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ABSTRACT

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

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. There is a widespread belief that such strong public investments in children contribute to a levelled playing field and promote social mobility. However, gaps in learning outcomes between children of rich and poor parents remain as high in Nordic countries as elsewhere in Europe. One explanation for this paradox is that the equalizing impacts of public investments are undone by parental investments in children of rich and poor families, which are as unequal in Nordic countries as in the rest of the European continent.

JEL Classification: J62, D63, I21, J24

Keywords: intergenerational transmission, inequality, education, human capital

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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, which are similar to other countries in Europe (especially in the later part of this period). This is surprising since Nordic countries are known for promoting policies especially protective of poor families and children, namely 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 levelled playing field, and foster social mobility.

It is plausible that the equalizing effects of strong public investments in Nordic countries are counteracted by the effects of parental investments in children, 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 the countervailing impacts from family behaviours (e.g. Goldthorpe (2016), and for an older reference with the same flavour, Coleman and Others (1966)).

In support of this idea, we show that SES gradients in the quality of the home learning environment (what we call parental investments in children, 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 0.7 and 0.8. Looking across years, within-country changes in SES gradients in parental investments account for more than 30% of the within-country (across time) variation in SES gradients in test scores. None of the other country characteristics we examine[2] is as strong a predictor of SES gradients in learning, either in the cross

[1] In addition, Neal and Johnson (1996) and Carneiro et al. (2005) 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.

[2] These are variables which we believed to be plausible predictors of intergenerational transmission and for which we were able to assemble at least a partial panel for the years between 2003 and 2018, namely: GDP per capita, returns to schooling, difference between top and bottom rates of income tax, government expenditure in education, proportion completing post secondary education, and school segregation.

section or in the panel.

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). While the PISA measures skills in adolescence, PIAAC measures skills in adulthood. However, 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. For example, the cross-country correlation between SES gradients in adult skills and measures of intergenerational mobility (or IGE, from Corak (2013)) is 0.13 for the cohorts born 1987 or later, but 0.85 for the cohorts born between 1957 and 1966 (for whom Nordic countries have low IGE and low SES gradients in skills).[3]

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

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. Relatively 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, they vary substantially across Europe, they are not strongly related to the IGE, but instead, 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.

The literature has mostly focused on documenting the geography and the trends in the intergenerational transmission of income or years of school, as proxies of economic status. Chetty et al. (2014) popularize this analysis by documenting the geography of the intergenerational trans-

[3]This may also be partly because the data used to measure the IGE in these countries includes primarily older cohorts, 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. However, there is no obvious evidence yet that the IGE is rising in Nordic countries relatively to the IGE elsewhere.

mission of income in the United States for the 1980-1982 birth cohort. On the other hand, Hertz et al. (2008) and Narayan et al. (2018) document the intergenerational transmission of years of schooling across countries and over time.[4]

A focus on income or years of schooling could, however, conceal an important part of the picture, since human capital formation starts much earlier in the life cycle (Carneiro and Heckman, 2003; Cunha and Heckman, 2007). This paper takes up the challenge of investigating the intergenerational transmission of learning outcomes, with a specific focus on measurement and comparability of its estimates across countries and over time.

We use data from PISA and PIAAC, which enable us to estimate measures of intergenerational transmission that are comparable across countries and over time, based on the design of these tests.[5] Our main measure of SES gradients in learning compares the test scores (math) between children whose mothers have completed high school or above with children whose mothers have not completed high school. We also show that our main results are robust to other measures of SES and that there is no correlation between the proportion of low-SES children and SES gradients in PISA scores, either across countries or over time.[6] This suggests no mechanical relationship between the proportion of low-SES status children and SES gradients.[7]

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). This 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. The PISA dataset tackles these concerns, enabling us to explore how the intergenerational transmission of learning outcomes and its geography has evolved in Europe over 20 years, much longer than the time

[4]Alesina et al. (2021), Neidhofer et al. (2018), Deutscher and Mazumder (2019), Acciari et al. (2022), Bell et al. (2023), Corak (2020) have followed in this effort and looked respectively at the geography of intergenerational mobility of income or years of schooling in Africa, Latin America, Australia, Italy, England and Canada. Card et al. (2022) study the intergenerational transmission of human capital - proxied by years of schooling - for children born in the 1920s in the United States.

[5]We concentrate on European countries to examine a more uniform institutional context.

[6]Our estimates are robust to using the following measures of SES: 1) father's education; 2) an indicator for whether mothers completed higher education; 3) an indicator for whether mothers have at least the median education within the country; and 4) the SES index of economic, social and cultural status (ESCS) developed by the PISA team. Using maternal education allows us to look at a well-defined measure, whereas other measures of SES, such as the PISA index of economic, social and cultural status (ESCS), which combines several variables (such as parental education, occupation, and possessions, like owning a car, among other variables). The ESCS potentially provides a more complete characterization of family environments, but does not have a scale.

[7]Regardless of the SES measure we use, the proportion of children of high and low SES varies considerably across countries. We show, therefore, that there is no correlation between the proportion of low-SES children and SES gradients in PISA scores, either across countries or over time, suggesting that there is no mechanical relationship between the proportion of low-SES status children and SES gradients. This could be potentially important because differences in the proportion of low-SES children in the country translate into differences in the composition of the low and high SES groups in a country. In such a setting one could question whether changes in SES gradients across countries were merely driven by the fact that, for example, low (high) SES children are very different in countries where the proportion of low (high) SES children is small than in countries where this proportion is large. Therefore, it is reassuring that there is no correlation between the proportion of low-SES children in a country and the SES gradients in PISA scores in that country. Furthermore, we show that our result is robust to restricting the sample only to native students.

horizons of the papers discussed above.[8]

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 outcomes, such as wealth (Charles and Hurst, 2003), health (Halliday et al., 2019), attitudes (Dohmen et al., 2011) and non-cognitive development (Attanasio et al., 2022).[9] Notably, we show that the main patterns we observe for the SES gradients in math scores hold also for the SES gradients in these other dimensions of success, highlighting the importance of thinking about success as multi-dimensional.

The closest papers to ours are Landerso and Heckman (2017) and Heckman and Landerso (2022). We partly build on their ideas, but focus primarily on adolescents' test scores. 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 also present new evidence that the relationship between SES gradients in test scores and the IGE in income may have changed substantially over time.

We also ask whether the positive cross-country relationship between IGE and cross-sectional inequality - also 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. 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 with 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 education, specifically in terms of years of schooling, are correlated with the levels of inequality in a country. Low-inequality countries, such as the Nordic countries, exhibit a lower influence of families on the their children's years of schooling, indicating the presence of a Gatsby Curve in years of schooling. Although Blanden et al. (2023) suggest a reasonable interpretation of these patterns, 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 Gatsby Curve in years of schooling.[10]

[8] In related work, Hanushek et al. (2020) show that the socio-economic gradients in test score has failed to close in the United States over 50 years using multiple datasets.

[9] Some of data reported in this paper is also available in PISA reports (OECD, 2018). Relatively to those reports we combine all available periods, relate mobility in learning to other measures of mobility and inequality, and study the determinants of mobility and its evolution over time.

[10] With regards to the Gatsby Curve, Durlauf et al. (2021) review much of the relevant literature and present various explanations. Some of the explanations offered behind the existence of the Gatsby are 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 inequality in aspirations (La Ferrara, 2019). Recently, some concerns have been raised regarding the existence of a Great Gatsby curve to start with. For example, Mogstad and Torsvik (2021) highlight that the Gatsby curve can be driven by 3 groups of countries. If you remove the extremes, namely

Our findings illustrate that the potential for public policy for levelling up opportunities in childhood may be more limited than it is widely believed. Especially for recent cohorts, disparities in parental investments in children produce 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 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, addressing directly the SES disparities in family investments. One difficulty, of course, is that it is challenging to interfere with behaviors taking place within very private family settings.

This paper is organized as follows. Section 2 discusses the data and the measure of intergenerational mobility in learning outcomes (i.e., SES gradients in test scores) we introduce in the paper. Section 3 describes the geography and trends in the intergenerational mobility in learning in Europe over the last two decades. In Section 4, we compare intergenerational mobility in learning and intergenerational transmission of income across countries and explore some of its possible determinants, with an emphasis on the role of parental investments and the use of PIAAC data. In Section 5, we present estimates for other measures of relative and upward mobility and in SES gradients in other traits. Finally, in Section 6, we extend the analysis to the 2022-PISA wave after COVID and discuss possible implications for the future. Section 7 concludes.

2 Intergenerational mobility in learning

2.1 PISA data

We use individual-level data from the PISA tests, containing information on 15-year-old students' learning outcomes in reading, mathematics and science. The tests are administered by the OECD every 3 years from 2000 to 2022 to 15-year-old students - when many students can choose whether or not to continue their schooling. They are designed to determine how well the students have mastered important courses and how well-prepared they are for 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

Scandinavian and Latin American countries, then the sign of the Gatsby curve would flip. Karlson and Landerso (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.

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 scores are explicitly designed to allow comparisons across countries and over time. To make the results comparable, test scores 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 effectively address the complexities of the survey design in the PISA data, we use survey weights and plausible values throughout the analysis. The inclusion of survey weights, as provided by PISA, allows for the estimation of population-level parameters, thereby ensuring the representativeness of the findings within the target population. Furthermore, rather than relying solely on a single test score for each student, we use the plausible values in the regression analysis. This approach explicitly accounts for the sampling variability and produces a more precise representation of the associated uncertainty related to the test scores. By estimating the regression models iteratively, employing different plausible values for the dependent variable in each iteration, researchers can obtain robust results, while effectively tackling the intricate nature of the PISA data.

Every wave of the PISA data includes a student, parent and school questionnaires. These additional questionnaires provide a wide range of information on students' and parents' characteristics, such as parents' education, 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 (results with alternative measures are also presented), as discussed in detail in Section 2.2.

It is important to check the extent to which data on parental SES in the PISA conforms or not 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 demonstrates a strong and close to 0.9 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, 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 is also reasonably high, reaching almost 0.6 (Panel B).[11]

[11] 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 mobility in learning

In this Section, we discuss the measures of intergenerational mobility in learning (i.e., SES gradients in test scores) 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 we use to define this variable).

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

$$R(Y)^k_{itc} = \alpha^k_{tc} + \beta^k_{tc} HS^P_{itc} + \epsilon_{itc} \tag{1}$$

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

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. We also compute the rank at the country level by ordering the each plausible value of the test scores in ascending order within each country, 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. However, the test score distributions may differ markedly across countries and such differences may affect the interpretation of the results. Appendix Table A2 shows that our results are robust to alternate measures of rank, as well as using different subjects. 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}. This is because there is a good overlap in the test score distributions across different countries (Appendix Tables A3 and A4).

β^k_{tc} measures the association between the mother's education (high school degree) and her child's rank in the distribution of math scores, for cohort t in country c. This represents a measure of *relative mobility* (higher values of this parameter correspond to lower mobility), i.e., the difference in learning ranks between children whose mothers have different levels of schooling.

α^k_{tc} 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 measure discussed in this Section as we consider it easier to interpret and more comparable. The results are, however, robust to using these alternate measures as shown in Appendix A.2, where we consider alternative ways to measure parental socio-economic background.[12] The correlation between the main measure of intergenerational mobility in learning presented in this Section and the alternate measures is usually above 0.6 (Appendix Table A2). In Section 5.1, we also show that there is no correlation between the proportion of low-SES children and SES gradients in PISA scores.

3 Intergenerational mobility in 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.[13] 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.[14]

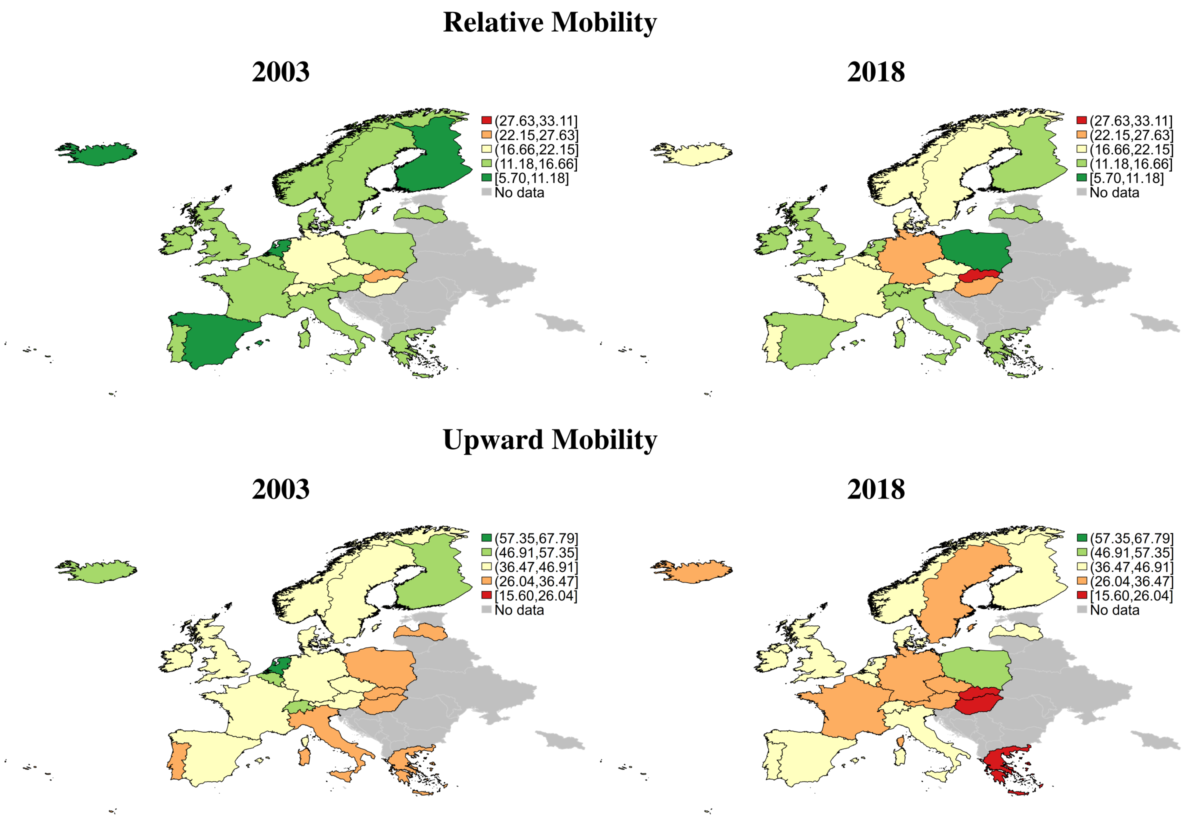
Together with Hungary and Slovakia, Germany is one of the three countries with lower relative learning mobility in Europe in 2003. Even though low-SES German students perform much worse than their high-SES counterparts, they perform much better than low-SES students in several other countries, such as 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.

[12] We show that the estimates are robust to measuring parental socio-economic background, using an indicator for whether the father has completed upper secondary education, an indicator for whether the mother has higher education, an indicator for whether the mother has at least the median education within the country and the rank of the index of economic, social and cultural status (ESCS) constructed by the PISA.

[13] We show estimates of intergenerational mobility in learning from 2003 because PISA begins to collect data on parental investment from 2003. Mobility measures for 2000 are available in Appendix Table A.4.

[14] All estimates of relative and upward mobility for each country and year are shown in Appendix Table A.4.

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.

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 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.[15] In addition, we observe that, across cohorts, SES gradients in test scores in the USA are similar to those in Europe (see Appendix Figure A5 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.

4 Correlates of intergenerational mobility in 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 turn to this next.

4.1 Intergenerational mobility in learning and inter/intra-generational inequality

We begin by asking if there is a relationship between SES gradients in learning and inter and intragenerational 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 with inequality across countries.

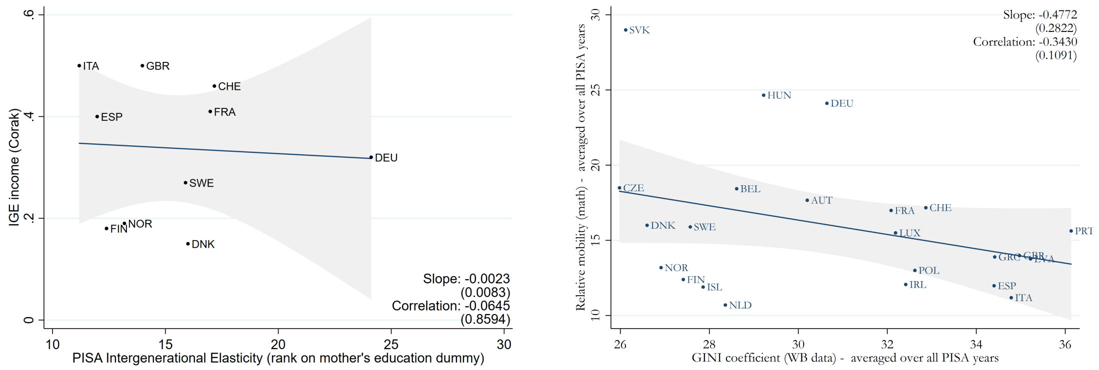
First, we document that surprisingly SES gradients in PISA scores are not correlated with estimates of the intergenerational transmission of income across countries (left panel of Figure 2). These results generalize the findings by Landerso and Heckman (2017) and Heckman and Landerso (2022), who argue that even though Denmark and the USA have very different levels of the intergenerational transmission of income, they have similar levels of intergenerational education mobility.

This hints towards a poverty trap in education. Relatively 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 especially helped by the strong welfare state when it concerns their children's learning.[16]

[15]Appendix Figure A3 shows the estimates of relative and upward mobility for each country and year. The figure presents the trends for each country (red line) against other countries (gray lines). Countries are ordered from the most mobile to least mobile, based on average mobility over the PISA waves. These patterns are robust to considering only the native population (Appendix Figure A4). 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 the SES gradients in test scores across countries and over time.

[16]It is possible that, as argued in Landerso and Heckman (2017) and Heckman and Landerso (2022), higher SES

Figure 2: Correlation between relative mobility (math) and GINI coefficient.



Note. The Left Figure presents the correlation between relative mobility in learning (math - averaged over all PISA years) and Income mobility measure from Corak (2013). The Right Figure present the correlation between the 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.

Second, we ask if there is a positive cross-country relationship between relative mobility in learning and inequality in society, known as the Great Gatsby Curve (Corak, 2013), which has been widely discussed in the academic and popular press.[17] The right panel of Figure 2 shows that SES gradients in PISA scores are, if anything, negatively correlated with income inequality. (We show below that even when we use other measures of inequality this correlation is often zero, but never positive.) 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.[18]

Unfortunately, the PISA survey does not include a measure of family income, so in order to have a measure of intragenerational inequality for each country we average of the GINI coefficient over the PISA years from the World Bank database. Even if measures of inequality are not always available for all countries and years, they are surely correlated over time, and it is not clear if it is even overall inequality that is the relevant measure for each cohort of students, rather than inequality in income in their parents' income. We also examine inequality in one of the SES indices available in the PISA, the ESCS index, to measure inequality in SES status among parents of each PISA cohort in each country. In Appendix Figure B2, we show that there is no strong

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).

[17] It is observed not only across countries, but also within (Chetty et al., 2014; Corak, 2020). It has however also been subject of controversy (Mogstad and Torsvik, 2021).

[18] Similar evidence is found in Carneiro and Toppeta (2022), using the test score data from Latin American Laboratory for Assessment of the Quality of Education (LLECE), and in Blanden et al. (2023), using PISA data. Similar patterns can also be found when using data from the Trends in International Mathematics and Science Study (TIMSS) and Progress in International Reading Literacy Study (PIRLS) studies, as shown in Appendix Figure B1 (Cardim and Carneiro, 2021). In Appendix Figure A6 we show that there is a strong cross-country correlation between SES gradients in learning measured in the TIMSS/PIRLS and PISA.

correlation between SES gradients in learning and inequality in ESCS in any of the PISA cohorts, similar to our findings reported above in Figure 2.[19]

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 in 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 below the age of 25 belong to the same cohorts that took the PISA test in its earliest rounds. In fact, when we compare SES gradients in learning for the same cohorts in 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 B4).

We 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, and the correlation between SES gradients in test scores and inequality. 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 inequality, or between SES gradients in test scores and the IGE.

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. 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 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.

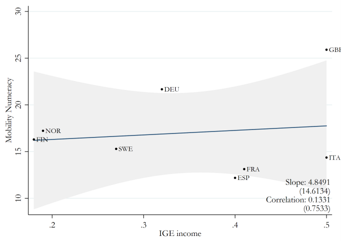
In sum, some of the Nordic countries appear to be on a trend to higher skill-inequality by family background, making them more similar to other countries in Europe, and this trend seems to have started several cohorts ago (Appendix Figure B5). At this point, we can only speculate

[19] Even if we link the SES gradients in learning from each PISA year to GINI coefficient (World Bank) averaged over all PISA years (Appendix Figure B3), we do not find evidence for a Gatsby curve.

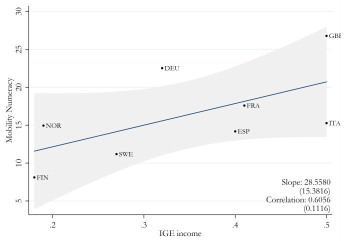
Figure 3: PIAAC - correlation between mobility in numeracy, IGE (Corak, 2013), GINI

Panel A: IGE income

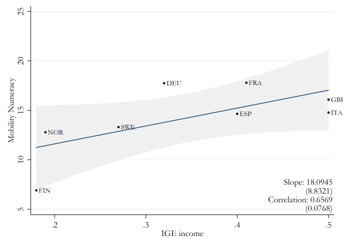
24 or less (born 1987 or later)



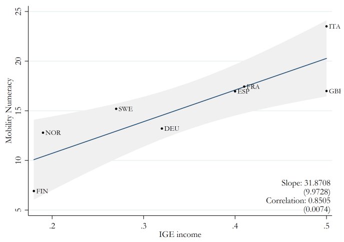
25-34 (cohort 1977-1986)



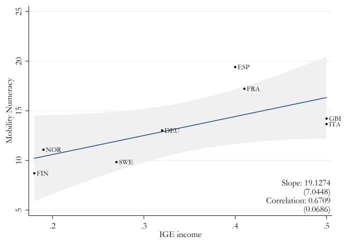
35-44 (cohort 1967-1976)



45-54 (cohort 1957-1966)

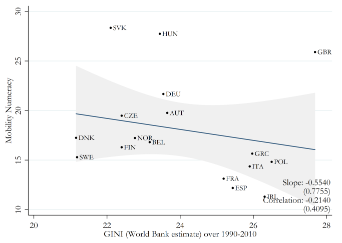


55 plus (born earlier than 1957)

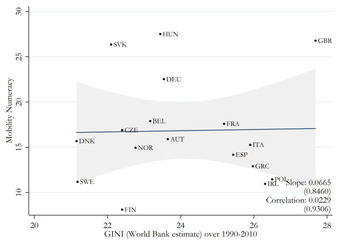


Panel B: GINI coefficient

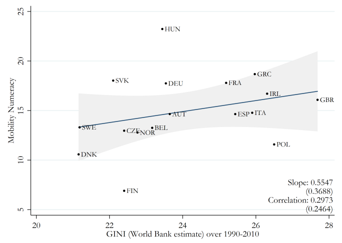
24 or less (born 1987 or later)



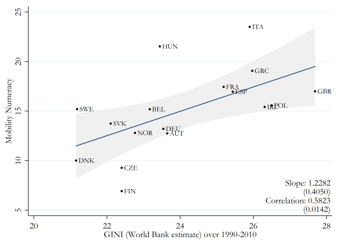
25-34 (cohort 1977-1986)



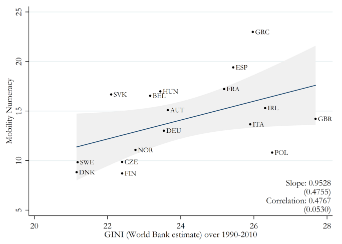
35-44 (cohort 1967-1976)



45-54 (cohort 1957-1966)



55 plus (born earlier than 1957)



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 in Panel B. 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.

about the sources of these changes. We turn to some descriptive results that may help illuminate this issue.

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. 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, and average education of the population 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 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).

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 environmental inputs, such as the child's access to adequate study conditions, technology, books and art. The factor model, described in detail in Appendix B.3.1, allows us to set the scaling assumption to obtain a comparable measure of parental investment across countries and over time. We measure the socio-economic gradients 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, which has been shown to be important for cognitive outcomes, while time investment is important for non-cognitive outcomes (Attanasio et al., 2020). A plausible concern is that the SES gradient in parental investment is capturing the same information as the ESCS index built by PISA. We 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 environmental inputs, such as possession of a desk, study space, literature. Second, Appendix Figure B6 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.3.1) 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).[20]

We begin by showing the correlation between each of these variables (averaged over all PISA years) and SES gradients in math scores (averaged over all PISA years) in Table 1. The variables most correlated with mobility in learning are: the age in which academic tracking starts, school segregation, and the SES gradients in parental investments.

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

Table 1: Correlates of relative mobility in learning

	Relative mobility (math)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log GDP per capita, PPP	-3.392 (2.976)							
Returns to secondary school		0.285* (0.137)						
Difference between top and lowest tax rates on personal income			-0.051 (0.072)					
Government expenditure on education (% of GDP)				-0.498 (0.569)				
% of population at least completed post-secondary					-0.037 (0.105)			
School tracking age						-0.987*** (0.319)		
School segregation							38.188*** (10.742)	
SES gradient in parental investment								0.841*** (0.128)
Observations	23	22	23	23	21	23	23	24
R^2	0.070	0.193	0.034	0.020	0.004	0.369	0.354	0.570

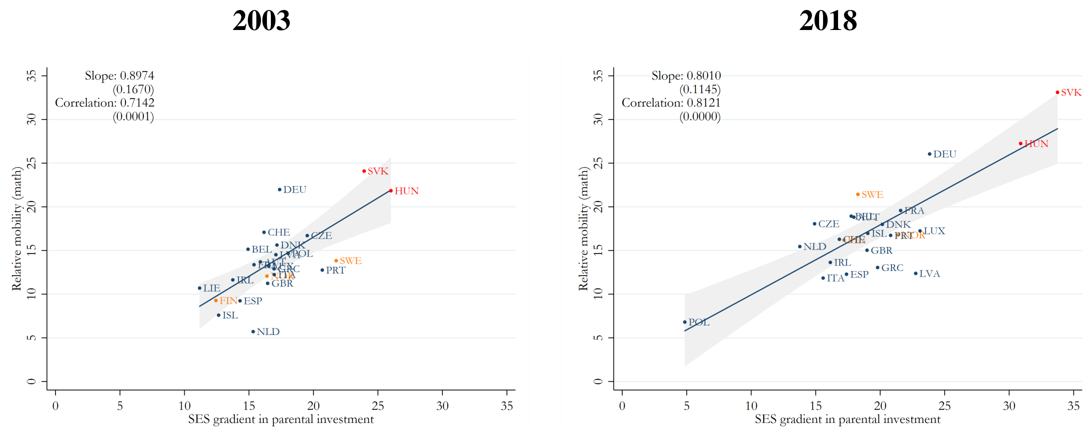
Note. Table shows the estimates from relative mobility in math (averaged over all PISA years) and country-level variables (averaged over all PISA years). We consider different sets of variables. Some are socio-economic variables: the returns to secondary school from the OECD, country GDP, and average education of the population. 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.3.1. Robust standard errors (*** p$<$0.01, ** p$<$0.05, * p$<$0.1).

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

[20] 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.

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.

Figure 4: Correlation between SES gradients in learning (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.3.1. 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.

Nordic countries do not have particularly high or low SES gradients in parental investments. While in 2003, Finland and 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, they may not take them up as effectively as more advantaged parents. On the 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 also search for potential predictors of SES gradients in parental investment, at least in the cross section. Two variables, which are correlated with SES gradients in parental investment, are related to social norms: (i) confidence in the education system, and (ii) perception that success depends strongly on parental wealth respectively from the 2017 European Value Study (EVS) and 2009 International Social Survey Programme (ISSP) on social inequality. This is shown in Appendix Figure B7.

4.4 Panel regressions

The cross-sectional associations between several variables and SES gradients in PISA scores, reported in the previous section, are interesting. However, 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 for math:

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

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 effect, 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 SES gradients in learning: 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 these variables across countries during the period we study. Therefore, we present results only for the other two variables.

Table 2: Panel regressions: relative mobility in learning

	Relative mobility (math)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log GDP per capita, PPP	-2.331						
	(3.577)						
Returns to secondary school		0.106*					
		(0.053)					
Difference between top and lowest tax rates on personal income			0.028				
			(0.066)				
Government expenditure on education (% of GDP)				-0.342			
				(0.565)			
% of population at least completed post-secondary					-0.124		
					(0.161)		
School segregation						7.888	
						(11.287)	
SES gradient in parental investment							0.564***
							(0.129)
Observations	160	118	137	117	66	159	142
R^2	0.803	0.841	0.808	0.819	0.866	0.802	0.881
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

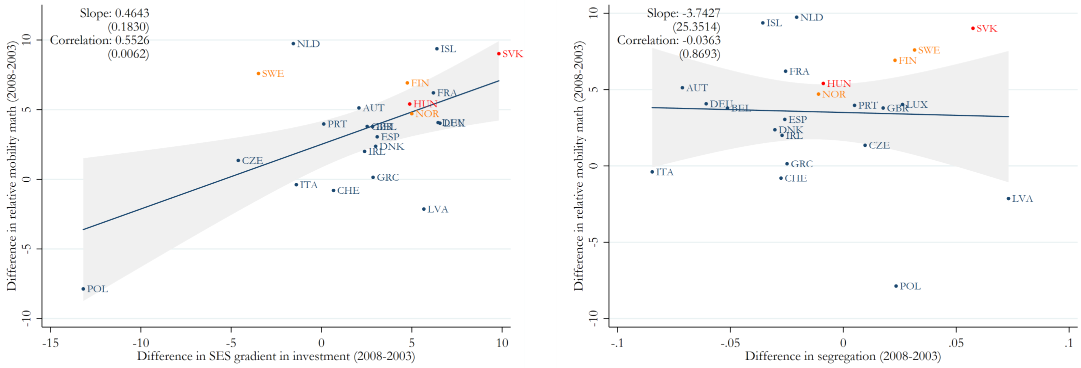
Note. The Table presents the panel estimates of relative mobility on economic variables with year and country fixed effects (equation (2)). The estimates of upward and relative mobility are based on equation (1), regression of the rank of the math score on a dummy equal to 1 if mother has at least upper 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).

Columns (6) and (7) 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 with changes in SES gradients in PISA scores.[21] We can also see these graphically in Figure 5, which plot changes in SES gradients in the PISA scores between 2003 and 2018 against changes in SES gradients in investment (left panel) and

[21]If we regress relative mobility in math on all the country- and time-varying variables, X_{tc}, considered in Table 2, the SES gradients in parental investment survives and remains statistically significant.

changes in segregation (right panel) during the same period.

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.3.1. 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.

There could be several potential drivers of SES gradients in learning. 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 learning across countries seems to be differences in SES gradients in parental investment in children. We cannot rule out that whatever factors drive differences in SES gradients in parental investments across countries or time also has an independent effect on SES gradients in PISA scores. It is interesting to think about what these factors may be.

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 countries. We show that there is no strong correlation between inequality in ESCS and SES gradients in parental investments (Appendix Figure B6). As mentioned in Section 4.3, the lack of correlation between inequality in ESCS and SES gradients in parental investments hints that the ESCS index and SES gradients in parental investment are capturing two different constructs. Furthermore, as we show above, income inequality is not correlated with SES gradients in the PISA.

In sum, our results suggest that the roots of inequality in child outcomes lie in the family, and even equalizing policies, such as those observed in Nordic countries, are not enough to counteract unequal family influences.

5 Other measures of SES gradients in child outcomes

5.1 Relative and 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 than 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, a disadvantaged student 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 student performs 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 student whose mothers have completed at least upper secondary and mothers that have not 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 almost 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).

As discussed above, 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 in the lower SES group potentially varies across countries and over time, affecting the interpretation of our findings.

We show that there is no clear correlation between the proportion of mothers with low levels of education and our estimates of relative mobility. When we examine upward mobility, in the panel there appears to be a positive association between changes in the proportion of disadvantaged children and changes in the outcomes of disadvantaged children, but which is not robust to the inclusion or not of the 2000 cohort in the analysis (see Appendix Table C2).[22]

5.2 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.4 for further details.

It is important, to the extent possible, to look beyond SES gradients in one academic subject. To measure students' educational and occupational aspiration, we follow La Ferrara (2019). Occupational aspiration is defined as a dummy equal to 1 for students who expect to have a white collar job. Educational aspiration is defined as 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 at 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. Then 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

[22] Furthermore, it is hard to make sense of such a positive correlation. Under the most standard selection mechanism, as the proportion of disadvantaged children declines, we would expect that the remaining disadvantaged children, if anything, have worse unobservables. After all, these are the ones that stay behind in a society where disadvantage (at least on this measure) is declining. If that is a reasonable hypothesis, the estimated correlation should be negative, not positive.

remaining years, and correlations for upward mobility measures, are available in Appendix Tables C3 and C4).

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 substantial 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.[23]

Table 3: Correlation among SES gradients (2018)

	Relative mobility in					
	Math	Read	Science	Educational aspiration	Occupational aspiration	Being on time at 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 at 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. Additionally, we do not find a correlation between SES gradients in these other traits and inequality, while we uncover a relationship between SES gradients in these other traits and the SES gradients in parental investment (Appendix Figure C4).

6 SES Gradients in Learning before and after COVID-19

This section compares SES gradients in learning in 2018 and 2022 (i.e., before and after the COVID-19 pandemic), using the recently released PISA data from the 2022 wave. 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.

From the 2022 data, we still observe that SES gradients in test scores are as high for Nordic countries as for the remainder of the countries in the sample (Appendix Figure D1). Similarly, we continue to see a strong correlation between SES gradients in test scores and SES gradients in

[23] Similar findings are found for SES gradients in self-efficacy which is only available for 2003 and 2012 (Appendix Figure C3).

parental investment (0.89). In fact, comparing Appendix Figure D2 with figure 4, we see that, if anything, this relationship becomes stronger.

Appendix Figure D3 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 is also observed when we examine the evolution in SES gradients in investments between 2018 and 2022, and shown in Appendix Figure D4.

Finally, Appendix Figure D5 presents the trends in upward and relative mobility across several countries, including the 2022-PISA wave. Although it is true that there a 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 be on trend, rather than exhibiting a break from the past. 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.

7 Conclusion

Standardized international tests show that there are very large differences in student knowledge across countries, even if we take only the case of Europe. Not only that, there are also staggering differences in the magnitudes 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 is (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.

Similarly, consider the average performance of disadvantaged students, i.e., students whose mothers have less than a secondary education. Taking these same four countries in 2003, in the Netherlands a disadvantaged student scores in the 60^{th} percentile of the European distribution of PISA scores, while disadvantaged students in Great Britain, Denmark and Germany score respectively in percentiles 44, 43, and 39. In 2018 the magnitudes of these parameters become, respectively, 44, 39, 38, 31, a dramatic and worrisome decline across the board.

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 latter 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 intra and intergenerational 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 by schools, age at which tracking first starts in the education system, and the SES gradients in parental investments. Of these three, only the latter shows a cross-sectional association that persists even when we consider the whole panel and account for country and time fixed effects. In other words, changes over time in SES gradients in parental investments are correlated with changes over time in SES gradients in PISA scores.

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 skill gradients among adolescents.

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.

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.

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*.

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.

Deutscher, N. and B. Mazumder (2019). Intergenerational mobility in Australia: National and regional estimates using administrative data. *Life Course Centre Working Paper Series*.

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.

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., A. Kourtellos, and C. M. Tan (2021). The Great Gatsby Curve. *Center for Open Science*.

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

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.

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., B. Mazumder, and A. Wong (2019). The intergenerational transmission of health in the United States: A latent variables analysis. *IZA Discussion Paper No. 12740*.

Hanushek, E. A., P. E. Peterson, L. M. Talpey, and L. Woessmann (2020). Long-Run Trends in the U.S. SES-Achievement Gap. *CESifo Working Paper Series* (8111).

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

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).

Karlson, K. and R. Landerso (2021, February). The making and unmaking of opportunity: Educational mobility in 20th century-Denmark. *Human Capital and Economic Opportunity Working Group*.

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 (2021, May). Family background, neighborhoods and intergenerational mobility. *National Bureau of Economic Research working paper* (28874).

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 (2018). PISA 2018 results (volume ii): Where all students can succeed. *Technical Report*.

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.

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

Woessmann, L. (2016, September). 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

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.

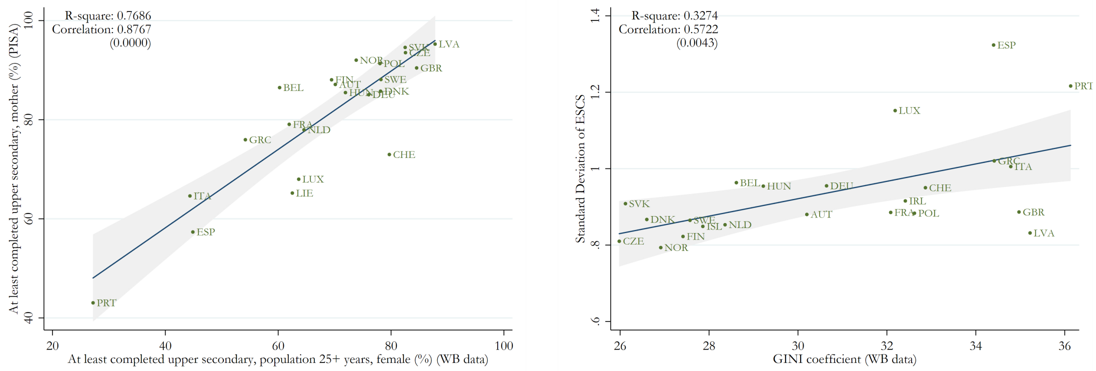
Table A1: International Standard Classification of Education (ISCED) levels

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.

Figure A1: Correlation between PISA and the World Bank data

Panel A Panel B



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 Robustness to alternate measures

The advantage of using the rank at European level is that the effect of mother's education on test score is more comparable as we are using the same distribution of test scores. However, the test score distributions may differ markedly across countries and such differences may affect the interpretation of the results. Appendix Table A2 shows that the correlation between the different measures is relatively high, providing confidence that the main results are robust to different definitions of mobility.

Reading test score - we estimate the mobility equation (1) by using the rank of the reading test score. The high correlation suggests that the main conclusions are robust to the subject of the test score used in the mobility measure.

Rank at country level - As a robustness, 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. Overall, the results are very similar and do not affect the main results observed when measuring learning mobility using the rank at the European level.

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 doing this 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 are considering. Constructing a European rank may be problematic if the test score distributions do not overlap across countries. Appendix Tables A3 and A4, however, show a good overlap of the test score distribution across countries.

Alternate measures of parental socio-economic status - We check if the results are robust to other definition of parental socio-economic status.

First, 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 ($\beta_{tc}^{math-father}$).

Second, we use a different definition of socio-economic status by defining the indicator variable taking value 1 if i's mother has completed higher education (HE_{itc}^{P}), and 0 otherwise (Appendix Table A1 describes the ISCED levels we use to define this variable). For each student i, country c, cohort t and subject k we estimate:

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

Third, we analyse a rank-rank measure using math test score and 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:

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

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 including books in the home. PISA has constructed the index in 2015, making it comparable over the waves.[2]

Fourth, 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_{itc}^{P}), and 0 otherwise. For each student i, country c, cohort t and subject k we estimate:

$$R(Y)_{itc}^{k} = \alpha_{tc}^{k-med} + \beta_{tc}^{k-med} ME_{itc}^{P} + \epsilon_{itc} \tag{5}$$

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

[2] ESCS components and the ESCS model has changed over cycles and with that, ESCS scores are not comparable across cycles directly. In order to enable a trends 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)

Table A2: 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			
$\beta\_tc^{math-uni}$	0.381*	0.461**	0.390*	0.338	1		
$\beta\_tc^{math-med}$	0.714***	0.784***	0.701***	0.676***	0.771***	1	
ρ_tc^{math}	0.763***	0.753***	0.711***	0.772***	0.373*	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}	0.889***	0.912***	0.771***	1.000			
$\alpha\_tc^{math-uni}$	0.712***	0.658***	0.013	0.435**	1.000		
$\alpha\_tc^{math-med}$	0.852***	0.866***	0.248	0.670***	0.894***	1.000	
μ_tc^{math}	0.737***	0.706***	0.362*	0.647***	0.618***	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), ρ_{tc}^{math} is relative mobility from equation (4), $\beta_{tc}^{math-med}$ is relative mobility in math from equation (5), α_{tc}^{math} is the main measure of upward mobility in math from equation (1), $\beta_{tc}^{math-father}$ 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), μ_{tc}^{math} is upward mobility from equation (4), $\alpha_{tc}^{math-med}$ is upward mobility in math from equation (5). (*** p<0.01, ** p<0.05, * p<0.1).

A.3 Descriptive statistics on test scores

Table A3: 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 A4: 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.4 Descriptive statistics on leaning mobility

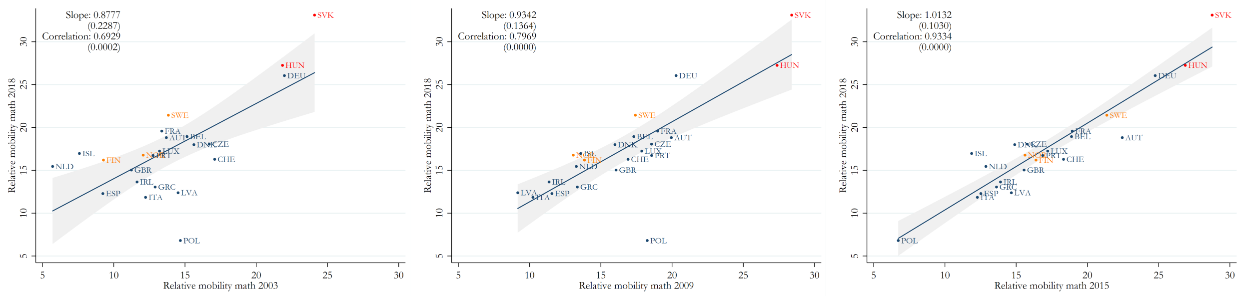
Table A5: Descriptive statistics on leaning mobility

cnt	Upward 2000	Relative 2000	Upward 2003	Relative 2003	Upward 2006	Relative 2006	Upward 2009	Relative 2009	Upward 2012	Relative 2012	Upward 2015	Relative 2015	Upward 2018	Relative 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.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 figure presents 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: Trends in learning mobility (math) by country (restricting sample to native population).

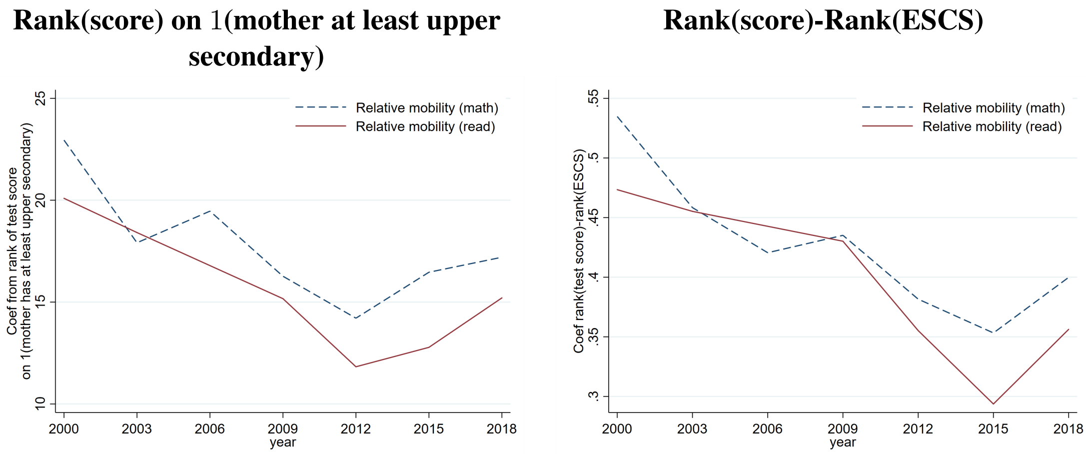
Relative Mobility

Upward Mobility

Note. The figure presents 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 Learning mobility in the United States

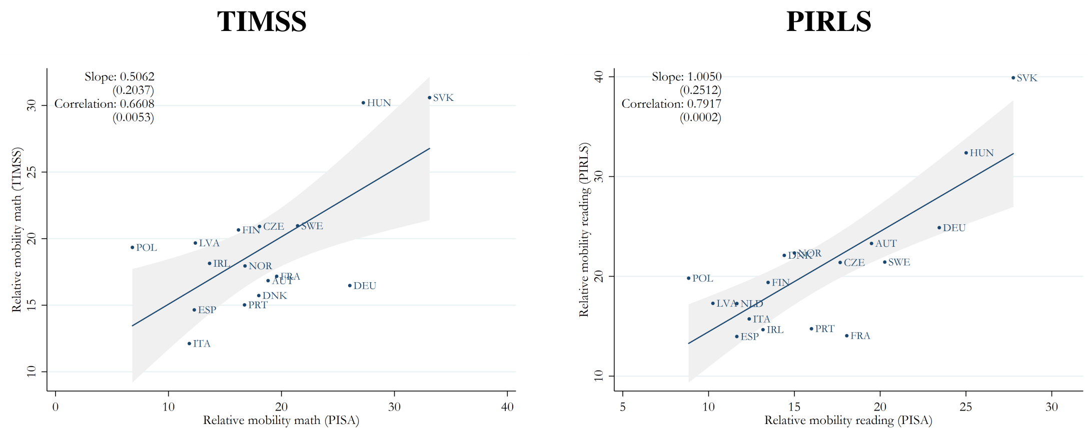
Figure A5: Learning mobility in the United States.



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)).

A.7 Correlation between mobility in PISA and TIMSS/PIRLS

Figure A6: 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^k_{tc} 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.

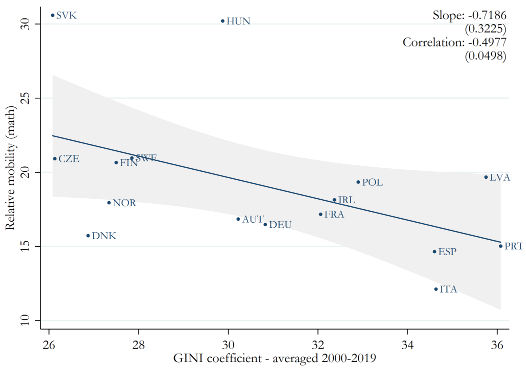
B Correlates of learning mobility

B.1 The Great Gatsby curve

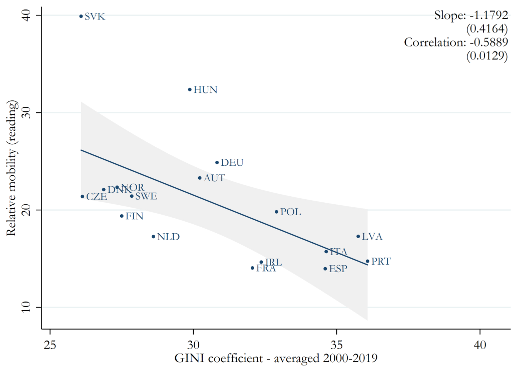
Figure B1: The Great Gatsby curves: learning mobility from TIMSS & PIRLS and GINI coefficient (World Bank).

Relative Mobility

TIMSS

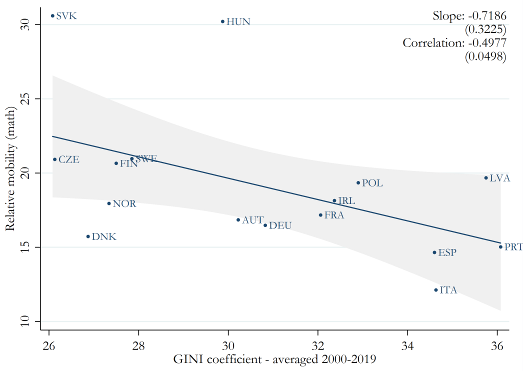


PIRLS

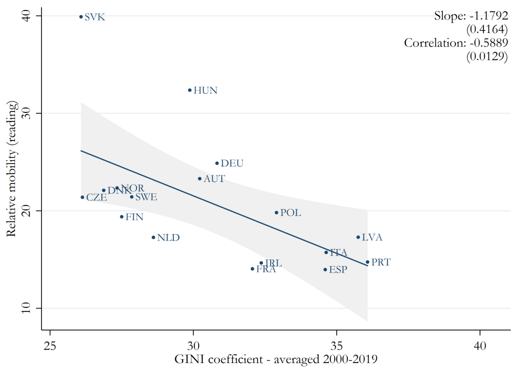


Upward Mobility

TIMSS

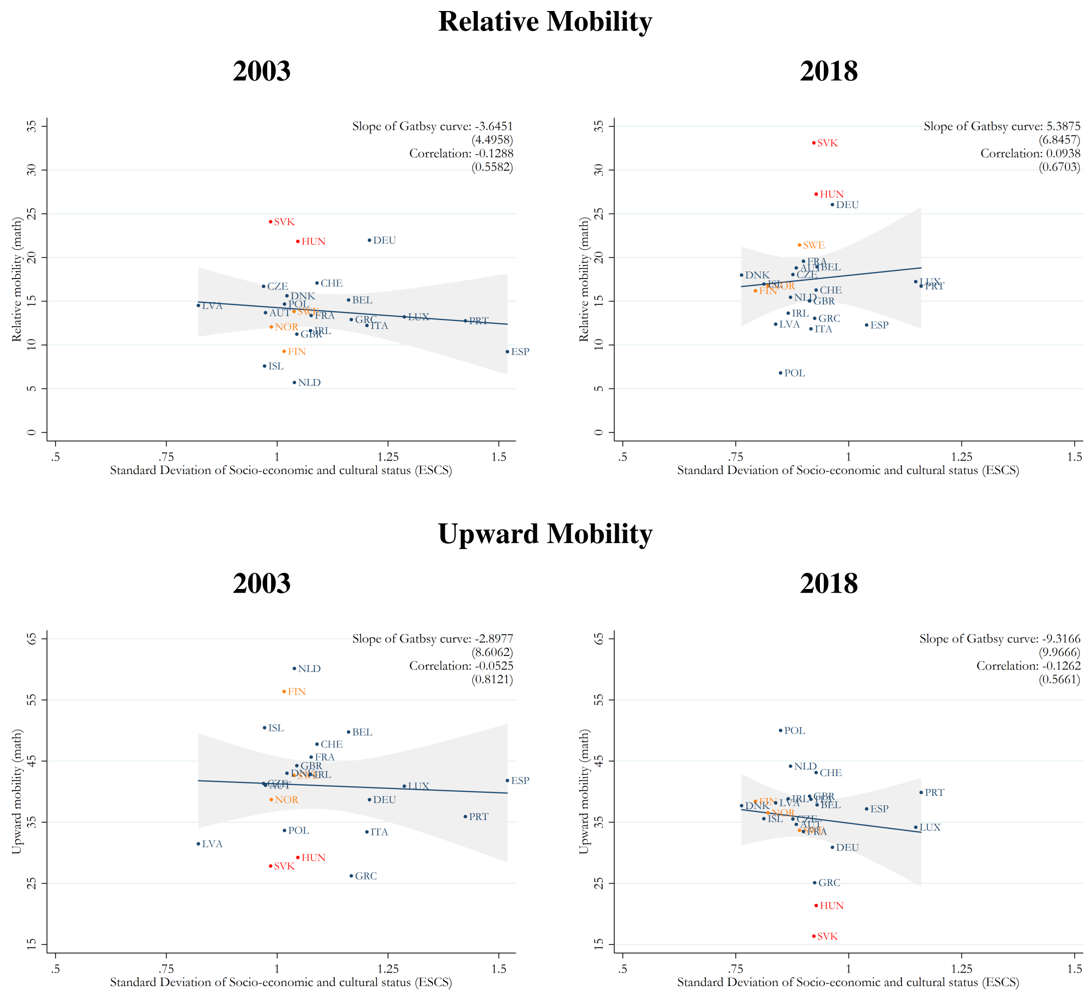


PIRLS



Note. The figure presents 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.

Figure B2: The Great Gatsby curves: learning mobility and standard deviation of ESCS index.



Note. The figure presents 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.

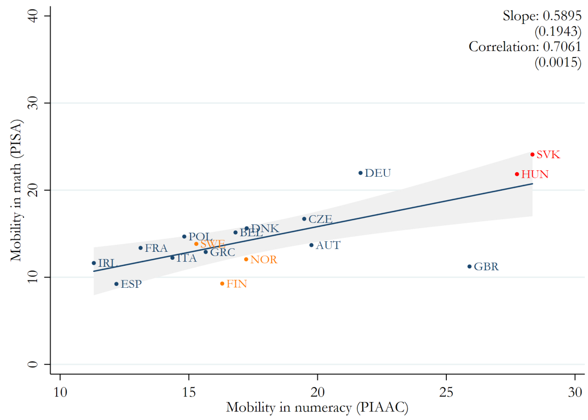
Figure B3: The Great Gatsby curves: learning mobility and GINI coefficient (World Bank).

Note. The figure presents 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.

B.2 Evidence from PIAAC data

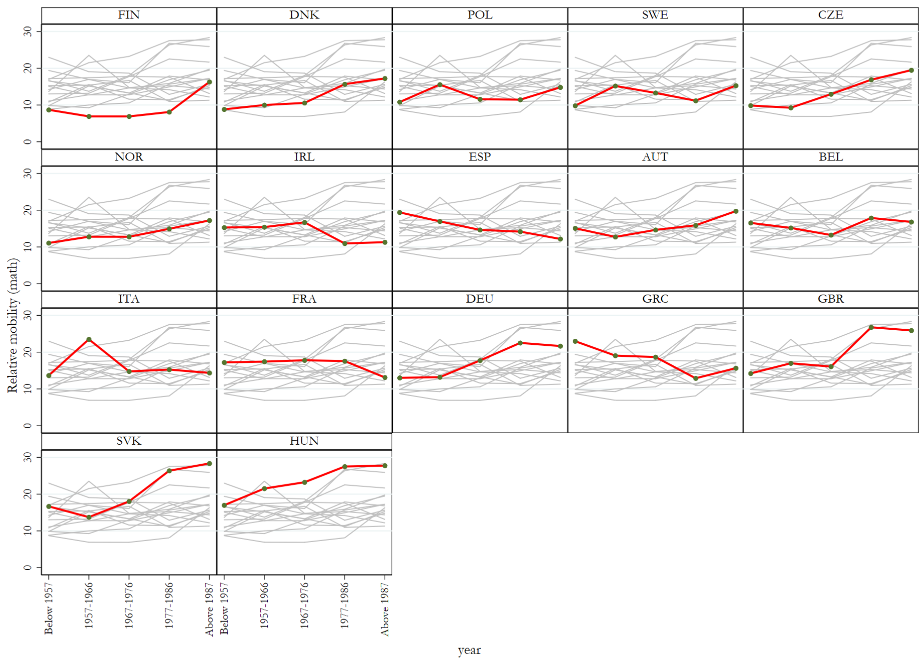
Figure B4: Correlation between mobility measure in PISA and PIAAC

Numeracy



Note. The Figures present 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 age group). 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 B5: 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_{tc}^{k} 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.3 SES gradients in Parental Investment

B.3.1 Measuring parental investment and wealth

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

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

$$m_{ict}^{*,j} = \alpha_{ct}^{j} + \lambda_{t}^{j\top} lnI_{ict} + \varepsilon_{ict}^{j} \tag{6}$$

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

1. Continuous variables: $m_{ict-1} = m_{ict-1}^{*}$;
2. Binary variables $m_{ict-1} \in \{0, 1\}$: $Prob\{m_{ict-1} = 1\} = Pr\{m_{ict-1}^{*} \geq 0\}$;
3. 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 (3) as items are caregorical. Since factors are unobserved and do not have a scale, this requires some identification to assure comparability, we set the scale and the location on the same item $j = 1$ across countries and over time. Namely, we set $\lambda_{ct}^{1} = 1$ and $\tau_{c1,t}^{1} = 0$ and $\alpha_{ct}^{j} = 0, \forall j$ 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.

The questions used for the parental investment index have been collected from 2003 and are presented below:[3]

- Possessions desk
- Possessions study place
- Possessions computer
- Possessions software
- Possessions textbooks
- Possessions <technical reference books>
- Possessions dictionary
- Possessions literature
- Possessions poetry

[3] 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

- Possessions art
- How many books at home

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

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

where $R(I)^k_{itc}$ 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 describes the ISCED levels we have used to define this variable).

β^I_{tc} measures 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.

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

B.3.2 Correlates of the socio-economic gradients in parental investment

Appendix Figure B6 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.

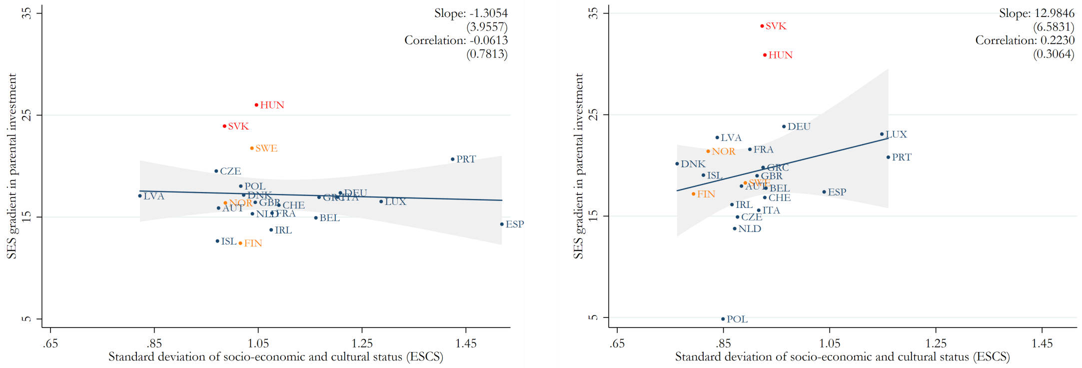
Therefore, we obtain information on the attitudes towards education to study possible correlates of SES gradients in parental investment. We use the data from the European Value Study (EVS) in 2017 and the International Social Survey Programme (ISSP) on social inequality in 2009. For the EVS, the question 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 how important?" (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.

The left panel of Appendix Figure B7 shows a negative cross-country correlation between confidence in the education system and the socio-economic gradients in parental investment, while the right panel shows a positive cross-country correlation between countries perceiving coming from a wealthy family to be important to succeed in life and the socio-economic gradients in parental investment.

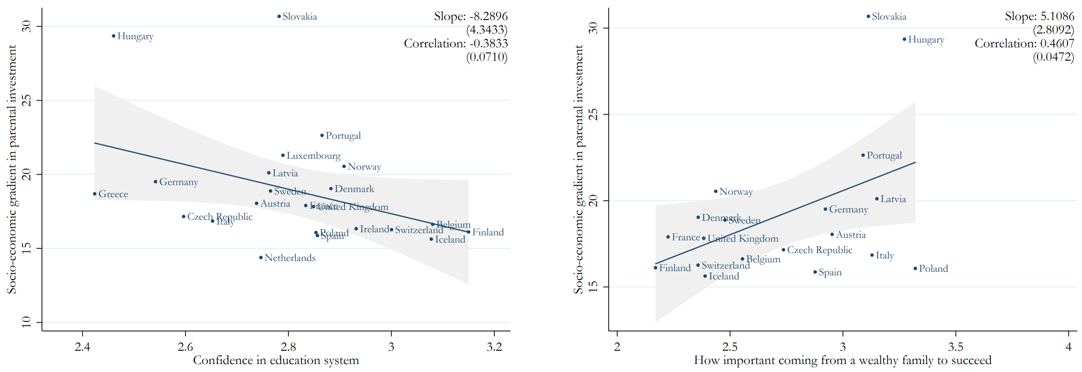
Figure B6: Correlation between SES gradients in parental investment and inequality in ESCS.

2003 **2018**



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.

Figure B7: Correlation between the SES gradients in parental investment and attitudes towards education.



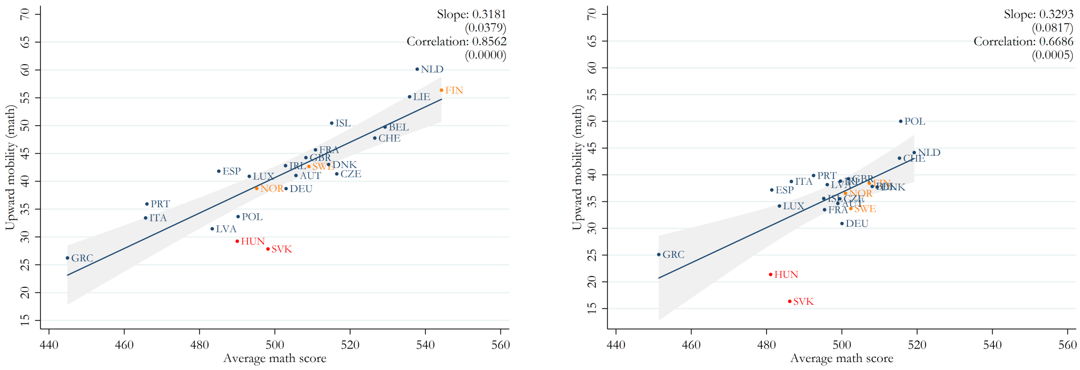
Note. The figures present the correlation between the socio-economics gradients in parental investment and attitudes towards education. The estimates of the socio-economics gradients in parental investment are based on regression of the rank of the parental investment on a dummy equal to 1 if mother 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, 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). For the ISSP, the question is "How important you think is coming from a wealthy family for getting ahead in life how important?" (answers: 1. Essential, 2. Very Important, 3 Fairly Important, 4. Not very important, 5. Not important at all, 8. cannot choose). 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.

C Other measures of SES gradients in child outcomes

C.1 Upward mobility

Figure C1: Correlation between upward mobility and average math score

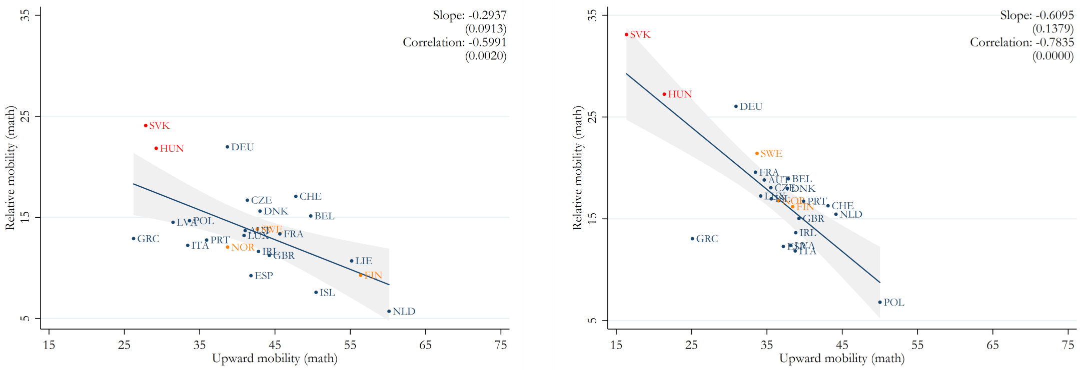
2003 **2018**



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)

2003 **2018**



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, PPP	10.384						
	(8.503)						
Returns to secondary school		-0.170*					
		(0.092)					
Difference between top and lowest tax rates on personal income			0.107				
			(0.097)				
Government expenditure on education (% of GDP)				-1.898			
				(1.500)			
% of population at least completed post-secondary					0.407		
					(0.277)		
School segregation						-6.730	
						(21.754)	
SES gradient in parental investment							-0.750***
							(0.229)
Observations	160	118	137	117	66	159	142
R^2	0.797	0.845	0.815	0.841	0.897	0.786	0.874
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 Do changes in composition drive changes in mobility?

Table C2: Panel regressions: mobility and mothers' education

	Relative mobility		Upward mobility	
	1	2	3	4
% mothers with less than upper secondary education	-0.116*	-0.042	0.152	0.234**
	(0.059)	(0.042)	(0.090)	(0.109)
Observations	165	165	165	165
R^2	0.102	0.798	0.065	0.815
Country FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes
	No year 2000			
	Relative mobility		Upward mobility	
	1	2	3	4
% 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 World Bank database. 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).

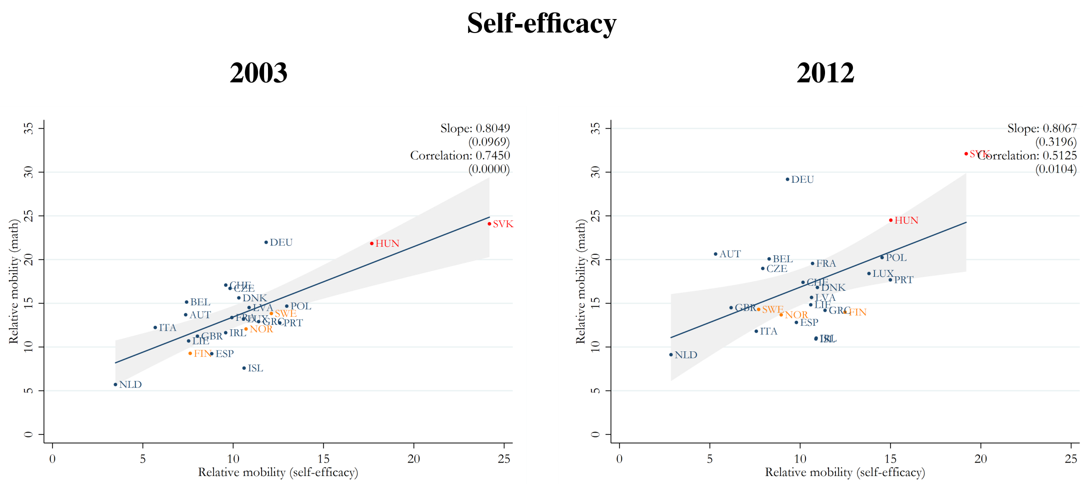
C.4 SES gradients in other traits

To measure students' educational and occupational aspiration, 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 (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 are available from the 2003, 2009, 2015 and 2018 wave, while information on occupational aspiration are available in the 2000, 2003, 2006, 2015 and 2018 wave.

Self-efficacy is 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 at school measured in 2000, 2003, 2012, 2015, and 2018 (Cunha and Heckman, 2007; Borghans et al., 2008). It is possible to measure relative and upward mobility 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.

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 C3: Correlation among the estimates of relative mobility in other traits in 2003 and 2015

				Relative mobility in (2003)		
Math	Read	Science	Educational	Occupational aspiration	Being on time aspiration	at 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 at 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 at 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 at 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 C4: Correlation among the estimates of upward mobility in other traits in 2003, 2015, 2018

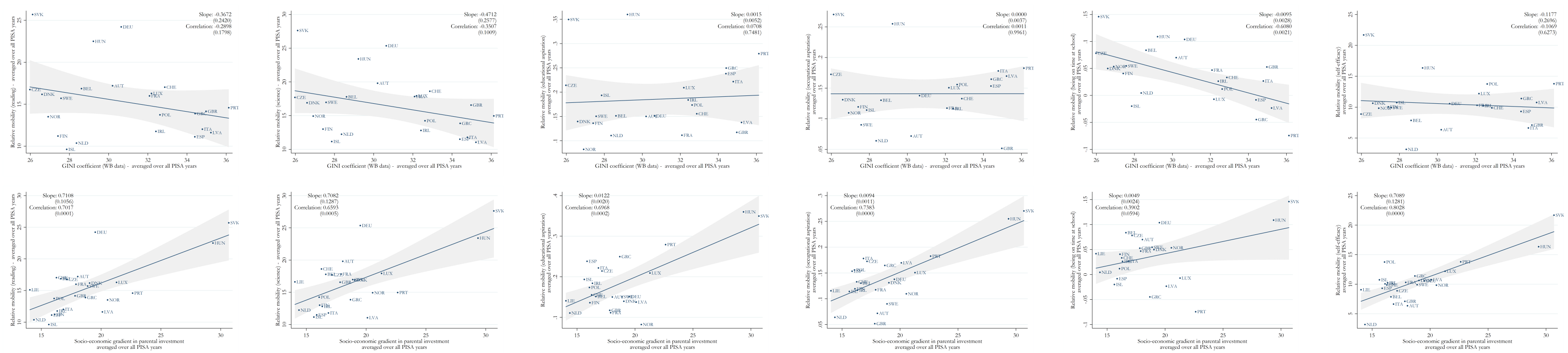
	Upward mobility in (2003)					
	Math	Read	Science	Educational aspiration	Occupational aspiration	Being on time at school
Math	1					
Read	0.726***	1				
Science	0.730***	0.832***	1			
Educational aspiration	-0.151	0.370	0.197	1		
Occupational aspiration	0.244	0.732***	0.437	0.720***	1	
Being on time at 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 at 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 at 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 at 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 at 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).

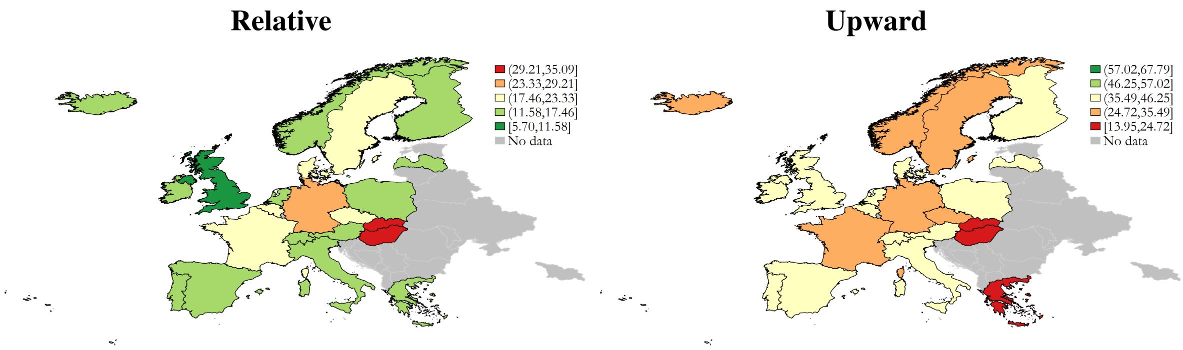
Figure C4: Correlation between SES gradients in other traits and GINI coefficient and SES gradients in parental investment.



Note. The figures present the correlation between the SES gradients and Gini coefficient (WB) in the top panel and the correlation between SES gradients and SES gradients in parental investment in bottom panel. 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 respective p-value in parenthesis.

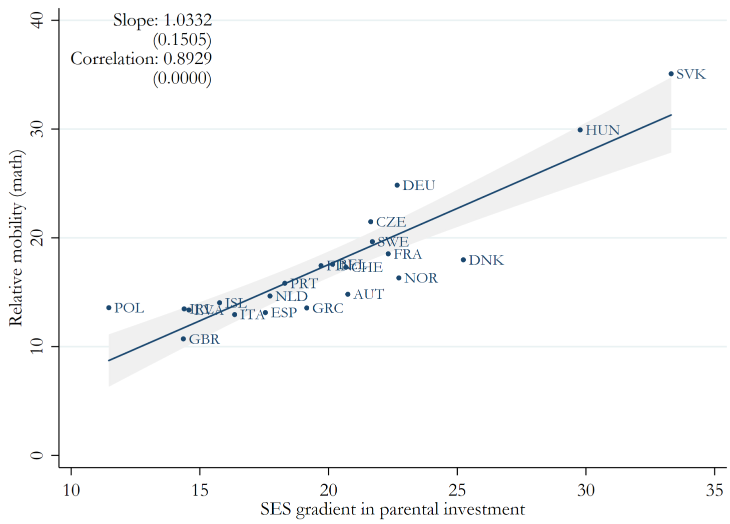
D 2022-PISA wave

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



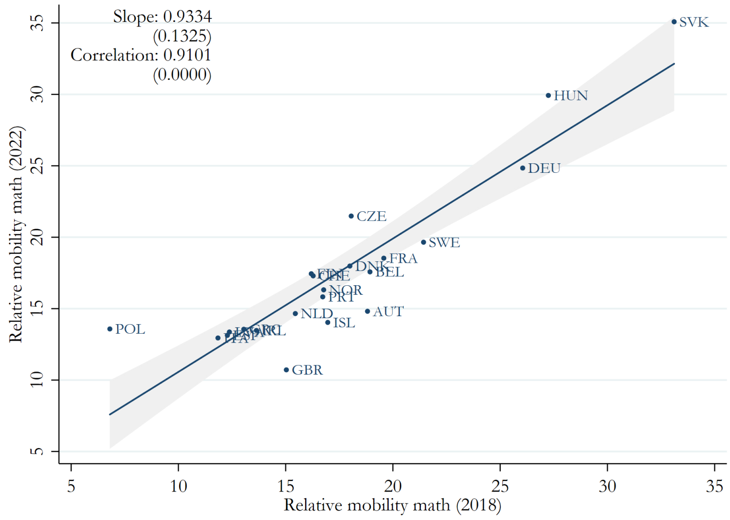
Note. The heat maps present the estimates of intergenerational mobility in learning for each country in 2022 (the estimates are based on equation (1), regression of the rank math score on dummy equal to 1 if mother has at least upper secondary). The relative mobility measure is β_{tc}^{math} from equation (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 SES gradients in test scores (math) and SES gradients in parental investment after COVID-19 (2022-PISA wave)



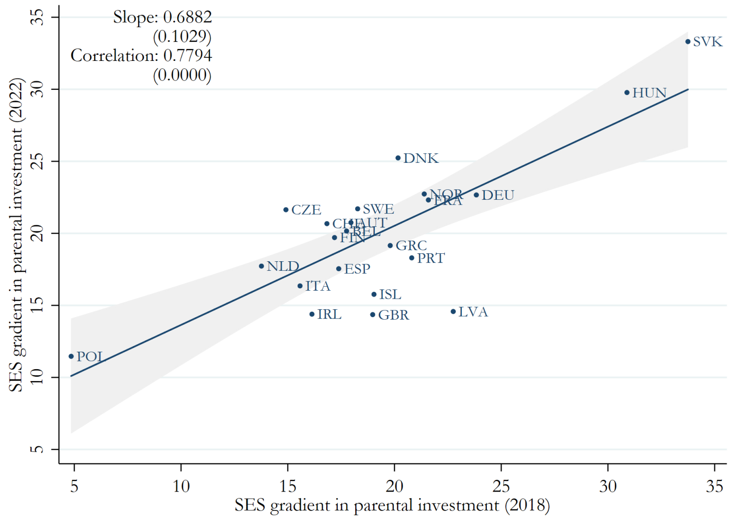
Note. The Figures present the scatter plots between SES gradients in test scores (math) and SES gradients in parental investment after COVID-19 (2022 PISA wave). The estimates of relative mobility are based on equation (1), regression of the outcome of interest on a dummy equal to 1 if mother has at least upper secondary. Details on how the SES gradients in parental investment is computed are available in Appendix B.3.1. 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 D3: Correlation between SES gradients in test scores (math) before and after COVID-19 (2018 vs. 2022-PISA wave)



Note. The Figures present the scatter plots between SES gradients in test scores (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 D4: Correlation between SES gradients in parental investment before and after COVID-19 (2018 vs. 2022-PISA wave)



Note. The Figures present 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.3.1. 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: Trends in learning mobility (math) by country with 2022-PISA wave.

Relative Mobility

Upward Mobility

Note. The figure presents 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.