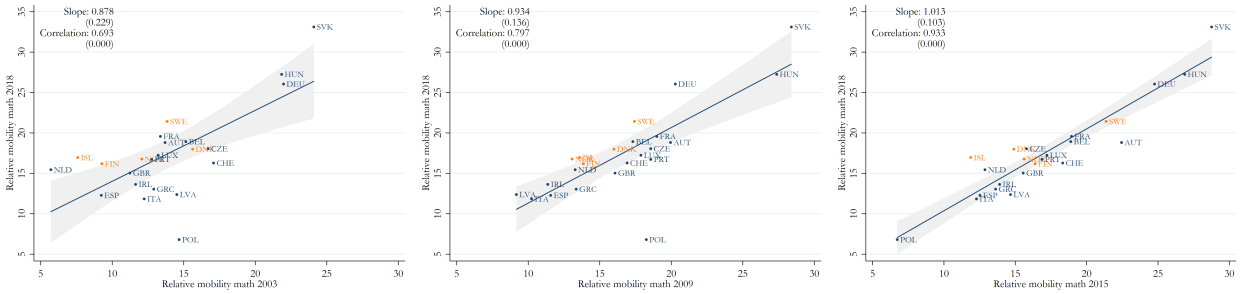
Table A5: Test score statistics, 2018

Country Name	Reading							Mathematics						
	Min	P25	P50	P75	Max	Mean	N	Min	P25	P50	P75	Max	Mean	N
AUT	163.36	412.73	488.16	557.72	771.94	484.39	6802	166.55	433.41	503.24	566.41	785.17	498.94	6802
BEL	145.69	421.39	497.6	567.82	801.94	492.86	8475	186.05	439.83	514.23	578.98	801.67	508.07	8475
CHE	70.28	412.76	488.08	557.74	796.57	483.93	5822	172.3	447.98	518.06	582.1	822.22	515.31	5822
CZE	164.68	422.06	491.61	559.9	804.6	490.22	7019	172.98	434.99	501.02	564.29	819.13	499.47	7019
DEU	164.65	424.21	503.81	575.87	836.03	498.28	5451	179.76	433.05	504.05	569.71	803.27	500.04	5451
DNK	130.35	438.56	504.41	566.12	791.55	501.13	7657	191.78	453.69	511.51	567.45	771.37	509.4	7657
ESP	147.93	413.24	479.21	542.51	799.77	476.54	35943	127.47	420.99	484.37	544.24	808.4	481.39	35943
FIN	145.86	455.09	526.9	591.18	823.9	520.08	5649	178.6	451.33	510.43	564.74	776.51	507.3	5649
FRA	139.57	422.89	496.94	566.62	807.17	492.61	6308	151.59	432.93	501.72	562.21	775.73	495.41	6308
GBR	160.47	435.36	506.3	574.83	846.54	503.93	13818	122.58	438.72	503.78	566.71	813.21	501.77	13818
GRC	157.19	390.2	459.73	526.46	771.41	457.41	6403	127.59	390.6	453.55	513.26	758.55	451.37	6403
HUN	180.88	406.69	479.06	547.24	776.83	475.99	5132	148.92	417.89	484.03	546.03	771.87	481.08	5132
IRL	207.82	456	519.95	582.64	797.02	518.08	5577	219.19	447.49	502.06	553.79	743.68	499.63	5577
ISL	163.82	402.48	477.44	549.44	795.8	473.97	3296	194.88	433.9	499.3	558.55	767.23	495.19	3296
ITA	142.5	413.14	481.34	544.63	785.98	476.28	11785	154.72	423.35	490.24	551.97	791.6	486.59	11785
LUX	153.3	392.36	471.54	547.95	804.29	469.99	5230	162.42	412.86	485.37	554.8	790.08	483.42	5230
LVA	170.92	415.21	480.49	542.35	775.1	478.7	5303	211.76	441.38	496.6	550.99	762.97	496.13	5303
NLD	129.98	410.44	486.41	562.18	794.29	484.78	4765	140.48	452.97	524.34	587.91	792.79	519.23	4765
NOR	153.17	430.32	506.15	575.84	810.56	499.45	5813	163.78	440.56	503.79	565.17	789.19	500.96	5813
POL	154.32	445.69	514.54	581.36	837.35	511.86	5625	192.84	454.78	516.78	577.96	810.78	515.65	5625
PRT	166.58	425.11	497.18	561.93	785.53	491.8	5932	158.4	426.04	497.29	561.71	799.26	492.49	5932
SVK	140.24	387.5	457.5	529.38	780.24	457.98	5965	119.08	419.55	491.72	556.45	801.07	486.16	5965
SWE	128	434.17	511.52	583.49	815.49	505.79	5504	193.5	440.51	504.89	566.84	788.26	502.39	5504

Note. The table presents the descriptive statistics on the reading and math test scores in 2018.

A.5 Trends in learning mobility by country

Figure A2: Correlation between relative mobility in math and its lags



Note. The figures present the correlation between relative mobility (math) in 2018 and its lags. The estimates are based on equation (1), regression of the rank math score on dummy equal to 1 if mother has at least completed upper secondary. The rank is computed at the European level. Higher values of relative mobility correspond to lower mobility. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

Figure A3: Trends in learning mobility (math) by country.

Relative Mobility

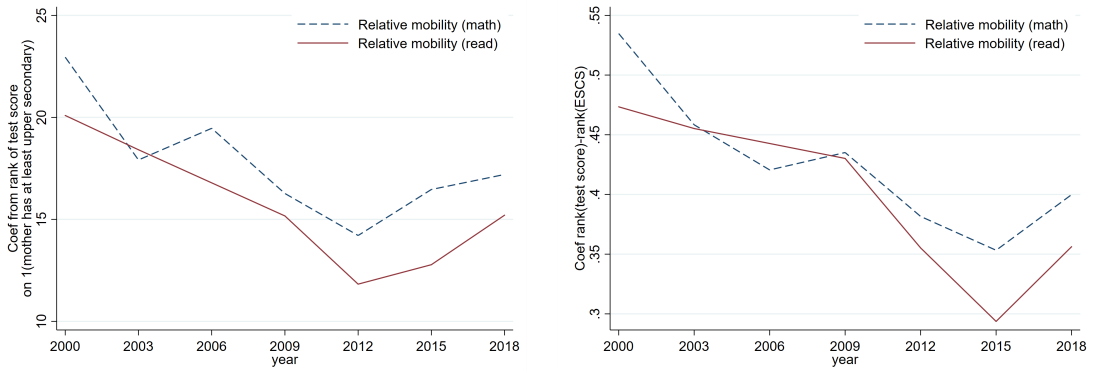


Upward Mobility



Note. The figures present the trends in relative and upward mobility for each country (red line) against other countries (gray lines). The estimates are based on equation (1), regression of the rank math score on dummy equal to 1 if mother has at least completed upper secondary. The rank is computed at the European level. Higher values of relative mobility correspond to lower mobility. Countries are ordered from the most to least mobile, based on average mobility over the PISA waves.

Figure A4: Learning mobility in the United States.



Note. The figures present the measures of learning mobility in the USA over time. The left panel presents the mobility measure computed by regressing the rank of the test score on a dummy equal to 1 if the mother has at least upper secondary (equation (1)). The right panel presents the mobility measure computed by regressing the rank of the test score on the rank of the ESCS index (equation (4)).

Figure A5: Trends in learning mobility (math) by country (restricting sample to native population).



Note. The figures present the trends in relative and upward mobility for each country (red line) against other countries (gray lines) restricting the sample to the native population. The estimates are based on equation (1) for the native population, regression of the rank math score on dummy equal to 1 if mother has at least completed upper secondary. The rank is computed at the European level for the native population. Higher values of relative mobility correspond to lower mobility. Countries are ordered from the most to least mobile, based on average mobility over the PISA waves. Immigrant status was not collected in the 2000 PISA wave.

A.6 Do changes in composition drive changes in mobility?

Table A6: Learning mobility and migrant students

	Relative mobility		**Upward mobility**	
% migrant students	0.014	0.091	0.148	-0.126
	(0.074)	(0.110)	(0.144)	(0.193)
Observations	142	142	142	142
R^2	0.001	0.819	0.036	0.829
Country FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes

Note. The table presents the regression of relative and upward mobility (math) on the proportion of migrant students from the PISA database (2003-2018). The estimates of upward and relative mobility are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. The estimates are presented with and without country and year fixed effects. Clustered standard errors at country level (*** p<0.01, ** p<0.05, * p<0.1).

Table A7: Learning mobility and mothers' education

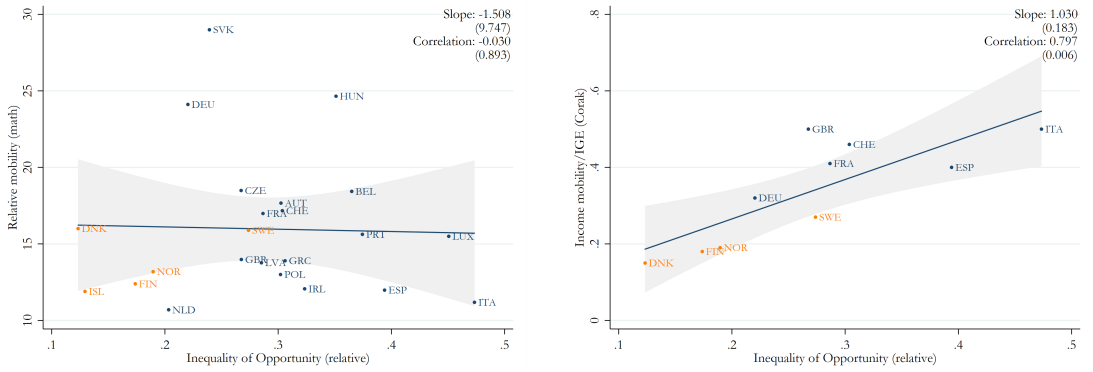
	Relative mobility		**Upward mobility**	
% mothers with less than upper secondary education	-0.107	-0.027	0.127	0.119
	(0.070)	(0.105)	(0.084)	(0.172)
Observations	142	142	142	142
R^2	0.076	0.817	0.044	0.830
Country FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes

Note. The table presents the regression of relative and upward mobility (math) on the proportion of mothers with less than upper secondary education from the PISA database (2003-2018). The estimates of upward and relative mobility are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. The estimates are presented with and without country and year fixed effects. Clustered standard errors at country level (*** p<0.01, ** p<0.05, * p<0.1).

B Correlates: intergenerational transmission of learning

B.1 Learning mobility and inequality of opportunity (relative)

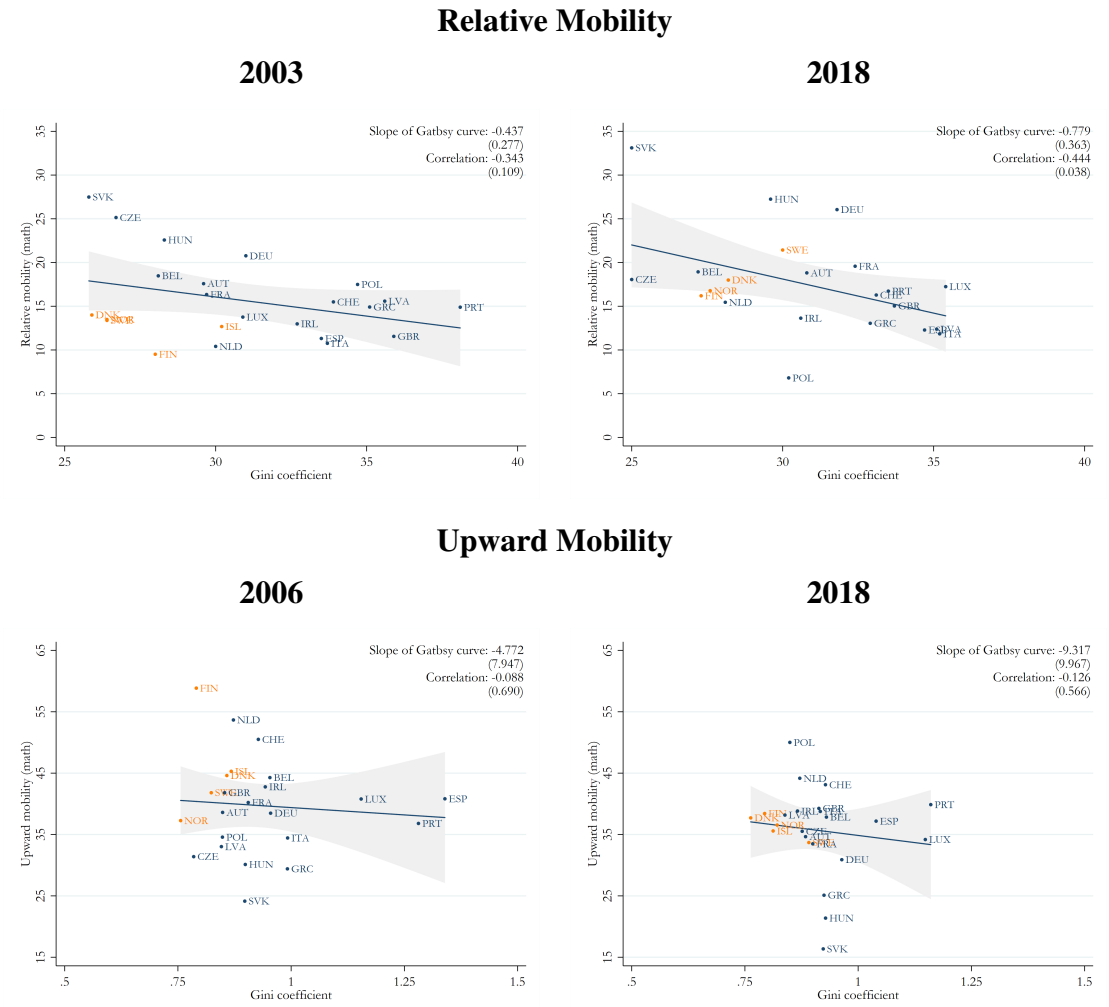
Figure B1: Correlation between relative mobility, inequality of opportunity, IGE (Corak, 2013)



Note. The left figure presents the correlation between relative mobility (math - averaged over PISA years) and inequality of opportunity (relative) in 2010 from https://www.equalchances.org/. The right figure present the correlation between income mobility measure from Corak (2013) and inequality of opportunity (relative) from https://www.equalchances.org/. Corak (2013)'s estimates of income mobility are measured as the elasticity between paternal earnings and a son's adult earnings, using data on a cohort of children born during the early to mid 1960s and measuring their adult outcomes in the mid to late 1990s. These IGE estimates are derived from published studies, adjusted for methodological comparability in Corak (2013). Equality of opportunity captures to what extent when everyone exerting the same degree of effort (or responsibility) attains the same level of advantage (or well-being), regardless of any predetermined circumstances beyond their control (Roemer, 1998). The estimates of upward and relative mobility are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

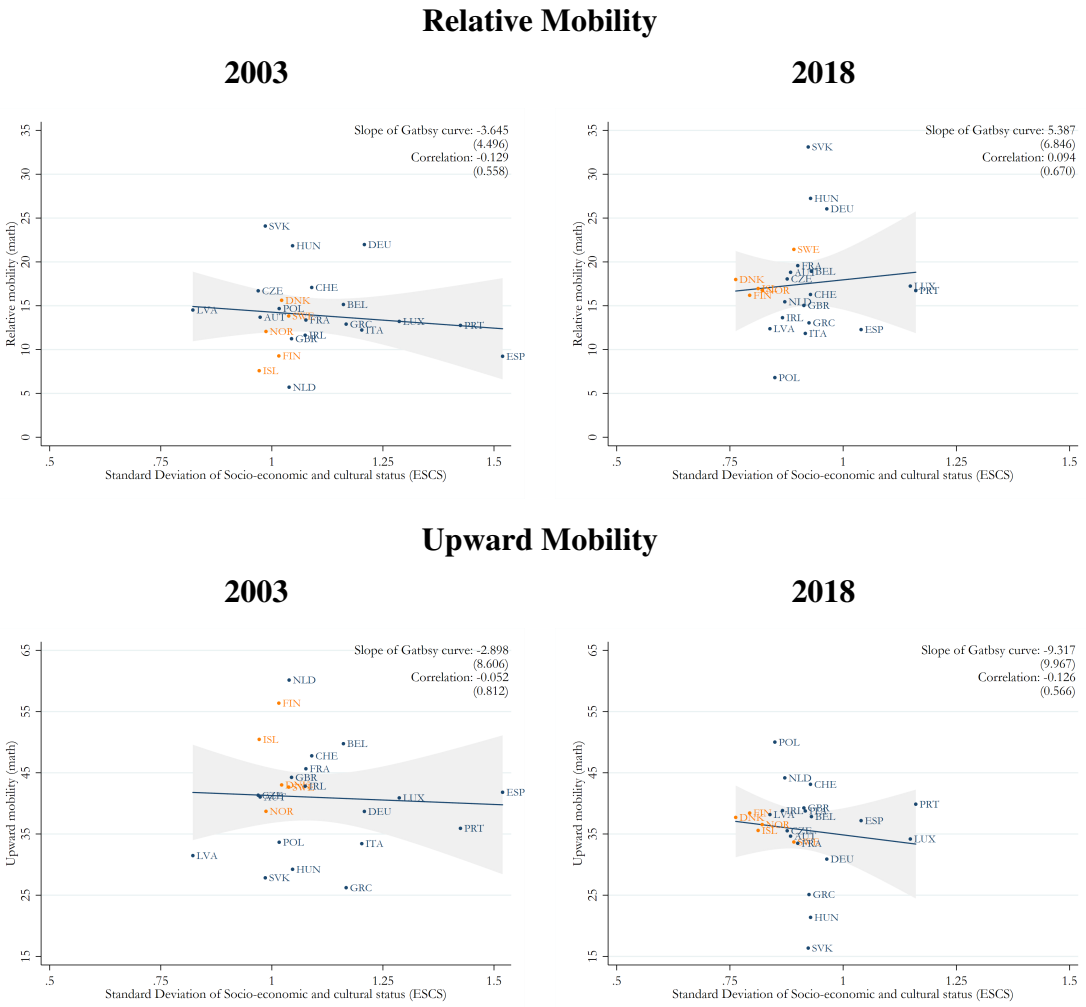
B.2 The Great Gatsby curve

Figure B2: The Great Gatsby curves: learning mobility and Gini coefficient (World Bank).



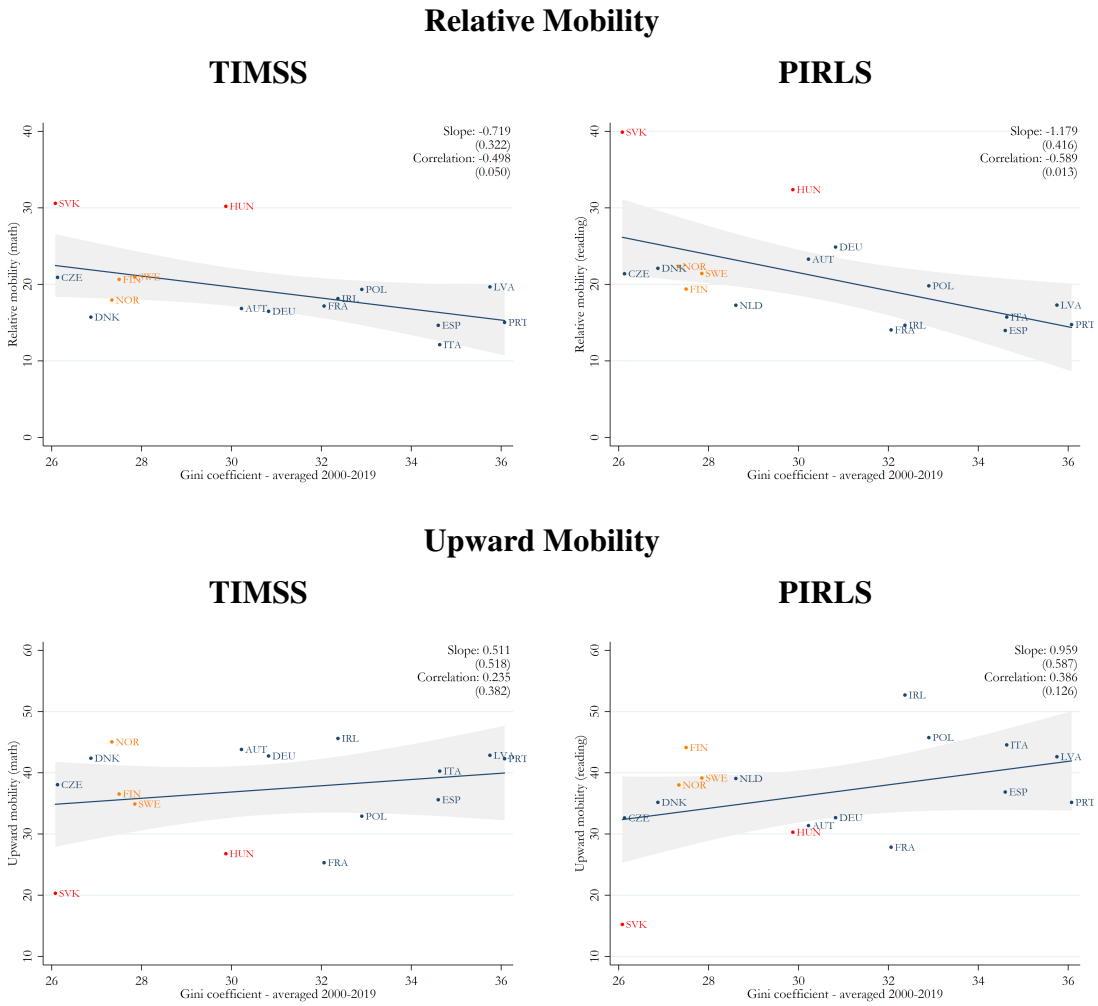
Note. The figures present the Gatsby curves by year. The estimates of relative mobility are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. The inequality measure is the Gini Coefficient from the World Bank database in the year of the PISA test. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

Figure B3: The Great Gatsby curves: learning mobility and standard deviation of ESCS index.



Note. The figures present the Gatsby curves by year. The estimates of relative mobility are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. The inequality measure is the standard deviation of ESCS index. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

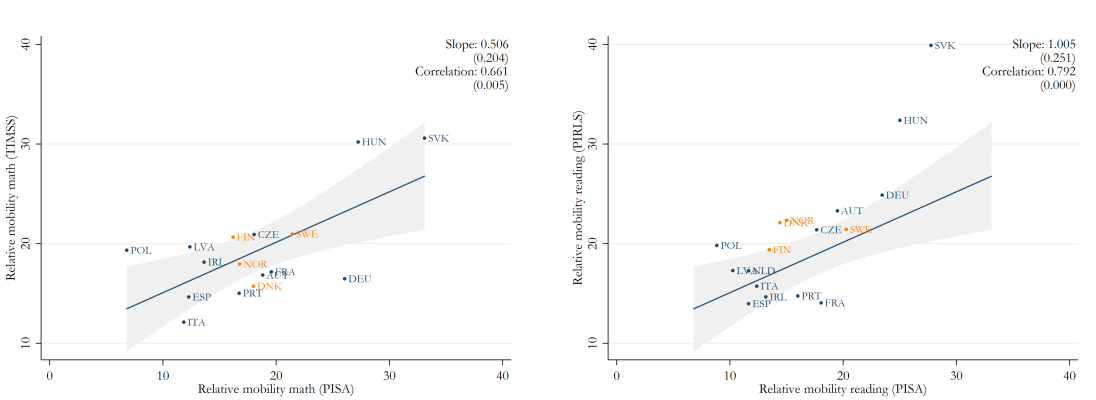
Figure B4: The Great Gatsby curves: learning mobility from TIMSS & PIRLS and Gini coefficient (World Bank).



Note. The figures present the Gatsby curves using the TIMSS and PIRLS data. The estimates of relative mobility are based on equation (1), regression of the rank of the math score (4-grade 2019 TIMSS)/ reading score (4-grade 2016 PIRLS) on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. The inequality measure is the Gini Coefficient from the World Bank database in the year of the PISA test. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

B.3 Correlation between mobility in PISA and TIMSS/PIRLS

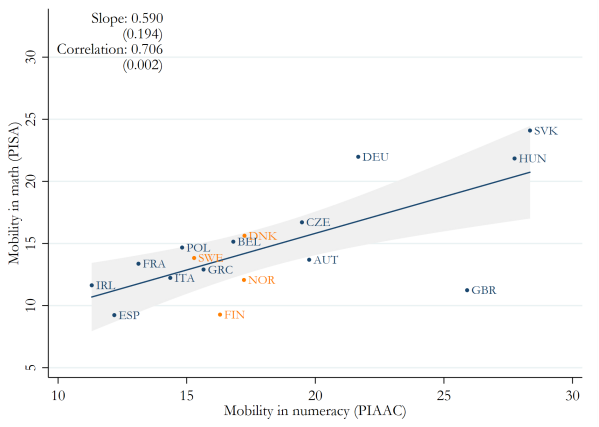
Figure B5: Correlation between mobility in PISA and TIMSS/PIRLS



Note. The figure presents the correlation between mobility in PISA and TIMSS. The mobility measure is the β_{tc}^{k} of regressing the rank of math skill on a dummy equal to 1 if the mother has at least upper secondary ((1)). The estimates of relative mobility are based on equation (1), regression of the rank of the math score (4-grade 2019 TIMSS)/ reading score (4-grade 2016 PIRLS) on a dummy equal to 1 if mother has at least upper secondary. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

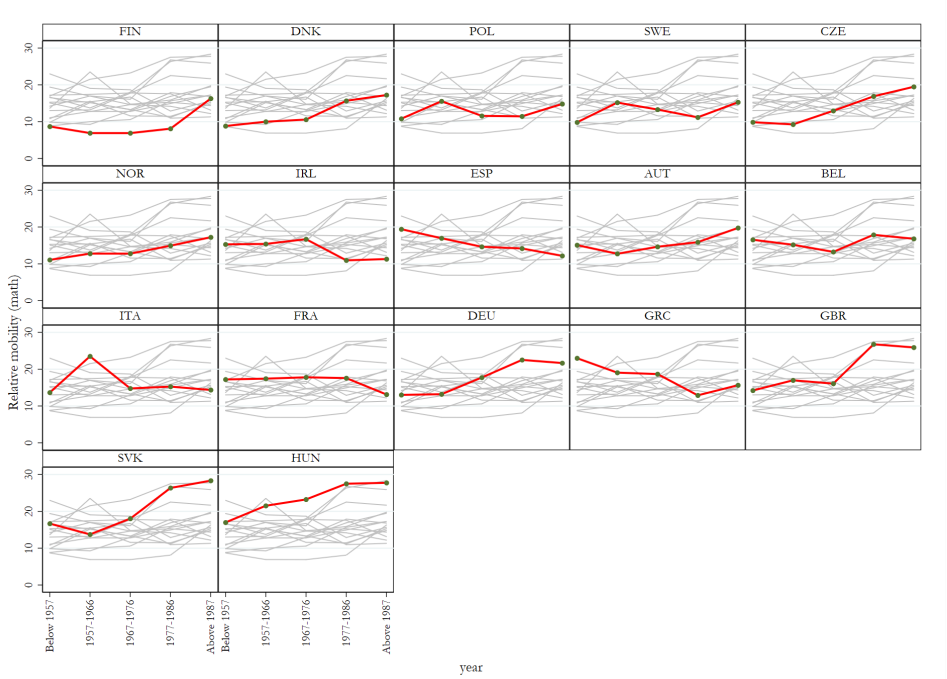
B.4 Evidence from PIAAC data

Figure B6: Correlation between mobility measure in PISA and PIAAC



Note. The figure presents the scatter plots between relative mobility in math (PISA) and relative mobility in numeracy (PIAAC) for the 2003 PISA cohort (i.e., the cohort overlapping with PIAAC one - born 1987 or later). Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the p-value in parenthesis.

Figure B7: Trends in mobility in numeracy skill by cohort (PIAAC data).



Note. The figure presents the trends in numeracy skill by cohort. The mobility measure is the β^k_{tc} of regressing the rank of numeracy skill on a dummy equal to 1 if the mother has at least upper secondary. The rank is at European and cohort level.

B.5 SES gradients in parental investment

B.5.1 Measuring parental investment

To construct a measure of parental investment in home educational resources that is comparable across countries and over time, we use a factor model specified in equation (6).

Assuming each latent item, $m^{*,j}_{ict}$ for question j, is additively separable in the logarithm of the latent factor, we have:

$$m^{*,j}_{ict} = \alpha^j_{ct} + \lambda^{j\top}_t lnI_{ict} + \varepsilon^j_{ict} \tag{6}$$

Depending on the nature of $m^{*,j}_{ict}$, we need to specify different models:

(i) Continuous variables: $m_{ict-1} = m^*_{ict-1}$;

(ii) Binary variables $m_{ict-1} \in \{0,1\}$: $Prob\{m_{ict-1} = 1\} = Pr\{m^*_{ict-1} \geq 0\}$;

(iii) Categorical variables $m_{ict-1} \in \{1,2,...,L\}$: $Prob\{m_{ict-1} = l\} = Pr\{\tau_{l-1} \leq m^*_{ict-1} \leq \tau_l\}$, where $\tau_0 = -\infty$;

We use the threshold model defined in (iii) as items are categorical. Given that factors are unobserved and lack a scale, ensuring comparability requires some identification. To achieve this, we fix the scale and location based on the same item $j = 1$ across countries and over time. Namely, we set $\lambda^1_{ct} = 1$ and $\tau^1_{c1,t} = 0$ and $\alpha^j_{ct} = 0, \forall j$ respectively. We use the following item "Possessions poetry" which has been asked across all the waves and countries. We use the weights provided by the OECD throughout the analysis to estimate the factor model.

The questions used for the parental investment index have been collected from 2003 and are presented below:[2]

- Possessions desk
- Possessions study place
- Possessions computer
- Possessions software
- Possessions textbooks
- Possessions <technical reference books>
- Possessions dictionary
- Possessions literature
- Possessions poetry
- Possessions art
- How many books at home

For each student i, country c and cohort t, we estimate:

$$R(I_{itc}) = \alpha^I_{tc} + \beta^I_{tc} HS^P_{itc} + e_{itc} \tag{7}$$

where $R(I_{itc})$ is the parental investment percentile rank (rank computed at European level) for student i, at time t, living in country c. HS^p_{itc} is an indicator variable taking value 1 if i's mother has completed at least upper secondary education, and 0 otherwise (Appendix Table A1).

β^I_{tc} measures the SES gradient in parental investment; i.e., the association between mother's education (high school degree) and her child's rank in distribution of parental investment, for cohort t and country c.

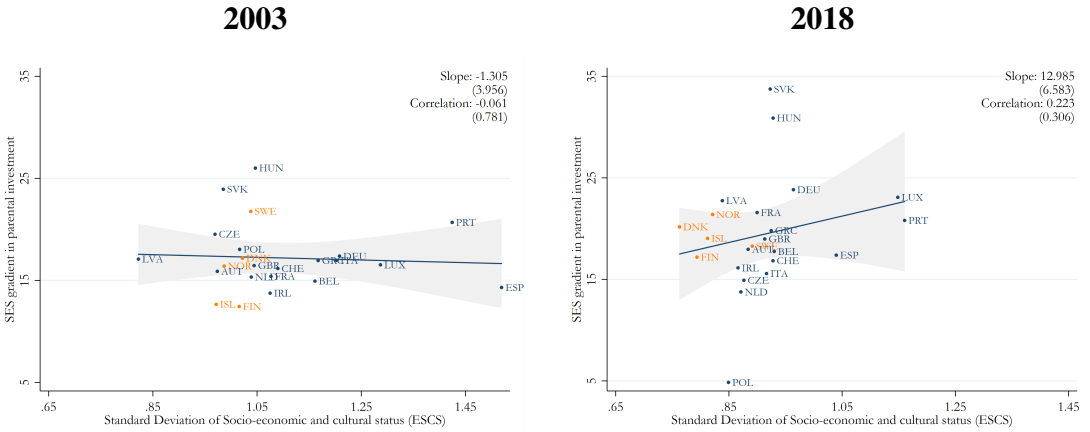
[2]More details on the questions can be found in the technical reports. Technical report 2003: page 283 https://www.oecd.org/education/school/programmeforinternationalstudentassessmentpisa/35188570.pdf Technical report 2006: Page 316 https://www.oecd.org/pisa/data/42025182.pdf Technical report 2009: page 288 https://www.oecd.org/pisa/pisaproducts/50036771.pdf Technical report 2012: page 316 https://www.oecd.org/pisa/pisaproducts/PISA-2012-technical-report-final.pdf Technical report 2015: page 304 https://www.oecd.org/pisa/data/2015-technical-report/PISA2015_TechRep_Final.pdf

α_{tc}^{I} measures the average level of investment in children whose mothers do not have upper secondary education.

B.5.2 Correlates of the socio-economic gradients in parental investment

Appendix Figure B8 shows a lack of correlation between inequality in ESCS and SES gradients in parental investments, hinting that inequality in the ESCS and SES gradients in parental investment are measuring two different factors.

Figure B8: Correlation between SES gradients in parental investment and inequality in ESCS.



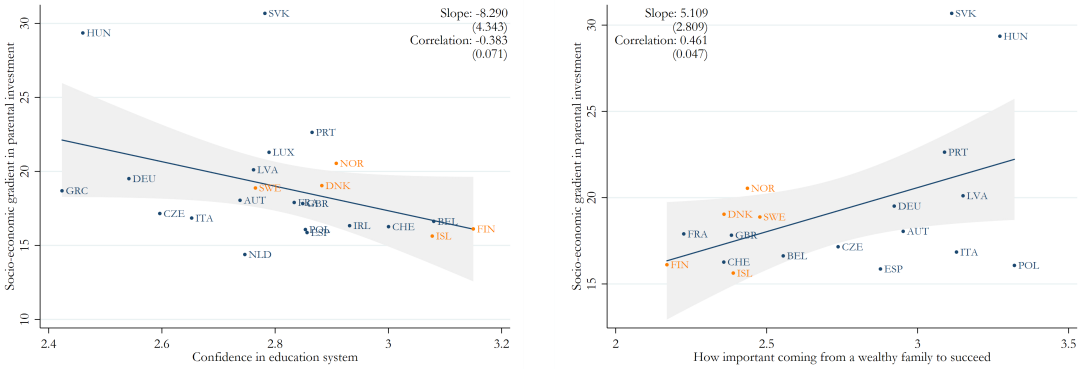
Note. The figures present the correlation between the SES gradients in parental investment and inequality in ESCS. The estimates of the socio-economics gradients in parental investment are based on regression of the rank of the parental investment on a dummy equal to 1 if mother has at least upper secondary (equation (7)). The rank is computed at the European level. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the p-value in parenthesis.

Appendix Figure B9 explores to what extent attitudes towards education correlate with SES gradients in parental investment, aiming to investigate the underlying mechanism. We use the data from the European Value Study (EVS) in 2008 and 2017 and the International Social Survey Programme (ISSP) on social inequality in 2009. For the EVS, the question is "How much confidence you have in the education system, is it a great deal, quite a lot, not very much or none at all? (Answers: 1. a great deal, 2. quite a lot, 3. not very much, 4. none at all). We reverse code the variable and recode cannot choose as missing (few people answer cannot choose). We then collapse the data to obtain the mean by country, using the weight provided by EVS.

For the ISSP, the question is "How important you think is coming from a wealthy family for getting ahead in life?" (Answers: 1. Essential, 2. Very Important, 3 Fairly Important, 4. Not very important, 5. Not important at all, 8. cannot choose). We reverse code

the variable and recode cannot choose as missing (few people answer cannot choose). We then collapse the data to obtain the mean by country, using the weight provided by ISSP.

Figure B9: Correlation between the SES gradients in parental investment and attitudes towards education.



Note. The figures present the correlation between the socio-economics gradients in parental investment (averaged over 2003-2018 PISA waves) and attitudes towards education. The estimates of the socio-economics gradients in parental investment are based on regression of the rank of the parental investment on a dummy equal to 1 if mother has at least upper secondary (equation (7)). The rank is computed at the European level. For the EVS, the question is "How much confidence you have in the education system? (answers: 1. none at all, 2. not very much,, 3. quite a lot, 4. a great deal). For the ISSP, the question is "How important you think is coming from a wealthy family for getting ahead in life?" (answers: 1. Not important at all, 2. Not very important, 3 Fairly Important, 4. Very Important, 5. Essential). Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the p-value in parenthesis.

B.6 Robustness: learning mobility and SES gradient in parental investment

Table B1: Robustness to outliers: learning mobility and SES gradient in parental investment

	Relative mobility (math)					
Excluding	AUT	BEL	CHE	CZE	DEU	DNK
SES gradient in parental investment	0.845***	0.866***	0.864***	0.858***	0.825***	0.841***
	(0.129)	(0.124)	(0.125)	(0.127)	(0.140)	(0.128)
Observations	23	23	23	23	23	23
R^2	0.579	0.605	0.593	0.598	0.643	0.570
Excluding	ESP	FIN	FRA	GBR	GRC	HUN
SES gradient in parental investment	0.828***	0.831***	0.845***	0.838***	0.840***	0.849***
	(0.132)	(0.132)	(0.129)	(0.128)	(0.127)	(0.187)
Observations	23	23	23	23	23	23
R^2	0.560	0.561	0.576	0.569	0.575	0.483
Excluding	IRL	ISL	ITA	LIE	LUX	LVA
SES gradient in parental investment	0.828***	0.828***	0.824***	0.879***	0.859***	0.853***
	(0.131)	(0.133)	(0.130)	(0.121)	(0.123)	(0.123)
Observations	23	23	23	23	23	23
R^2	0.563	0.558	0.570	0.586	0.584	0.590
Excluding	NLD	NOR	POL	PRT	SVK	SWE
SES gradient in parental investment	0.821***	0.862***	0.836***	0.881***	0.678***	0.841***
	(0.137)	(0.119)	(0.131)	(0.114)	(0.150)	(0.128)
Observations	23	23	23	23	23	23
R^2	0.548	0.604	0.562	0.599	0.362	0.570

Note. The table presents the robustness to outliers for learning mobility and SES gradient in parental investment. The relationship between learning mobility and SES gradient in parental investment is re-estimated by excluding each country one by one. The estimates of relative mobility are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. Robust standard errors (*** p<0.01, ** p<0.05, * p<0.1).

Table B2: Robustness to other definitions: learning mobility and SES gradient in parental investment

	Relative mobility					
Definition	$\beta_{tc}^{math-father}$	β_{tc}^{read}	β_{tc}^{math-c}	$\beta_{tc}^{math-uni}$	$\beta_{tc}^{math-med}$	ρ_{tc}^{math}
SES gradient in parental investment	0.839***	0.714***	0.865***	0.411**	0.387**	0.623***
	(0.169)	(0.105)	(0.123)	(0.165)	(0.141)	(0.198)
Observations	24	24	24	24	24	23
R^2	0.458	0.492	0.641	0.209	0.232	0.149
	Upward mobility					
Definition	$\alpha_{tc}^{math-father}$	α_{tc}^{read}	α_{tc}^{math-c}	$\alpha_{tc}^{math-uni}$	$\alpha_{tc}^{math-med}$	μ_{tc}^{math}
SES gradient in parental investment	-1.482***	-1.375***	-0.869***	-0.696**	-0.945***	-0.577***
	(0.139)	(0.231)	(0.200)	(0.259)	(0.168)	(0.182)
Observations	24	24	24	24	24	23
R^2	0.631	0.626	0.537	0.234	0.365	0.266

Note. The table presents the robustness to other definitions of learning mobility for the relationship between learning mobility and SES gradient in parental investment. The other measures are defined in Appendix A.3 and reported in the note of the Table. $\beta_{tc}^{math-father}$ is the measure of relative mobility in math from equation (1) when using the father's education dummy instead of the mother's, β_{tc}^{read} is the main measure of relative mobility in reading from equation (1), β_{tc}^{math-c} is relative mobility in math from equation (1) when rank is computed within the country, $\beta_{tc}^{math-uni}$ is relative mobility in math from equation (3), $\beta_{tc}^{math-med}$ is relative mobility in math from equation (5), ρ_{tc}^{math} is relative mobility from equation (4) using the rank of the parents' ESCS. α_{tc}^{math} is the main measure of upward mobility in math from equation (1), $\alpha_{tc}^{math-father}$ is the main measure of upward mobility in math from equation (1) when using the father's education dummy instead of the mother's, α_{tc}^{read} is the main measure of upward mobility in reading from equation (1), α_{tc}^{math-c} is upward mobility in math from equation (1) when rank is computed within the country, $\alpha_{tc}^{math-uni}$ is upward mobility in math from equation (3), $\alpha_{tc}^{math-med}$ is upward mobility in math from equation (5), μ_{tc}^{math} is upward mobility from equation (4) using the rank of the parents' ESCS. Robust standard errors (*** p<0.01, ** p<0.05, * p<0.1).

Table B3: Robustness to outliers in the panel regression: learning mobility and SES gradient in parental investment

	Relative mobility (math)					
Excluding	AUT	BEL	CHE	CZE	DEU	DNK
SES gradient in parental investment	0.557***	0.572***	0.560***	0.552***	0.555***	0.565***
	(0.131)	(0.127)	(0.133)	(0.146)	(0.141)	(0.131)
Observations	136	136	136	136	136	136
R^2	0.882	0.882	0.883	0.892	0.873	0.883
Excluding	ESP	FIN	FRA	GBR	GRC	HUN
SES gradient in parental investment	0.568***	0.554***	0.575***	0.571***	0.570***	0.563***
	(0.129)	(0.132)	(0.127)	(0.129)	(0.129)	(0.131)
Observations	136	136	136	136	136	136
R^2	0.877	0.880	0.883	0.881	0.884	0.863
Excluding	IRL	ISL	ITA	LIE	LUX	LVA
SES gradient in parental investment	0.564***	0.565***	0.560***	0.553***	0.569***	0.573***
	(0.131)	(0.131)	(0.132)	(0.133)	(0.131)	(0.131)
Observations	136	136	136	138	136	136
R^2	0.880	0.882	0.879	0.884	0.882	0.894
Excluding	NLD	NOR	POL	PRT	SVK	SWE
SES gradient in parental investment	0.590***	0.581***	0.392***	0.572***	0.607***	0.593***
	(0.117)	(0.122)	(0.112)	(0.129)	(0.122)	(0.113)
Observations	136	136	136	136	136	136
R^2	0.887	0.885	0.887	0.883	0.841	0.897

Note. The table presents the robustness in the panel to outliers for learning mobility and SES gradient in parental investment. The relationship between learning mobility and SES gradient in parental investment is re-estimated by excluding each country one by one. The estimates of relative mobility are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. Clustered standard errors at the country level (*** p<0.01, ** p<0.05, * p<0.1).

Table B4: Robustness to other definitions in the panel regression: learning mobility and SES gradient in parental investment

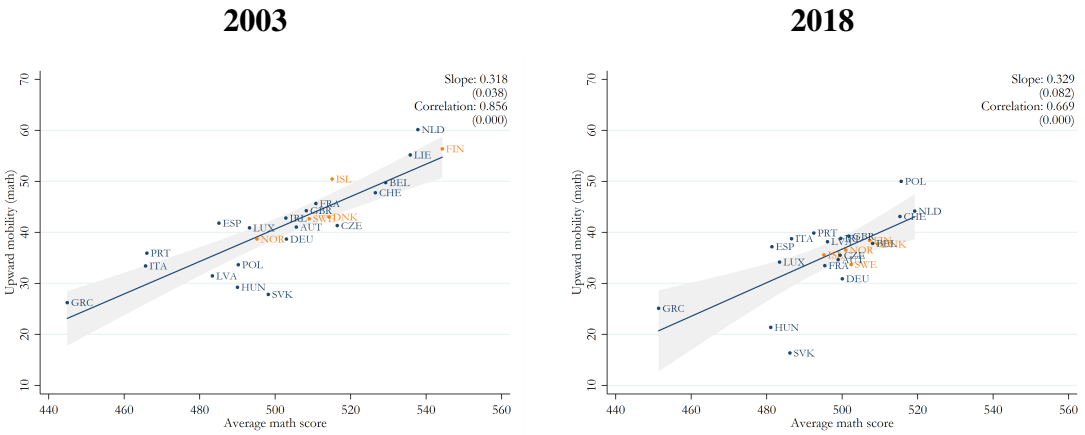
			Relative mobility			
Definition	$\beta_{tc}^{math-father}$	β_{tc}^{read}	β_{tc}^{math-c}	$\beta_{tc}^{math-uni}$	$\beta_{tc}^{math-med}$	ρ_{tc}^{math}
SES gradient in parental investment	0.242***	0.502***	0.581***	0.116	0.126	-0.006
	(0.077)	(0.118)	(0.138)	(0.072)	(0.099)	(0.085)
Observations	142	142	142	142	142	137
R^2	0.876	0.880	0.882	0.780	0.678	0.868
			Upward mobility			
Definition	$\alpha_{tc}^{math-father}$	α_{tc}^{read}	α_{tc}^{math-c}	$\alpha_{tc}^{math-uni}$	$\alpha_{tc}^{math-med}$	μ_{tc}^{math}
SES gradient in parental investment	-0.424**	-0.596***	-0.554***	-0.236	-0.282	-0.142
	(0.154)	(0.167)	(0.164)	(0.142)	(0.183)	(0.127)
Observations	142	142	142	142	142	137
R^2	0.883	0.878	0.896	0.856	0.808	0.743

Note. The table presents the robustness in the panel to other definitions of learning mobility for the relationship between learning mobility and SES gradient in parental investment. The other measures are defined in Appendix A.3 and reported in the note of the Table. $\beta_{tc}^{math-father}$ is the measure of relative mobility in math from equation (1) when using the father's education dummy instead of the mother's, β_{tc}^{read} is the main measure of relative mobility in reading from equation (1), β_{tc}^{math-c} is relative mobility in math from equation (1) when rank is computed within the country, $\beta_{tc}^{math-uni}$ is relative mobility in math from equation (3), $\beta_{tc}^{math-med}$ is relative mobility in math from equation (5), ρ_{tc}^{math} is relative mobility from equation (4) using the rank of the parents' ESCS. α_{tc}^{math} is the main measure of upward mobility in math from equation (1), $\alpha_{tc}^{math-father}$ is the main measure of upward mobility in math from equation (1) when using the father's education dummy instead of the mother's, α_{tc}^{read} is the main measure of upward mobility in reading from equation (1), α_{tc}^{math-c} is upward mobility in math from equation (1) when rank is computed within the country, $\alpha_{tc}^{math-uni}$ is upward mobility in math from equation (3), $\alpha_{tc}^{math-med}$ is upward mobility in math from equation (5), μ_{tc}^{math} is upward mobility from equation (4) using the rank of the parents' ESCS. Clustered standard errors at the country level (*** p<0.01, ** p<0.05, * p<0.1).

C Other measures of SES gradients in child outcomes

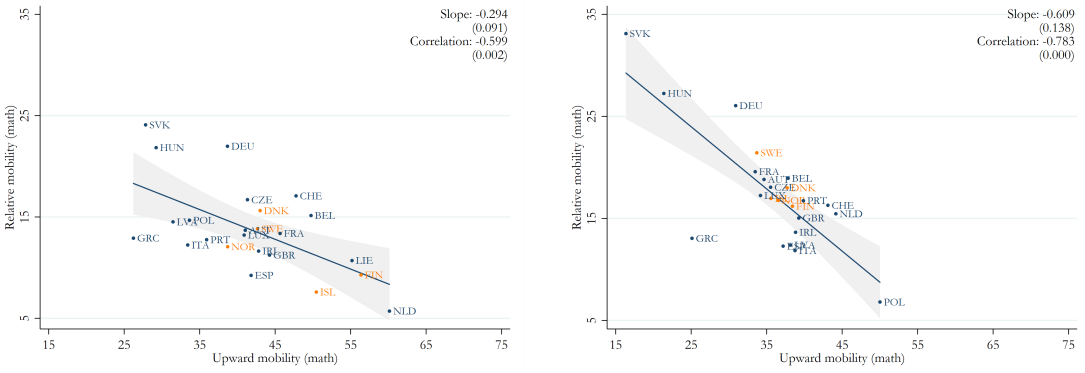
C.1 Upward mobility

Figure C1: Correlation between upward mobility and average math score



Note. The figures present the correlation between upward mobility and average math score. The estimates of upward mobility are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

Figure C2: Correlation between upward and relative mobility (math)



Note. The figures present the correlation between upward and relative mobility. The estimates of upward and relative mobility are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

C.2 Panel estimates: upward mobility in test scores

Table C1: Panel regressions: upward mobility in learning

	Upward mobility (math)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log GDP per capita	8.172						3.302
	(10.032)						(9.299)
Returns to secondary school		-0.170*					-0.114
		(0.092)					(0.211)
Difference between top and lowest tax rates on personal income			0.107				0.114
			(0.097)				(0.138)
Government expenditure on education (% of GDP)				-1.898			-1.736
				(1.500)			(1.308)
School segregation					-6.633		5.317
					(21.710)		(29.794)
SES gradient in parental investment						-0.750***	-0.801**
						(0.229)	(0.287)
Observations	160	118	137	117	159	142	74
R^2	0.792	0.845	0.815	0.841	0.786	0.874	0.921
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. The table presents the panel estimates of upward mobility in math scores on economic variables with year and country fixed effects (equation (2)). The estimates of upward and relative mobility are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. Clustered standard errors at the country level (*** p<0.01, ** p<0.05, * p<0.1).

C.3 SES gradients in other traits

To measure students' educational and occupational aspirations, we follow La Ferrara (2019). Occupational aspiration is defined as a dummy equal to 1 for students who expect to have a job with an International Socio-Economic Index of Occupational Status (ISEI)$\geq$65 at the age of 30 - i.e. a white collar job. Educational aspiration is defined as a dummy equal to 1 for students who expect to study at university. Information on educational aspiration is available from the 2003, 2009, 2015 and 2018 waves, while information on occupational aspiration is available in the 2000, 2003, 2006, 2015 and 2018 waves.

Self-efficacy measures the extent to which individuals believe in their own ability to engage in certain activities and perform specific tasks, especially when facing adverse circumstances (Bandura, 1977, 1991). PISA measures self-efficacy in math abilities in 2003 and 2012 by combining students' responses to questions on how confident they feel about having to solve certain calculations.

To measure non-cognitive skills, we look at the probability of being on time to school in 2000, 2003, 2012, 2015, and 2018 (Cunha and Heckman, 2007; Borghans et al., 2008).

It is possible to measure relative and upward mobility in these traits by estimating equation (1) where the outcome is one of the traits we describe above. Then relative mobility is the difference in a certain trait between high and low SES and upward mobility

is the average outcome of low SES.

Table C2: Correlation among the estimates of relative mobility in other traits in 2003 and 2015

	Relative mobility in (2003)					
	Math	Read	Science	Educational aspiration	Occupational aspiration	Being on time to school
Math	1					
Read	0.845***	1				
Science	0.859***	0.965***	1			
Educational aspiration	0.458*	0.298	0.314	1		
Occupational aspiration	0.615**	0.461*	0.493*	0.760***	1	
Being on time to school	0.694***	0.692***	0.782***	0.343	0.528**	1

	Relative mobility in (2015)					
	Math	Read	Science	Educational aspiration	Occupational aspiration	Being on time to school
Math	1					
Read	0.936***	1				
Science	0.973***	0.966***	1			
Educational aspiration	0.125	0.220	0.0938	1		
Occupational aspiration	0.236	0.290	0.192	0.810***	1	
Being on time to school	0.597***	0.640***	0.632***	-0.114	-0.0717	1

Note. The table presents the correlation among different measures of relative mobility in 2003 and 2015. Each measure has been estimated by regressing the outcome of interest on dummy equal to 1 if mother has at least upper secondary (equation (1)). (*** p<0.01, ** p<0.05, * p<0.1).

Table C3: Correlation among the estimates of upward mobility in other traits in 2003, 2015, 2018

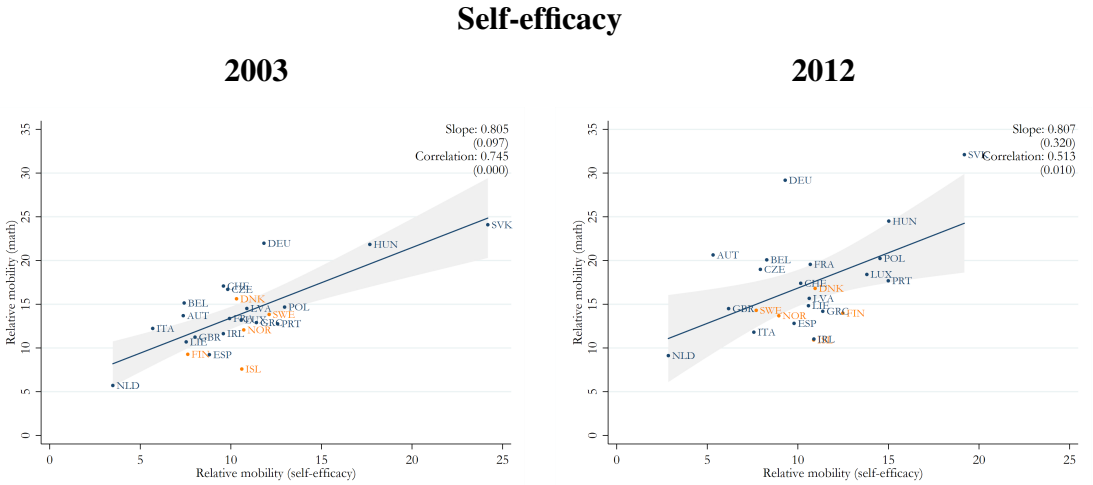
	Upward mobility in (2003)					
	Math	Read	Science	Educational aspiration	Occupational aspiration	Being on time to school
Math	1					
Read	0.726***	1				
Science	0.730***	0.832***	1			
Educational aspiration	-0.151	0.370	0.197	1		
Occupational aspiration	0.244	0.732***	0.437	0.720***	1	
Being on time to school	0.262	-0.213	-0.0826	-0.637**	-0.756***	1

	Upward mobility in (2015)					
	Math	Read	Science	Educational aspiration	Occupational aspiration	Being on time to school
Math	1					
Read	0.826***	1				
Science	0.887***	0.927***	1			
Educational aspiration	0.131	0.158	0.179	1		
Occupational aspiration	0.239	0.342	0.312	0.316	1	
Being on time to school	0.109	0.288	0.285	-0.0259	0.290	1

	Upward mobility in (2018)					
	Math	Read	Science	Educational aspiration	Occupational aspiration	Being on time to school
Math	1					
Read	0.889***	1				
Science	0.934***	0.949***	1			
Educational aspiration	0.416**	0.482**	0.460**	1		
Occupational aspiration	0.610***	0.679***	0.568***	0.570***	1	
Being on time to school	0.196	0.369*	0.253	0.203	0.445**	1

Note. The table presents the correlation among different measures of upward mobility in 2003, 2015 and 2018. Each measure has been estimated by regressing the outcome of interest on dummy equal to 1 if mother has at least upper secondary (equation (1)). (*** p<0.01, ** p<0.05, * p<0.1).

Figure C3: Correlation between relative mobility in learning (math) and mobility in self-efficacy.



Note. The figures present the correlation between relative mobility in learning (math) and mobility in self-efficacy. The estimates of relative mobility are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper secondary. The rank is computed at the European level. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the respective p-value in parenthesis.

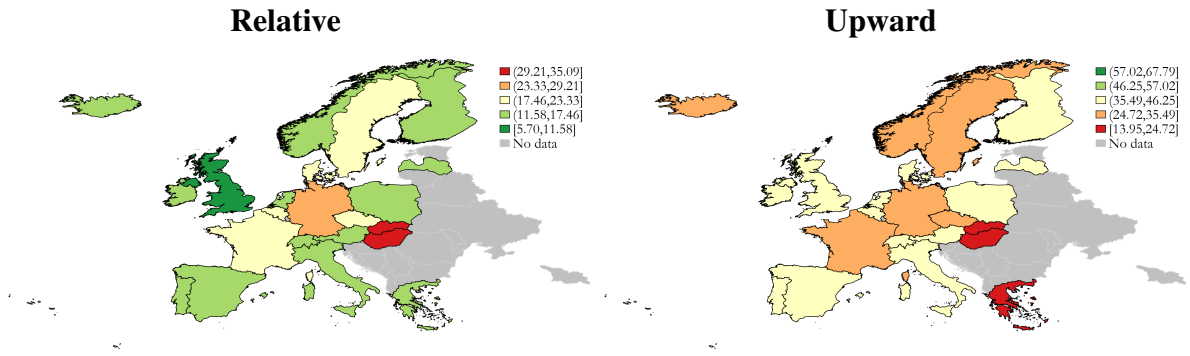
Table C4: Mobility in other traits and SES gradient in parental investment

	Relative mobility in					
	Read	Science	Occupational aspiration	Educational aspiration	Being on time	Self-efficacy
SES gradient in parental investment	0.714***	0.708***	0.009***	0.012***	0.005*	0.709***
	(0.105)	(0.129)	(0.001)	(0.002)	(0.002)	(0.128)
Observations	24	24	24	24	24	24
R^2	0.492	0.435	0.545	0.486	0.152	0.644

Note. The table presents the correlation between relative mobility in other traits and the socio-economic gradient in parental investment (averaged over the PISA years). The estimates of relative mobility are based on equation (1), regression of trait on a dummy equal to 1 if mother has at least upper secondary. Robust standard errors (*** p<0.01, ** p<0.05, * p<0.1).

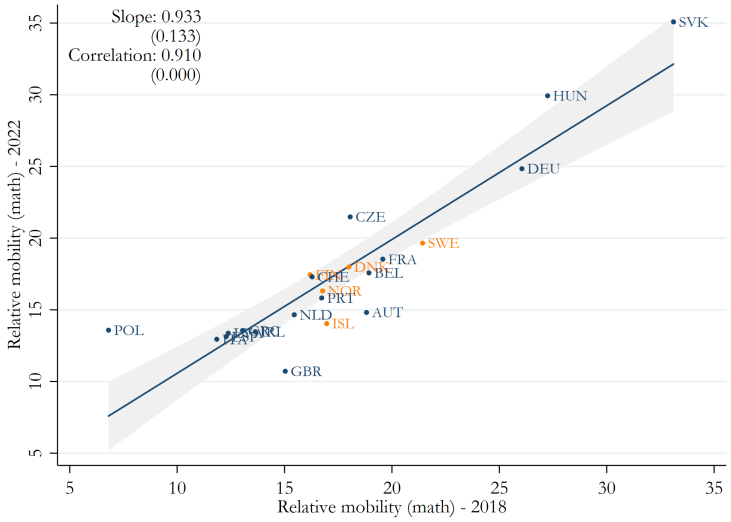
D 2022-PISA wave

Figure D1: Heat map of intergenerational mobilities in learning (math score) in 2022



Note. The heat maps present the estimates of intergenerational mobility in learning for each country in 2022 (the estimates are based on equation (1), regression of the rank math score on dummy equal to 1 if mother has at least upper secondary). The relative mobility measure is β_{tc}^{math} from equation (1). The upward mobility (α_{tc}^{math}) is the average rank of test score of children whose mothers do not have upper secondary. The rank is computed at the European level. Green areas are the most mobile and red areas are the least mobile. The intervals are the same for each year.

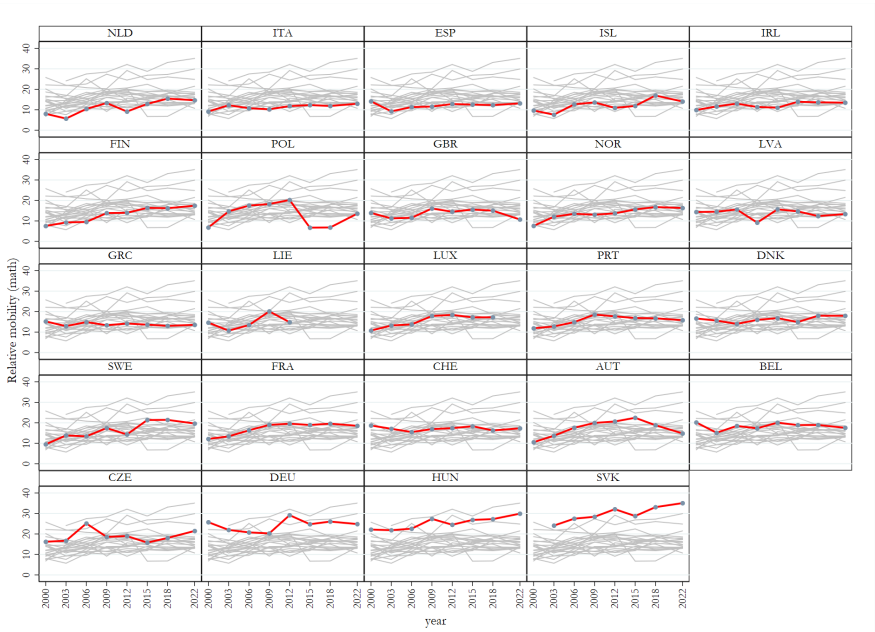
Figure D2: Correlation between relative mobility (math) before and after COVID-19 (2018 vs. 2022-PISA wave)



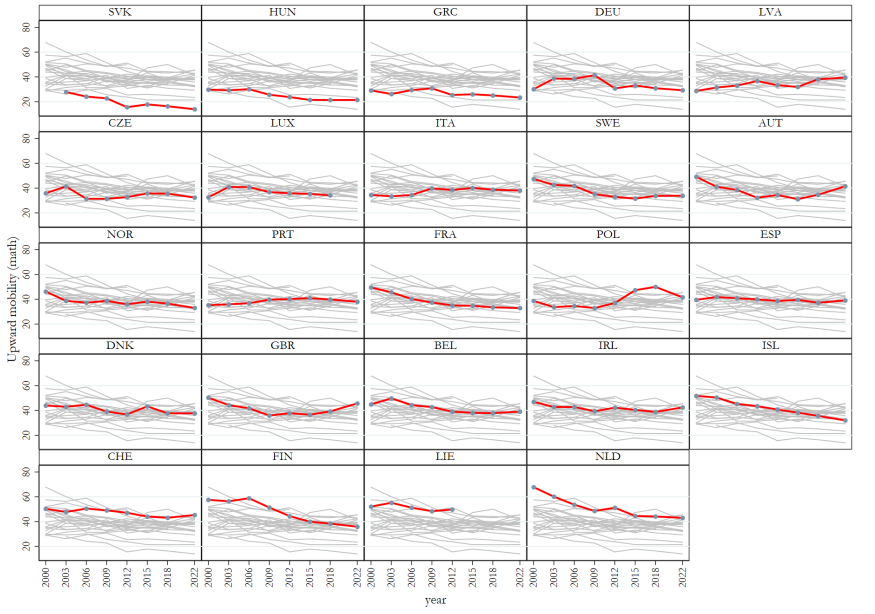
Note. The figure presents the scatter plots between relative mobility (math) before and after COVID-19 (2018 vs. 2022-PISA wave). The estimates of relative mobility are based on equation (1), regression of the outcome of interest on a dummy equal to 1 if mother has at least upper secondary. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the p-value in parenthesis.

Figure D3: Trends in learning mobility (math) by country with 2022-PISA wave.

Relative Mobility

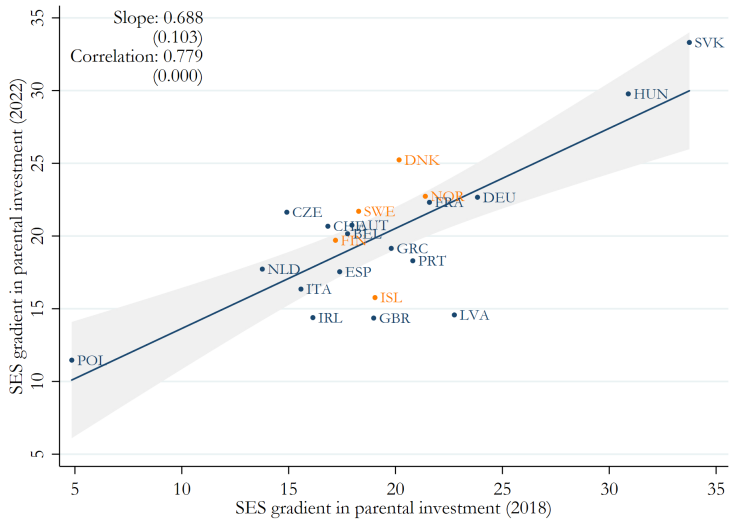


Upward Mobility



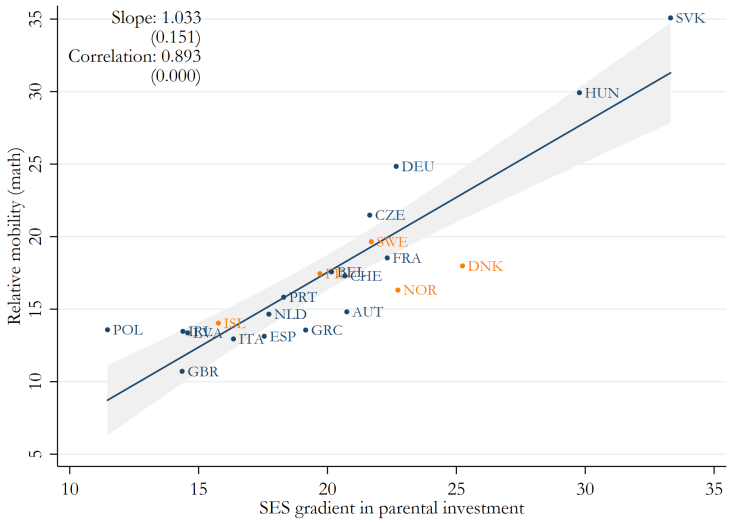
Note. The figures present the trends in relative and upward mobility for each country with 2022-PISA wave (red line) against other countries (gray lines). The estimates are based on equation (1), regression of the rank math score on dummy equal to 1 if mother has at least completed upper secondary. The rank is computed at the European level. Higher values of relative mobility correspond to lower mobility. Countries are ordered from the most to least mobile, based on average mobility over the PISA waves.

Figure D4: Correlation between SES gradients in parental investment before and after COVID-19 (2018 vs. 2022-PISA wave)



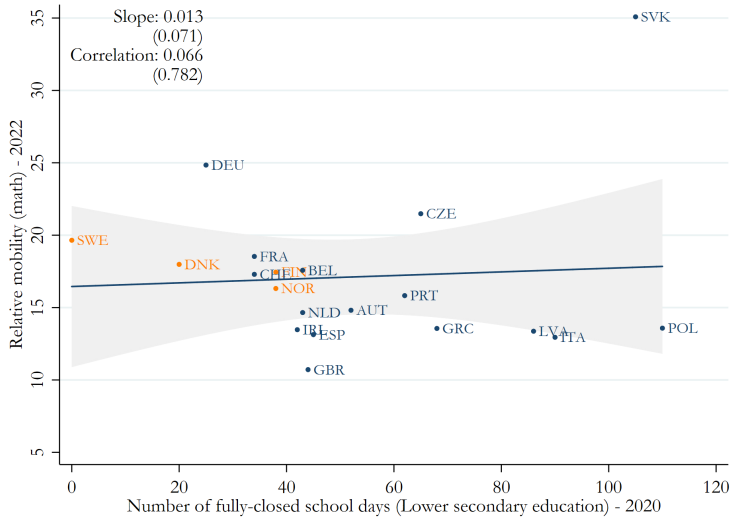
Note. The figure presents the scatter plots between SES gradients in parental investment before and after COVID-19 (2018 vs. 2022-PISA wave). Details on how the SES gradients in parental investment is computed are available in Appendix B.5.1. The estimates of the SES gradient in parental investment are based on equation (1), regression of the outcome of interest on a dummy equal to 1 if mother has at least upper secondary. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the p-value in parenthesis.

Figure D5: Correlation between relative mobility (math) and SES gradients in parental investment after COVID-19 (2022-PISA wave)



Note. The figure presents the scatter plots between relative mobility (math) and SES gradients in parental investment after COVID-19 (2022 PISA wave). The estimates of relative mobility are based on equation (1), regression of the outcome of interest on a dummy equal to 1 if mother has at least upper secondary. Details on how the SES gradients in parental investment is computed are available in Appendix B.5.1. Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the p-value in parenthesis.

Figure D6: Correlation between relative mobility (math) after COVID-19 (2022-PISA wave) and the number of fully-closed school days (Lower secondary education) in 2020



Note. The figure presents the scatter plots between relative mobility (math) after COVID-19 (2022-PISA wave) and the number of fully-closed school days (Lower secondary education) in 2020. The estimates of relative mobility are based on equation (1), regression of the outcome of interest on a dummy equal to 1 if mother has at least upper secondary. The number of fully-closed school days (Lower secondary education) in 2020 is from OECD (2021). Confidence interval at 95% level in gray. The notes in the figures show the slope with the respective standard error in parenthesis and the correlation with the p-value in parenthesis.