

Cross-national differences in socioeconomic achievement inequality in early primary school: The role of parental education and income in six countries

Jascha Dräger^{1*}, Elizabeth Washbrook², Thorsten Schneider³, Hideo Akabayashi⁴, Renske Keizer⁵, Anne Solaz⁶, Jane Waldfogel⁷, Sanneke de la Rie⁵, Yuriko Kameyama⁴, Sarah Kwon⁸, Kayo Nozaki⁹, Valentina Perinetti Casoni², Shinpei Sano¹⁰, Alexandra Sheridan⁶ and Chizuru Shikishima¹¹

¹ University of Strathclyde, United Kingdom

² University of Bristol, United Kingdom

³ Leipzig University, Germany

⁴ Keio University, Japan

⁵ Erasmus University of Rotterdam, Netherlands

⁶ INED, France

⁷ Columbia University, United States

⁸ University of Chicago, United States

⁹ Osaka University of Economics, Japan

¹⁰ Kobe University, Japan

¹¹ Teikyo University, Japan

* Corresponding author, jascha.draeger@web.de, School of Education, University of Strathclyde, 141 St James Rd, Glasgow G4 0LT, United Kingdom

Funding

The Development of Inequalities in Child Educational Achievement: A Six Country Study (DICE) is an Open Research Area (ORA)-funded project. We gratefully acknowledge funding support from the Economic and Social Research Council (ESRC Grant ES/S015191/1, United Kingdom); the Agence Nationale de la Recherche (ANR grant ANR-18-ORAR-0001, France), the Deutsche Forschungsgemeinschaft (DFG, Germany, SCHN 1116/1-1; WE 1478/12-1), the Nederlandse Organisatie voor Wetenschappelijk Onderzoek (NWO, The Netherlands, grant number 464.18.102), and Japan Society for the Promotion of Science (JSPS, Japan, grant number JPJSJRP 20181402).

Acknowledgements

We also acknowledge the following data sources for the current paper:

France: We are grateful to the DEPP institute for allowing us to use their data, as well as for helping us with data variables and documentation, and providing us additional variables at the school level particularly useful for this work.

Germany: This paper uses data from the National Educational Panel Study (NEPS). The NEPS is carried out by the Leibniz Institute for Educational Trajectories (LifBi, Germany) in cooperation with a nationwide network.

Japan: The data for this analysis, Japan Household Panel Survey (JHPS/KHPS) and Japan Child Panel Survey (JCPS) were provided by the Panel Data Research Center (PDRC), Keio University.

Netherlands: The Generation R Study is conducted by the Erasmus MC, University Medical Center Rotterdam in close collaboration with the Erasmus University Rotterdam and the city of Rotterdam. We gratefully acknowledge the contribution of children and parents. The general design of Generation R Study is made possible by long-term financial support from Erasmus MC, University Medical Center Rotterdam, Netherlands Organization for Health Research and Development (ZonMw) and the Ministry of Health, Welfare and Sport.

UK: We are grateful to the Centre for Longitudinal Studies (CLS), UCL Social Research Institute, for the use of these data and to the UK Data Service for making them available. However, neither CLS nor the UK Data Service bear any responsibility for the analysis or interpretation of these data.

US: The U.S. results are based on restricted-use data from the Early Childhood Longitudinal Study: Kindergarten Class of 1998-99 (ECLS-K). This study is sponsored by the National Center for Education Statistics (NCES) at the U.S. Department of Education and conducted by Westat with assistance from the Survey Research Center (SRC) and the School of Education at the University of Michigan and from Educational Testing Services (ETS). The findings reported in this paper are solely the responsibility of the authors and do not necessarily represent the official views of NCES or other agencies.

Cross-national differences in socioeconomic achievement inequality in early primary school: The role of parental education and income in six countries

Abstract

This paper presents comparative information on the socioeconomic status (SES) gradients in literacy skills at age 6-8, drawing on harmonized national datasets from France, Germany, Japan, the Netherlands, the United Kingdom, and the United States. We investigate whether understanding of comparative SES gradients in early-to-mid childhood depends on the operationalization of SES (parental education, income, or both); and whether differences in inequalities at the end of lower secondary schooling documented in international large-scale assessments are already present when children have experienced at most two years of formal compulsory schooling. We find marked differences in the SES gradient in early achievement across countries that are largely insensitive to the way SES is measured, and that seem to mirror inequalities reported for older students. We conclude that country context shapes the link between parental SES and children's educational achievement, with country differences rooted in the early childhood period.

Keywords

educational inequality; student achievement; ex-post harmonization; primary school entry; cross-national research

Introduction

Analysis of data from international large-scale assessments (ILSAs) like PISA at age 15 shows that stratification in educational achievement by family socioeconomic status (SES) is pervasive but by no means uniform across countries. Research based on the ILSAs has been invaluable for advancing understanding of how the features of formal education systems mitigate or exacerbate inequalities (e.g. van de Werfhorst & Mijs, 2010) but leaves important questions about the role of wider family and social processes unanswered. A small but growing body of work has sought to compare inequalities earlier in the life course than is possible with the ILSAs, at ages when children have only limited exposure to formal schooling and the influence of the home environment is greater (e.g. Bradbury et al., 2019; Linberg et al., 2018; Passaretta et al., 2022). This body of research has shown that large SES disparities predate school entry and differ significantly in magnitude across countries, but to date comparisons have been limited by the range of countries considered and the differences in the way SES is operationalized. This paper extends this work by considering the stratification of early achievement, by harmonizing data from a wider selection of countries than any previous study and considering two key dimensions of SES.

This paper therefore provides new evidence on inequalities in achievement test scores among children aged 6-8 using data from six advanced industrialized countries – France, Germany, Japan, the Netherlands, the United Kingdom and the United States – harmonized and analyzed by a team of national researchers who are participants in the “Development of Inequalities in Child Educational Achievement: A Six Country Study” project (Olczyk et al., 2021). As children experienced at least two years of formal primary schooling, the paper delivers insights into the extent to which cross-national variation in achievement inequalities at later age are already

present in early-to-mid-childhood. We draw on findings from studies of inequalities later in the life course showing that different dimensions of SES have independent effects on children's development (e.g. Bukodi et al., 2021; Mood, 2017). Using only one dimension to measure SES results in an underestimation of inequalities (Bukodi & Goldthorpe, 2013; Eriksson et al., 2021) and, more seriously for cross-national work, could result in distorted comparisons when the components of SES are correlated differently within countries (Marks, 2011). While many indicators have been proposed as components of SES, here we focus on two: parental education and household income. Parental education and household income provide advantages for children via different mechanisms and may vary in the extent to which their effects are shaped by country context. By disaggregating and comparing the contribution of two major components of SES to overall stratification, it throws light on whether the penalties for children associated with low parental education and low household income differ across countries, and on the sorts of biases that are likely to occur when SES is operationalized in terms of a single indicator.

In short, our paper aims to answer three research questions:

1. Do we see the same cross-national patterning of inequalities in early primary school as at the end of lower secondary school?
2. How large is the unique contribution of parental education and income on child achievement?
3. How does the impact of different SES dimensions on child achievement differ across countries?

Cross-national differences in SES gradients in achievement at age 15 and earlier

To provide context, we start with results from the largest and most recognized international survey on student achievement, PISA. PISA measures parental socioeconomic status via its index of economic, social, and cultural status (ESCS), a composite derived by combining measures of parental education, occupation and an index of home possessions designed to proxy for material wealth and cultural capital (OECD, 2019, p.52). The OECD defines the “strength” of the SES gradient in terms of the proportion of outcome variance explained by SES – the R^2 . We adopt the same approach in our analysis as the R^2 can provide a summary measure of inequality when multiple components of SES are disaggregated into different predictor variables, and it incorporates information about achievement over the full range of the SES distribution.

In Table 1, the six countries explored in this study are ordered in terms of the percent of variation in reading scores at age 15 explained by the ESCS index (OECD, 2019). The OECD average as well as the most and least unequal OECD countries are included to facilitate wider comparison. The average percent of variance in reading performance explained by ESCS across OECD countries is 12%, but this varies between 6.2% in Estonia and 19.1% in Hungary, a more than three-fold difference. The countries represented in this study span a good range of the OECD distribution, with France and Germany towards the top of the range at 17-17.5% and Japan towards the bottom at 8%, a more than two-fold difference. The US is ranked third among the study countries in terms of achievement inequality, with an R^2 value equal to the OECD average, with the Netherlands and the UK showing inequalities lower than the OECD average but nevertheless higher than Japan. The results from the latest round of PISA for our six study countries, therefore, suggest that achievement inequalities at the end of lower secondary

schooling were highest in Germany and France, and lowest in Japan. Results on inequalities in mathematics instead of reading re-iterated this picture (see Table 1).

[TABLE 1 HERE]

The earliest point at which children from large numbers of countries are surveyed by the ILSAs is in fourth grade (in PIRLS and TIMSS), when children are aged 9 to 10 and will have been exposed to formal systems of compulsory schooling for up to five years. Research using PISA (age 15), PIRLS (grade 4) and TIMSS (grade 4 and 8) has addressed the question of how SES gradients in achievement compare across countries at different stages of schooling using a pseudo-cohort or a differences-in-differences approach (e.g. Contini & Cugnata, 2020; Dämmrich & Triventi, 2018; Rözer & van de Werfhorst, 2019; Strello et al., 2021). These ILSA studies have the advantage that they can consider a large range of countries; to model that factors that are associated with country-level changes in inequality over time; and draw on measures that have been constructed to be internationally comparable, at least within a single ILSA. Insights from these studies include that cross-national differences in the SES gradient are already apparent at the end of primary school and these differentials exhibit stability over time – countries with high inequalities in primary school tend to have higher inequalities in secondary school (Contini and Cugnata, 2020).

A few previous studies present comparative information on achievement inequalities earlier than grade 4, based on country-specific data sets. Passaretta et al. (2022) present estimates of gaps in language/literacy skills by parental education in Germany, the UK and the Netherlands at multiple time points between ages 5 and 11. They show parental education gradients at age 5 are largest in Germany, followed by the UK, and the smallest in the Netherlands. This ranking is

unchanged by age 7-8, despite a greater steeping of the gradient in both Germany and the Netherlands over the period.

Linberg et al. (2018) compare gaps at age 6-7 in language/literacy and maths skills in Germany and the US, again by parental education, and find significantly larger gaps in Germany. Finally, a series of studies looks at early childhood cognitive achievement gaps in the US, the UK, Australia and Canada by parental education (Bradbury et al., 2015), relative income group (Bradbury et al., 2012) and absolute income group (Bradbury et al., 2019). Regardless of the way SES is operationalized, gaps are significantly larger in the US than in the other three countries.

To summarise, the existing evidence suggests that early achievement gaps are larger in Germany followed by the US, the UK and finally the Netherlands. Considered alongside the evidence from PISA in relation to inequalities at age 15 (Table 1), there is a good case that international differences in childhood socio-economic inequality are already apparent by the time children begin school and remain largely, although not perfectly, stable over time. To date, no study has considered more than three of our study countries simultaneously nor included France or Japan with respectively very high and very low level of inequality at age 15.

Measurement of SES in comparative studies

As mentioned above, PISA measures parental socioeconomic status via its index of economic, social and cultural status (ESCS) (OECD, 2019, p.52). This measure has the advantage of incorporating information of multiple dimensions of parental socio-economic resources, but it clearly has the drawback that it disguises differences in the implications of the individual components for children's development across country contexts (Eriksson et al., 2021). Many countries rely on child reports of parents' SES characteristics, which may be highly error-prone

(Jerrim & Micklewright, 2014) and household income information is not collected at all in the fourth grade ILSAs. Comparative studies of inequalities using the primary school ILSAs are therefore often forced to rely on a measure of number of books in the home to operationalize parental SES, an indicator which is arguably a poor proxy for SES (Engzell, 2021).

Our research tries to disentangle the SES gradient that existed at the school entry from later influence of schooling structures. Compared to the evidence available from the 4th grade ILSAs, SES gradients in achievement measured just prior to, or as close as possible to, the point of school entry provide a purer measure of initial inequalities. To gain an in-depth and fine-grained comparative understanding of how the major aspects of parental socioeconomic resources relate to outcomes in early childhood, we must turn to harmonized studies of national datasets. In addition, the quality of measures of parental SES available in national cohort studies far exceeds those collected in the ILSAs.

Existing comparative work on inequalities in early-to-mid childhood has utilised only single indicators of SES, most commonly highest parental education but sometimes income (see above). We would expect that the use of a single indicator will understate the “true” degree of inequality because SES is a multi-dimensional concept. This becomes problematic in comparative work if the indicator selected differs in its association with the remaining unmeasured components of SES across countries: countries in which the indicator is a better “proxy” for overall SES will show a stronger association with achievement outcomes, all else equal, and we risk misinterpreting this as evidence of greater social stratification in general.

The components of SES are likely to confer benefits for children via different mechanisms. Net of other socio-economic resources, higher parental education is expected to increase the quantity of stimulating interactions parents provide for their children (Bukodi & Goldthorpe, 2013). More

highly educated parents engage in more complex conversations with their children; use a richer vocabulary; provide higher instruction quality when learning with children; and have higher expectations for their children's educational attainment (e.g., Davis-Kean, 2005; Hoff, 2003; Raviv et al., 2004).

Variations in disposable income, however, again net of other socio-economic resources, are associated with the ability of parents to make more investments in children's human capital (i.e., Family Investment Model) (Becker & Tomes, 1986). This includes investment in children's basic needs (e.g., housing and food), learning materials, and stimulating activities and services (including childcare or private schools). Parents with high income can also afford to reside or relocate to neighbourhoods that are better suited to foster children's development (Leventhal & Brooks-Gunn, 2000; Owens, 2018). Furthermore, shortages in income increase parental stress and thereby might lead to less involved and more inconsistent parenting (i.e., Family Stress Model) (Conger & Conger, 2002).

Cross-country variation in the association of different components of SES with achievement

On the face of it, we might expect more variability in the income-achievement association across countries than in the parental education-achievement relationship. Countries differ considerably in their overall levels of income inequality; in the extent, targeting, and manner in which the state offers financial subsidies and in-kind services; and in their degree of residential segregation. All these factors could affect the way children's lived environments differ for a given differential in their place in the income hierarchy, i.e. how different the living conditions of "rich" and "poor" children are in different societies. It is perhaps less obvious why the effect of parental education on children's development, net of income, should differ across countries. Mediation of these effects is more linked to intimate intra-family interactions that take place within the home, and to

some extent to genetic mechanisms, that would seem less sensitive to the macro context. The extent to which children are exposed to compensating or reinforcing childcare environments outside the home, however, may play some moderating role.

The economic model of parenting of Doepke & Zilibotti (2019) provides a further rationale for why achievement gaps by parental education, as well as by income group, may differ across countries. Their model suggests that incentives to adopt certain styles of parenting are affected by the broader social context and that some parenting styles are considerably easier for parents with high levels of education. Specifically, the benefits of adopting an authoritative parenting style are hypothesized to be greater in systems where the stakes are higher, that is, where economic inequality in adulthood is greater and/or where education systems are more competitive.

Although the constraints imposed on parents by lack of financial resources, and by low educational attainment, may have different implications for children in different contexts, we would also expect some portion of their effects to be shared, both because educational attainment is a crucial determinant of parental income (Erola et al, 2016) and because there will be unmeasured parental traits (such as intelligence, self-efficacy, and a conscientious personality) that correlate with both (Briley et al, 2014; Krapohl et al, 2014).¹

Data

We use recent microlevel data for France, Germany, Japan, the Netherlands, UK, and the US. The datasets, measurement waves and sample sizes are summarized in Table 2. In this table, and in all subsequent figures and tables, we order the countries in terms of the R^2 from the regression of PISA reading scores on ESCS shown in Table 1; this aids interpretation of our subsequent results and maintains consistency in presentation.

[TABLE 2 HERE]

For France, we use data of the DEPP panel, primary school (La Direction de l'évaluation, de la prospective et de la performance; DEPP, 2011). The target population of the DEPP primary school panel are children starting primary school in September 2011. DEPP sampled 977 primary schools in continental France, and randomly selected one class per school. For Germany, we use the data of the National Educational Panel Study Starting Cohort 2 (NEPS SC2), a sample that can be assumed to be representative for first grade in the year 2011-12 (Blossfeld & Roßbach, 2019). For the United States, we use the data of the Early Childhood Longitudinal Study, Kindergarten Class of 2010-11 (ELCS-K:2011; Tourangeau et al., 2015). The ECLS-K sampled a nationally representative cohort of children who attended kindergarten in fall 2010 and spring 2011. For the Netherlands, we analyze the data of Generation-R study (Gen-R; Jaddoe et al., 2006). The target population of Gen-R were expecting mothers living in the municipality of Rotterdam, with an expected delivery date between April 2002 and January 2006. For the UK, we use the data of the Millennium Cohort Study (UCL Social Research Institute, 2021). The MCS is a large-scale longitudinal study representative for children born in 2000-2001 and living in the UK at an age of nine months. For Japan, we use the data of the Japan Child Panel Study (JCPS). Unlike the data sources for the other countries, the JCPS surveys children in households recruited as part of the two household panel studies (the JHPS and KHPS), so data on children at a given age are collected over a range of calendar years. The JCPS has been conducted every year from 2010 to 2014 and every 2 years from 2014. We use data from 2010 to 2018 to maximize sample size.

We excluded all children who are not living with at least one biological parent and children who did not participate in the achievement tests, leaving us with analytical sample sizes of between

N=820 (for Japan) and N=13,798 (for the UK). We selected survey waves to harmonize the age of children at assessment as well as possible across countries: all sample children varied between 6 and 8 in age, and were in either the first or second year of primary school, when assessed. Age and exposure to schooling do not align perfectly in this sample of countries – Dutch children, for example, were younger than the German ones but had been in compulsory schooling for a year longer. Some variation in one or other of these factors is inevitable in a cross-sectional comparison of achievement across countries; we return to the possible implications of this variation for our results in the Discussion section.

As Table 2 makes clear, most of the study cohorts were born in or around 2005 although the UK cohort was born a little earlier, around 2001, and the Gen-R and JCPS sampled from a wider range of birth years than the other studies. The PISA results shown in Table 1 relate to cohorts born in 2003 (who were therefore age 15 in 2018). The cohort alignment is therefore good, but not perfect, with children in our early childhood samples generally born around two years after the children surveyed in PISA 2018.

Dependent Variable: Achievement. The outcome of interest is students' language/literacy achievement in the first or second years of primary school.² In a robustness check, we consider mathematics achievement, which however, is not available for the Netherlands. Skills in both domains were measured with standardized tests and, where available, we use children's latent abilities as estimated based on item-response theory. To make gaps in skill levels comparable across countries, we standardize test scores to a mean of zero and a standard deviation of one in each country. For brevity we henceforth refer to our primary measures as tests of literacy skills, however, we recognize that tests vary in the extent to which they assess verbal and/or reading

skills (see Appendix A for further information on the content domains covered by the instruments and their comparability).

Independent Variable: Parental Education. For all six countries, we categorize parents' education into three categories: high, middle, and low. Our main specification employs the "dominance" approach, that is, we code a single variable capturing the highest qualification of either parent who is co-resident with the child. The highest educational category contains those parents who have at least a bachelor's degree. The lowest educational group contains parents with no qualification beyond the socially expected minimum (at least a grade C qualification at the end of compulsory schooling in the UK; baccalauréat general in France, graduation from the lower school track with a vocational degree in Germany; high school diploma in Japan and the United States; junior general or pre-vocational training in the Netherlands). The medium education group contains all parents that do not fall into the high or low education category (Bradbury et al., 2015). In sensitivity analyses, we explore a more fine-grained definition that distinguishes the highest qualification of the mother/main carer and the father/partner, if one is present in the household.

Independent Variable: Household Income. We measure the income of the households in the same year as children's achievement. The wording of the questions and the extent to which they include tax and/or transfer payments in the definition of income differs across surveys (see Appendix B). We use a measure of relative income position within countries – income quintile groups – on the basis that taxes and transfers will affect the variance of the income distribution but should have little impact on the rank ordering of households by income. Before defining quintile groups, we equalize the original survey measures of income by dividing income by the square root of the household size. In a robustness check, we use a quintile measure derived from

income averaged over multiple years/survey waves, in an attempt to approximate permanent income. The number of additional measurements of income and their timing, however, differs considerably across the datasets, so this measure cannot be considered fully harmonized across countries.

Control variables. Our baseline regression models include a minimal set of control variables that we would not expect to be correlated with SES but that are likely to contribute to the achievement variance: gender and age of child at assessment and, for Japan, also survey wave. Controlling for variables like these should improve the precision of the estimates by removing differences in the residual variance due the sampling differences across countries. In additional analyses, we control for a set of demographic characteristics, harmonized as far as possible across countries: family composition (two biological parents vs. single parents vs. stepfamilies); migration background (at least one parent born abroad vs. no parent born abroad), and foreign language spoken in the home.³ Controlling for these characteristics gives some insight into whether national differences in SES gradients result from differences in the relative demographic composition of low and high SES groups.

Multiple Imputation. We use multiple imputations with chained equations to impute missing values in independent variables (Royston & White, 2011). We use all variables considered in the analyses for the imputation and additional auxiliary variables like parents' employment status and welfare benefit receipt and create 20 imputed data sets. Descriptive statistics for the weighted imputed samples are provided in Table 3. (See Appendix C for further details on missing data and imputation.)

[TABLE 3 HERE]

Methods

We employ OLS models to estimate the components of achievement scores. We run four different models:

$$M1. \textit{Achievement} = \beta_1 * \textit{Controls} + \varepsilon_1$$

$$M2. \textit{Achievement} = \beta_2 * \textit{Controls} + \gamma_2 * \textit{Education} + \varepsilon_2$$

$$M3. \textit{Achievement} = \beta_3 * \textit{Controls} + \delta_3 * \textit{Income} + \varepsilon_3$$

$$M4. \textit{Achievement} = \beta_4 * \textit{Controls} + \gamma_4 * \textit{Education} + \delta_4 * \textit{Income} + \varepsilon_4$$

We use the effect size measure ‘partial eta-squared’ (partial η^2) (Cohen, 1973; Richardson, 2011) to evaluate the contributions of parental education and income to differences in achievement. The partial η^2 capture the difference in the explained variance (R^2) when comparing an OLS model with and without the variables of interest. This allows us to capture the joint effect of parental education and income on child achievement in a single summary statistic: the difference in the R^2 when comparing Model 4 and Model 1, $R^2[M4]-R^2[M1]$, the gross contribution to the variance made by parental education alone, $R^2[M2]-R^2[M1]$, and the gross contribution to the variance made by income alone, $R^2[M3]-R^2[M1]$. The difference between the joint contribution of both variables and the gross contribution of education resp. income gives the net contribution of income ($R^2[M4]-R^2[M2]$) and education ($R^2[M4]-R^2[M3]$). The difference between the gross and net contributions of each indicator is a constant ($R^2[M2]+R^2[M3]-R^2[M4]-R^2[M1]$) and represents the shared contribution that cannot be decomposed.

We adjust standard errors for the sampling design and apply survey weights. Where possible we used the weights provided by the survey designers. For the Gen-R survey, no survey weights were provided and we estimated inverse probability of attrition weights. For JCPS and NEPS, a

set of survey weights were created by the raking method to align with national population characteristics. To compare partial η^2 across countries, their standard errors are estimated using bootstraps resampling (Banjanovic & Osborne, 2016) on the imputed data sets (Schomaker & Heumann, 2018). Individuals are sampled into the bootstrap according to their survey weights.

Results

Figure 1 shows the joint contribution made by indicators of highest parental education and parental income quintile group to the variance in language/literacy scores at age 6-8, that is, $R^2[M4] - R^2[M1]$. With the notable exception of the position of France, the ordering of countries by the social gradient in early primary school is identical to the ordering at age 15 from PISA 2018 shown in Table 1.

Germany has by far the strongest gradient and Japan the weakest, with the US, the Netherlands, and the UK in intermediate positions. Within this group of five countries, cross-national differences are quite distinct, with 8 of the 10 pairwise comparisons reaching statistical significance (with $p < .05$); only the gradient for the Netherlands is not statistically distinguishable from the US or UK gradients (Appendix Table D1). The gradient for Germany is more than four times larger than the gradient for Japan.

[FIGURE 1 HERE]

France is the exception from the remarkable stability in the relative degree of social inequality in our results and the results from PISA, which emerges for the other five countries. In PISA, inequalities are of similar size in France and Germany, yet at age 6-8 the gradient in France is only one-third the size of that in Germany and is significantly lower than in every country studied other than Japan. This difference is intriguing and suggests that the process by which France and

Germany end up with similarly high inequalities in adolescence is rather different. Low SES children start a long way behind in Germany and remain there, whereas low SES children start on a remarkably equal footing in France in international terms but fall behind sharply during the course of schooling. We consider the anomalous position of France further in the Discussion section.

Figure 2 goes on to explore how our conclusions about cross-national variation in early achievement inequality would be affected if we were to characterize SES solely in terms of highest parental education (panel a), or income quintile group (panel b), rather than considering them jointly. In each panel, the solid bars represent the gross contribution of the first SES indicator, or the percent of variation explained when the second SES indicator is omitted from the model. The open bars represent the net contribution of the second SES indicator, or the increment in explanatory power when the second indicator is added to the first. In both panels, the gross contribution of the first indicator and the net contribution of the second indicator sum to the overall social gradient shown previously in Figure 1. To illustrate for the example of France, parental education alone (the gross contribution of education) can account for 5.8% of the variation in achievement. Adding income to the model (the net contribution of income) increases the amount of variance explained by 1.0 percentage points, producing an overall gradient of 6.8%. The alternative decomposition, in which income is entered first, gives a gross contribution of income of 4.6% and a net contribution of education of 2.2%, which again sum to 6.8%. The difference between the gross and net contributions for each indicator reflects the shared contribution of the variance that cannot be decomposed: for France this is 3.6% ($= 5.8 - 2.2 = 4.6 - 1.0$) (see Appendix Table D1).

[FIGURE 2 HERE]

Several points emerge from Figure 2. First, parental education and income both make unique contributions to the social gradient – the omission of either leads to a reduction in variance explained. Second, education is the relatively stronger predictor of the two. On average across the six countries, a model based solely on education results in a 2.1 percentage point reduction in the variance explained compared to when both education and income included; the equivalent reduction for a model based solely on income is higher at 3.3 percentage points. Third, the comparative picture is affected relatively little if SES is operationalized in terms of a single indicator, rather than in terms of the joint contribution of both education and income. Although the gross gradients are slightly more compressed in panel (b) than in panel (a) – differences in countries' social gradients are less distinct when SES is operationalized solely in terms of income – the ordering of countries and the significance of pairwise differences is identical across Figure 1 and both panels of Figure 2 (Appendix Table D1). Hence it appears that cross-national comparisons of the social gradient in childhood achievement are relatively insensitive to the way in which SES is measured, at least among this sample of six countries.

A comparison of the net and gross contributions of each SES indicator provides further insight into the source of country differences in the overall gradient. There is much less country variation in the net contributions of education and income than in the gross contributions. For both indicators, the net contributions for the US, the Netherlands, and the UK range between 2.1 and 3.0 percentage points and not statistically distinguishable. The net contribution of income in Germany is also within this range (2.6 percentage points; panel a) but where Germany stands out is its very high net contribution of education (7.1 percentage points; panel b). In contrast, the net contribution of income is relatively low in France and Japan (1.0 and 1.3 percentage points respectively; panel a) but the net contributions of education in those countries are in line with the

intermediate countries (2.2 and 3.2 percentage points, panel b). The greater country variation in the gross than in the net contributions to the social gradient implies that cross-country differences are primarily rooted in differences in the shared SES component. In fact, all pairwise country differences in this shared component of the variation are statistically significant with the sole exception of the comparison between the Netherlands and the US (Appendix Table D1).

Extensions and robustness checks

As discussed in the methods section, we could have chosen alternative operationalizations of key concepts, could have used alternative model specifications, and could have used additional control variables. Therefore, we conducted robustness checks to evaluate whether we would have obtained the same substantial results (for more details see Appendix E).

First, we do not consider potential interactions between parental education and income in the main analysis. However, when adding all interaction terms between education and income groups, they were not statistically significant in any country and the increase in explained variance were negligible (results available upon request).

Next, we explored the contribution of demographic composition to the social gradients by adding indicators, where available, for family structure, presence of a foreign-born parent and whether a foreign language is spoken in home to the set of baseline controls. The results, provided in Appendix Tables E1 to E3, show that the pattern of cross-country differences from the original specification remains largely intact, however the average percent of variation explained by parental education and income across the six countries falls from 10.6% to 7.0%, indicating that demographic differences contribute in a non-trivial way to the social gradient. Controlling for demographic composition reduces the social gradient by most in Germany and least in France

and Japan, so that country differences in the remaining social gradients become more compressed.

Our main specification uses the “dominance approach” to characterize parental education. However, even when considering the education of both parents (if they are present), the increment in achievement variance explained was small and relatively similar in all countries, ranging from 0.2 and 0.3 percentage points in Japan and the US, respectively, to 0.6 percentage points in Germany and 0.7 in the Netherlands (see Appendix Table E4).

We were conscious household income measured in a single year is liable to measurement error and will pick up transitory fluctuations that tend to bias downwards the estimated contribution of income to explained variance in achievement. Yet, when using average incomes over several years, the contribution of income changed very little. However, results are only indicative because average income could not be harmonized across the different datasets.

Finally, we repeated our main analyses using mathematics, rather than literacy, test scores for the five countries in which they were available (with the Netherlands omitted). In some respects, patterns were broadly similar, in that the social gradients were comparatively weak in Japan and France and high in Germany (Appendix Figures E1 and E2; Table E5). Country differences, however, were less marked in mathematics than in reading. The percent of variance explained jointly by education and income was higher in mathematics than in literacy in the US and Japan, but lower in maths than in literacy in Germany and the UK. As a result, contrary to the case for literacy, differences between Germany and the US, and between the UK and Japan, were not statistically significant.

Discussion

This study has provided estimates of the degree of SES-related achievement inequality at ages 6-8 in six advanced industrialized countries, for the first time considering the role of both parental education and household income in a joint framework and has contrasted cross-national patterns with those found in PISA when children have experienced 7-9 more years in the formal schooling system. Several intriguing findings have emerged.

First, we find evidence of marked country-level variation in the SES gradients in early primary school, with an ordering that remains highly (although not perfectly) stable in international rankings of achievement inequalities at age 15. Findings are largely consistent with previous work on smaller subsets of countries that use differing methodologies: SES gradients in early-to-mid childhood are stronger in Germany than the US (Linberg et al., 2018), the UK and the Netherlands (Passaretta et al., 2022) and stronger in the US than the UK (Bradbury et al., 2015). The gradient documented here for the Netherlands is stronger than for the UK whereas Passaretta et al. (2022) find the reverse, but this can be accounted for by the urban nature of our Dutch sample, which is drawn from the ethnically diverse city of Rotterdam. When demographic composition is controlled, the SES gradient is weaker in the Netherlands than in the UK, consistent with Passaretta et al.'s findings. This study adds to the existing evidence base by harmonizing data from two countries not previously considered in cross-national work – France and Japan – showing that SES gradients in both these countries are weaker than in the other four countries. Further, we show that our understanding of cross-national variation in early SES gradients is not sensitive to whether SES is characterized in terms of parental education, or income, or both. National differences are apparent in, and driven by, variation in the shared component of the achievement variance that cannot be decomposed into separate sources.

Parental education is relatively the stronger predictor of the two, but income also exerts an independent influence, net of parental education.

These findings raise the question of why children's learning environments are more strongly differentiated by SES in some countries than others. We cannot fully rule out the possibility that our results are affected by differences in the sub-domains of literacy skills measured by the tests in different countries, and/or by differences in age or exposure to compulsory schooling or pre-school (which coverage, and affordability differ across country) when children were assessed.

While acknowledging that methodological explanations could play a role, we focus here on substantive explanations due to social context. As the early childhood period is one in which the influence of parental choices and behaviours is paramount (as opposed to later periods when schools, peers and children themselves become more influential), a model that focuses on how the incentives and constraints of parents respond to the macro environment provides a useful theoretical framework.

Doepke and Zilibotti's (2019) economic model of parenting is based on the assumption that different parenting styles vary in their implications for children's school achievement and also in their costs to parents, in terms of time, money, and psychological resources. SES will bite more sharply, and "parenting gaps" will be wider, in contexts where the returns to intensive parenting are greater. In addition to societal inequality and the structure of the education system, family policy can play a role in relaxing the constraints on lower SES families by subsidizing the costs of parenting, for example in terms of time (e.g. paid parental leave) and money (e.g. access to affordable high-quality childcare).

We assess the salience of this framework for understanding why SES gradients vary in the sample of six study countries with respect to income inequality, features of the early childhood

education and care (ECEC) and school structure and government spending (for an overview see Appendix Table D2). We begin with the two countries with the weakest SES gradients in achievement – France and Japan. The low SES gradient in France is largely consistent with Doepke and Zilibotti’s framework. France has relatively low income inequality, as captured by the Gini coefficient, consistent with relatively weak incentives for parents to invest heavily in the future economic success of their children. French children do not experience high-stakes school tracking at the end of primary school, as in Germany or the Netherlands. Further, social expenditure on families in France is high, particularly in relation to the percent of GDP devoted to ECEC, which is more than double the OECD average. In France, preschool from age 3 onwards is free, almost universal, and tends to be of high quality. Responsibility for preschool lies with the Ministry of National Education and preschool teachers are required to have at least a three-year college degree and must pass the national exam (Olczyk et al., 2021). Together, this is indicative of a context in which incentives for parents to prioritize their children’s educational achievement are relatively weak, income differentials between the rich and poor are relatively compressed, and the state helps to equalize access to investments in children, all of which would be expected to attenuate the SES gradient in achievement.

Japan, however, provides an example of a country with an SES gradient that is equally low or even lower than in France, but a very different institutional context. Income inequality is higher in Japan, and social expenditures on the family are much lower, than in any of the three Continental European countries. Like France, Japan does not practice early tracking, but the example of the US shows this is not in itself sufficient to restrain the SES gradient. The weak connection between parental SES and children’s early achievement in Japan is therefore something of a puzzle, however, one can conjecture at least three reasons: First, Japan is known

as a highly homogeneous society with an extremely low rate of inward migration, and relatively little social grading in the timing and ordering of family transitions (Raymo & Iwasawa, 2016). Preschool is near universal also in Japan, over 95% of children attend some form of certified preschool with the national curriculum guideline at least two years before the compulsory education. They may collectively serve to dampen differences between socioeconomic groups. Second, other reasons put forward for why SES gradients in East Asian countries are more compressed than in Western societies are broadly-held cultural norms, such as filial piety and high values placed on education as a virtuous lifelong pursuit, and highly standardized education systems, although the evidence on this is mixed (Kim, 2019). Finally, the college earnings premium in Japan is much lower than the other five countries (van der Velden and Bijlsma 2016). Therefore, despite a high-income inequality, parents may not have a strong incentive for monetary investment in early childhood education, explaining a relatively low contribution of household income on children than parental education. Regardless of the explanation, the example of Japan shows that relatively high economic inequality and low social expenditure can co-exist with very modest achievement inequalities.

Turning to the two countries with intermediate SES gradients, the Netherlands and the UK, we again see sharply contrasting institutional contexts. Income inequality is the lowest in the Netherlands of all the six study countries but second highest in the UK (see Appendix Table D2). Set against this, the Netherlands has a system of early school tracking and only moderate social expenditure on families by OECD standards, while the UK system does not use early tracking in lower secondary school and has levels of family expenditure that are well above the OECD

average. Although the two countries exhibit similar moderate SES gradients, the nature of the incentives and constraints faced by low SES parents seem rather different.

The final pair of countries, Germany and the US, which have the strongest SES gradients among this sample, are also strikingly different in their contextual characteristics. The strong SES gradient in the US is as we might expect, given its very high level of income inequality, low level of spending on ECEC, and weak social safety net (see Appendix Table D2). Differences in the material resources available to parents at the top and bottom of the socioeconomic spectrum will be more marked in the US than in other countries and will be offset less by public policy. By this logic, the SES gradient should be weaker in Germany than the US, given its lower Gini coefficient and higher social spending, but in fact the German gradient is equally as large if not larger. Our supplementary analyses showed that the disadvantageous composition of low SES groups in Germany, in terms of migrant status, home language and family structure, plays some role in accounting for its exceptionally strong gradient in early literacy skills but this does not provide a full explanation.

The most obvious interpretation is that Germany's early tracking system creates very strong incentives for parents to prioritize children's academic performance in the early-to-mid childhood period, in attempts to secure access to an academically-oriented Gymnasium at age 10, rather than in intermediate Realschule or vocationally-oriented Hauptschule. This is consistent with other research that has shown high SES gradients in early tracking countries are already evident in primary school, before tracking has taken place (Rözer & van de Werfhorst, 2019; Strello et al., 2021). Further, relatively low levels of ECEC expenditure may inhibit the ability of low SES parents in Germany to access high-quality compensatory childcare settings. The childcare ideology in Germany has been described as "explicitly familial" in that, historically, publicly

funded institutional childcare was socially stigmatized, mothers were viewed as the ideal caregivers of children, and church and family were relied upon when parental care was not possible (Lokteff & Piercy, 2012). It is possible, therefore, that the influence of parents, and of mothers in particular, on children's environments is offset less by exposure to contrasting extrafamilial environments in Germany than in other countries. Our finding that there is an unusually strong net effect of parental education on literacy skills in Germany, independent of income, is consistent with the idea that social grading in parental interactions disproportionately underlies the SES gradient, relative to social grading in financial resources. Nevertheless, it is still somewhat surprising that the SES gradient is stronger in Germany than in the US, a country with far higher income inequality and a much weaker social safety net.

Of course, age at school tracking and income inequality are only very partial indicators of the degree of competitiveness in the education system and in the economy respectively. The incentives for parents to prioritize academic achievement in children early in the life course will depend on the extent to which achievement confers access to superior schools, classrooms and universities (or ones that are perceived to be superior), and in the degree to which educational attainment determines economic opportunity, as opposed to factors like wealth or social connections. Nevertheless, this simplistic analysis suggests that the extent of the early SES gradient in a country results from a complex interplay of different factors, none of which are either necessary or sufficient to flatten achievement inequalities in isolation. While the overall degree of income inequality in a society may be relatively resistant to policy initiatives, avoidance of competitive high-stakes transition points in the education system and state support for early childhood services are potential mechanisms that can respectively act on parental incentives and constraints to help mute socioeconomic differences in the early years.

Moreover, the striking stability in the SES gradients at age 6-8 and those at age 15 reported in PISA suggest that reducing inequalities prior to school entry may have far-reaching effects on social mobility. This proposition is further supported by findings from longitudinal research that shows inequalities change relatively little over the course of schooling (e.g. Bradbury et al., 2015; Farkas & Beron, 2004; Skopek & Passaretta, 2021), and from ILSA research that the ranking of countries in terms of SES gradients in primary and secondary school is relatively stable (Contini & Cugnata, 2020). However, the case study of France reminds us that a note of caution is needed about focusing attention exclusively on environments in the early years. The strong French SES gradient in PISA suggests that the benefits for equality of its world-leading preschool system are completely eroded over the course of primary and lower secondary schooling, such that it ends up with an internationally high gradient by age 15, with a level similar to that in Germany. Progress along elementary schooling is very unequal depending on the student's social background (Caille, & Rosenwald, 2006), tending to enlarge the initial SES gap in skills. The reasons for the enlarging gap are unclear, although factors noted by Doepke and Zilibotti (2019), such as the extremely hierarchical teacher-led nature of the French schooling system, its high rates of grade repetition, and the existence of elite prestigious lycees and Grand Ecoles, may play a role. Cayouette-Remblière (2016) pointed also that the schooling conditions such as the nature of the school exercises and homework that may excludes low SES children if they do not benefit from the help of a supportive adult, and the weak encouraging system that can affect the confidence of the most disadvantaged students. Further research using longitudinal data is needed to help understand the factors that can successfully sustain low inequalities at school entry over the longer term or that can remediate high inequalities.

Notes

1) SES reflects more than just education and income, and ideally, we might like to consider components such as social class, social status and wealth, although the unique variance captured by each additional indicator will become progressively smaller. It is not possible to harmonise measures of occupational status or wealth across our datasets and we argue that the implications of these SES components for children's human capital are likely to be more salient at older ages than in early childhood. For example, the independent contributions of social status (social capital and networks) are most relevant for entering prestigious institutions or finding jobs, and wealth offers an insurance against (potential) adverse life events or failures. Moreover, in empirical research on social stratification measures of income are becoming more frequent and replace measures of social class (Barone et al., 2022).

2) It is important to recognize, however, that the tests of language skills we use were not designed to align with PISA's definition of reading literacy (OECD, 2019, p.35). Hence it is not possible to compare the R²s from PISA directly with those presented in this study on a within-country basis. We focus our discussion on the rank ordering of countries but do not attempt to infer whether the SES gradient within individual countries strengthens or weakens as children age.

3) Parental country of birth and home language(s) are not recorded in the data for Japan. In addition, step- and biological parents cannot be distinguished in the data for Japan, so all two-parent families are combined into one category.

References

- Banjanovic, E. S., & Osborne, J. W. (2016). Confidence intervals for effect sizes: Applying Bootstrap Resampling. *Practical Assessment, Research, and Evaluation, 21*, 5.
<https://doi.org/10.7275/dz3r-8n08>
- Barone, C., Hertel, F. R., & Smullenbroek, O. (2022). The rise of income and the demise of class and social status? A systematic review of measures of socio-economic position in stratification research. *Research in Social Stratification and Mobility, 78*, 100678.
<https://doi.org/10.1016/j.rssm.2022.100678>
- Becker, G. S., & Tomes, N. (1986). Human capital and the rise and fall of families. *Journal of Labor Economics, 4*(3 Pt. 2), 1–47. <https://doi.org/10.1086/298118>
- Blossfeld, H.-P., & Roßbach, H.-G. (Eds.). (2019). *Education as a lifelong process: The German National Educational Panel Study (NEPS)* (2. ed., vol. 3). Springer VS.
<https://doi.org/10.1007/978-3-658-23162-0>
- Bradbury, B., Corak, M., Waldfogel, J., & Washbrook, E. (2012). Inequality in early childhood outcomes. In J. Ermisch, M. Jäntti, T.M. Smeeding (Eds.), *From parents to children: The intergenerational transmission of advantage* (pp. 87-119). Russell Sage Foundation.
- Bradbury, B., Corak, M., Waldfogel, J., & Washbrook, E. (2015). *Too many children left behind: The U.S. Achievement gap in comparative perspective*. Russell Sage Foundation.
- Bradbury, B., Waldfogel, J., & Washbrook, E. (2019). Income-related gaps in early child cognitive development: Why are they larger in the United States than in the United Kingdom, Australia, and Canada? *Demography, 56*(1), 367–390. <https://doi.org/10.1007/s13524-018-0738-8>

- Briley, D. A., Domiteaux, M., & Tucker-Drob, E. M. (2014). Achievement-relevant personality: Relations with the Big Five and validation of an efficient instrument. *Learning and Individual Differences, 32*, 26–39. <https://doi.org/10.1016/j.lindif.2014.03.010>
- Bukodi, E., & Goldthorpe, J. H. (2013). Decomposing 'social origins': The effects of parents' class, status, and education on the educational attainment of their children. *European Sociological Review, 29*(5), 1024–1039. <https://doi.org/10.1093/esr/jcs079>
- Bukodi, E., Goldthorpe, J. H., & Zhao, Y. (2021). Primary and secondary effects of social origins on educational attainment: New findings for England. *The British Journal of Sociology, 72*(3), 627–650. <https://doi.org/10.1111/1468-4446.12845>
- Caille, J. P., & Rosenwald, F. (2006). Les inégalités de réussite à l'école élémentaire: construction et évolution. France, portrait social, 115–137. <https://www.insee.fr/fr/statistiques/1373137?sommaire=1373141>
- Cayouette-Remblière, J. (2016). *L'école qui classe. 530 élèves du primaire au bac*. PUF.
- Cohen, J. (1973). Eta-squared and partial eta-squared in fixed factor ANOVA designs. *Educational and Psychological Measurement, 33*(1), 107–112. <https://doi.org/10.1177/001316447303300111>
- Conger, R. D., & Conger, K. J. (2002). Resilience in midwestern families: Selected findings from the first decade of a prospective, longitudinal study. *Journal of Marriage and Family, 64*(2), 361–373. <https://doi.org/10.1111/j.1741-3737.2002.00361.x>
- Contini, D., & Cugnata, F. (2020). Does early tracking affect learning inequalities? Revisiting difference-in-differences modeling strategies with international assessments. *Large-scale Assessments in Education, 8*, 14. <https://doi.org/10.1186/s40536-020-00094-x>

- Dämmrich, J., & Triventi, M. (2018). The dynamics of social inequalities in cognitive-related competencies along the early life course—A comparative study. *International Journal of Educational Research*, 88, 73-84. <https://doi.org/10.1016/j.ijer.2018.01.006>
- Davis-Kean, P. E. (2005). The influence of parent education and family income on child achievement: The indirect role of parental expectations and the home environment. *Journal of Family Psychology*, 19(2), 294–304. <https://doi.org/10.1037/0893-3200.19.2.294>
- DEPP. (2011). Repères et références statistiques sur les enseignements, la formation et la recherche.
- Doepke, M., & Zilibotti, F. (2019). *Love, money, and parenting: How economics explains the way we raise our kids*. Princeton University Press.
- Engzell, P. (2021). What do books in the home proxy for? A cautionary tale. *Sociological Methods & Research*, 50(4), 1487-1514. <https://doi.org/10.1177/0049124119826143>
- Eriksson, K., Lindvall, J., Helenius, O., & Ryve, A. (2021). Socioeconomic status as a multidimensional predictor of student achievement in 77 societies. *Frontiers in Education*, 6, 731634. <https://doi.org/10.3389/educ.2021.731634>
- Erola, J., Jalonen, S., & Lehti, H. (2016). Parental education, class and income over early life course and children's achievement. *Research in Social Stratification and Mobility*, 44, 33–43. <https://doi.org/10.1016/j.rssm.2016.01.003>
- Farkas, G., & Beron, K. (2004). The detailed age trajectory of oral vocabulary knowledge: Differences by class and race. *Social Science Research*, 33(3), 464-497. <https://doi.org/10.1016/j.ssresearch.2003.08.001>

- Hoff, E. (2003). The specificity of environmental influence: Socioeconomic status affects early vocabulary development via maternal speech. *Child Development, 74*(5), 1368–1378.
<https://doi.org/10.1111/1467-8624.00612>
- Jaddoe, V. W. V., Mackenbach, J. P., Moll, H. A., Steegers, E. A. P., Tiemeier, H., Verhulst, F. C., Witteman, J. C. M., & Hofman, A. (2006). The Generation R Study: Design and cohort profile. *European Journal of Epidemiology, 21*, 475–484. <https://doi.org/10.1007/s10654-006-9022-0>
- Jerrim, J., & Micklewright, J. (2014). Socio-economic gradients in children’s cognitive skills: Are cross-country comparisons robust to who reports family background? *European Sociological Review, 30*(6), 766–781. <https://doi.org/10.1093/esr/jcu072>
- Kim, S. (2019). Is socioeconomic status less predictive of achievement in East Asian countries? A systematic and meta-analytic review. *International Journal of Educational Research, 97*, 29–42. <https://doi.org/10.1016/j.ijer.2019.05.009>
- Krapohl, E., Rimfeld, K., Shakeshaft, N. G., Trzaskowski, M., McMillan, A., Pingault, J. B., ..., Plomin, R. (2014). The high heritability of educational achievement reflects many genetically influenced traits, not just intelligence. *Proceedings of the National Academy of Sciences, 111*(42), 15273–15278. <https://doi.org/10.1073/pnas.1408777111>
- Leventhal, T., & Brooks-Gunn, J. (2000). The neighborhoods they live in: The effects of neighborhood residence on child and adolescent outcomes. *Psychological Bulletin, 126*(2), 309–337. <https://doi.org/10.1037/0033-2909.126.2.309>
- Linberg, T., Schneider, T., Waldfogel, J., & Wang, Y. (2019). Socioeconomic status gaps in child cognitive development in Germany and the United States. *Social Science Research, 79*, 1–31. <https://doi.org/10.1016/j.ssresearch.2018.11.002>

- Lokteff, M., & Piercy, K. W. (2012). “Who cares for the children?” Lessons from a global perspective of child care policy. *Journal of Child and Family Studies*, 21, 120-130.
<https://doi.org/10.1007/s10826-011-9467-y>
- Marks, G. N. (2011). Issues in the conceptualisation and measurement of socioeconomic background: Do different measures generate different conclusions? *Social Indicators Research*, 104(2), 225–251. <https://doi.org/10.1007/s11205-010-9741-1>
- Mood, C. (2017). More than money: Social class, income, and the intergenerational persistence of advantage. *Sociological Science*, 4, 263–287. <https://doi.org/10.15195/v4.a12>
- OECD (2019). *PISA 2018 results (Volume II): Where all Students can succeed*. OECD Publishing.
- OECD (2022). *OECD Family Database*. <http://www.oecd.org/els/family/database.htm>
- Olczyk, M., Schneider, T., Washbrook, E., & DICE-team. (2021). *National context and socioeconomic inequalities in educational achievement: An overview of six high-income countries: France, Germany, Japan, the Netherlands, United Kingdom, and United States* (Working Paper No. 267). INED. <https://www.ined.fr/en/publications/editions/document-travail/national-context-and-socioeconomic-inequalities-in-educational-achievement/>
- Owens, A. (2018). Income Segregation between School Districts and Inequality in Students’ Achievement. *Sociology of Education*, 91(1), 1–27.
<https://doi.org/10.1177/0038040717741180>
- Passaretta, G., Skopek, J, & van Huizen, T. (2022). Is social inequality in school-age achievement generated before or during schooling? A European perspective. *European Sociological Review*, jcac005. <https://doi.org/10.1093/esr/jcac005>

Raviv, T., Kessenich, M., & Morrison, F. J. (2004). A mediational model of the association between socioeconomic status and three-year-old language abilities: The role of parenting factors. *Early Childhood Research Quarterly, 19*(4), 528–547.

<https://doi.org/10.1016/j.ecresq.2004.10.007>

Raymo, J. M., & Iwasawa, M. (2016). *Diverging destinies: The Japanese case*. Springer.

Richardson, J. T. (2011). Eta squared and partial eta squared as measures of effect size in educational research. *Educational Research Review, 6*(2), 135–147.

<https://doi.org/10.1016/j.edurev.2010.12.001>

Royston, P., & White, I. (2011). Multiple Imputation by Chained Equations (MICE): Implementation in Stata. *Journal of Statistical Software, 45*(4), 1-20.

<https://doi.org/10.18637/jss.v045.i04>

Rözer, J. J., & van de Werfhorst, H. G. (2019). *Achievement inequalities and the impact of educational institutions*. (ISOTIS Report (D 1.4a)). University of Amsterdam.

Schomaker, M., & Heumann, C. (2018). Bootstrap inference when using multiple imputation. *Statistics in Medicine, 37*(14), 2252–2266. <https://doi.org/10.1002/sim.7654>

Skopek, J., & Passaretta, G. (2021). Socioeconomic inequality in children's achievement from infancy to adolescence: The case of Germany. *Social Forces, 100*(1), 86–112.

<https://doi.org/10.1093/sf/soaa093>

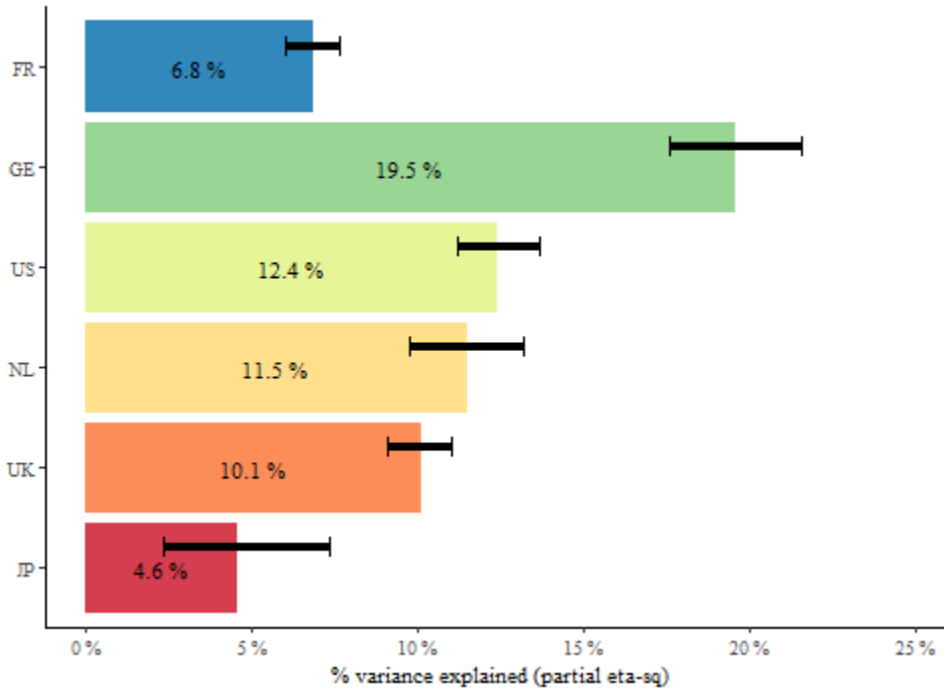
Strello, A., Strietholt, R., Steinmann, I., & Siepmann, C. (2021). Early tracking and different types of inequalities in achievement: difference-in-differences evidence from 20 years of large-scale assessments. *Educational Assessment, Evaluation and Accountability, 33*(1), 139-

167. <https://doi.org/10.1007/s11092-020-09346-4>

- Tourangeau, K., Nord, C., Lê, T., Sorongon, A.G., Hagedorn, M.C., Daly, P., & Najarian, M. (2015). *Early Childhood Longitudinal Study, Kindergarten Class of 2010–11 (ECLS-K:2011), User’s manual for the ECLS-K:2011 kindergarten data file and electronic codebook, public version (NCES 2015-074)*. U.S. Department of Education. National Center for Education Statistics. <https://nces.ed.gov/pubs2015/2015074.pdf>
- UCL Social Research Institute. (2021). *Millennium Cohort Study: Seventh survey, 2001-2018*. (6th Edition). UK Data Archive. SN: 4683. Centre for Longitudinal Studies.
- van der Velden, R. & Bijlsma, I. (2016). College Wage Premiums and Skills: A Cross-Country Analysis. *Oxford Review of Economic Policy*, 32(4), 497–513. <https://doi.org/10.1093/oxrep/grw027>
- van de Werfhorst, H. G., & Mijs, J. J. B. (2010). Achievement inequality and the institutional structure of educational systems: A comparative perspective. *Annual Review of Sociology*, 36, 407–428. <https://doi.org/10.1146/annurev.soc.012809.102538>

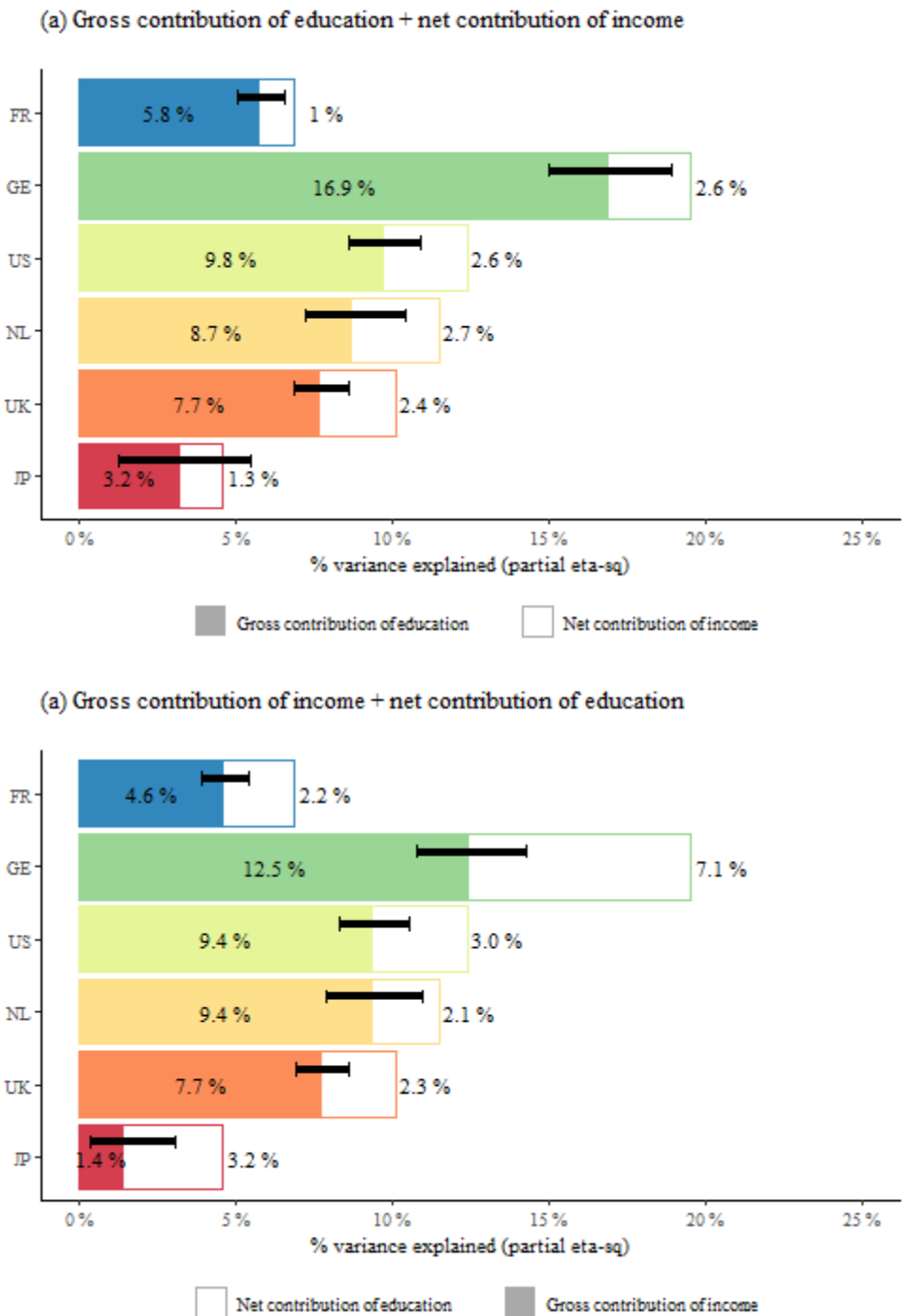
Figures and Tables

Figure 1. Percent of variance in literacy scores at ages 6-8 accounted for by SES: joint contribution of parental education and income group



Note: Error bars are bootstrapped 95% confidence intervals. Estimates are the partial eta-squareds from the joint model including indicators of education and income simultaneously, $R^2[M4] - R^2[M1]$.

Figure 2. Alternative decompositions of the percent of variance in literacy scores at age 6-8 accounted for by parental SES



Note: The filled bars in panels (a) and (b) represent the increase in the R-squared when first education, and then income, are added individually to a model including only baseline controls, i.e. $R^2[M2] - R^2[M1]$ and $R^2[M3] - R^2[M1]$ respectively. Error bars are bootstrapped 95% confidence intervals on these gross contribution components. The open bars represent the net contribution of income (panel a) and of education (panel b), or the drop in R-squared when the second non-focal SES indicator is excluded from the model. The combined length of the filled and open

bars together, therefore, is the partial eta-squared from the joint model including both indicators of SES shown in Figure 1.

Table 1. Socioeconomic inequalities in achievement at age 15 in selected countries from PISA 2018

Country	% of variance in reading performance explained by ESCS (R^2)		% of variance in mathematics performance explained by ESCS (R^2)	
	%	S.E.	%	S.E.
France	17.5	(1.3)	21.1	(1.5)
Germany	17.2	(1.4)	18.0	(1.6)
United States	12.0	(1.4)	16.1	(1.5)
Netherlands	10.5	(1.3)	13.5	(1.7)
United Kingdom	9.3	(1.0)	11.6	(1.1)
Japan	8.0	(1.2)	9.0	(1.4)
OECD average	12.0	(0.2)	13.8	(0.2)
OECD highest		Hungary		Hungary
	19.1	(1.7)	23.8	(1.9)
OECD lowest		Estonia		Canada
	6.2	(0.8)	7.8	(0.7)

Source: OECD (2019). Estimates of the percent of variance explained in reading and mathematics performance are taken from Tables II.B1.2.3 and II.B1.2.4 respectively (<https://doi.org/10.1787/888934038609>).

Table 2: Data and assessment instruments in the six countries

	France	Germany	United States	Netherlands	United Kingdom	Japan
Survey	DEPP panel primary school	NEPS SC2	ELCS-K: 2011	Generation R	MCS	JCPS
Birth cohorts	2005	2005-06	2005	2002-06	2000-02	2002-2012
Mean age at assessment: (SD)	6.0 years (0.1)	7.1 years (0.4)	7.1 years (0.4)	6.2 years (0.6)	7.2 years (0.2)	8.0 years (0.6)
School grade at assessment	Cours préparatoire (CP)	Grade 1	1 st grade	Group 2	Year 2	Grades 1 and 2
Baseline sample size	15,188	6,734	15,750 ^a	7,853	18,552	862
Analytical sample size	13,297	5,365	10,250 ^a	5,599	13,355	820
Language/literacy achievement test	DEPP Early Reading (Prelecture) score	Adapted PPVT score (receptive vocabulary)	ECLS-K Reading score	CITO TVK score (receptive vocabulary)	BAS II Word Reading score	JCPS Japanese language test
Mathematics Achievement test	DEPP Mathematics test	NEPS Mathematics test	ECLS-K Mathematics test	-	NFER Progress in Maths test	JCPS Mathematics test

^a All ECLS-K sample sizes are rounded to the nearest 50 in accordance with NCES statistical disclosure rules.

Table 3. Descriptive Statistics (imputed and weighted data)

	FR	GE	US	NL	UK	JP
Highest education						
High	0.26	0.27	0.39	0.55	0.32	0.35
Middle	0.35	0.51	0.34	0.30	0.29	0.35
Low	0.38	0.22	0.27	0.15	0.39	0.31
Mother/main carer's education						
High	0.20	0.18	0.33	0.46	0.22	0.14
Middle	0.33	0.54	0.35	0.33	0.25	0.43
Low	0.46	0.28	0.33	0.21	0.53	0.42
Father/partner's education						
High	0.17	0.19	0.25	0.42	0.23	0.31
Middle	0.23	0.37	0.23	0.24	0.21	0.20
Low	0.47	0.26	0.31	0.16	0.34	0.46
Partner not present	0.12	0.17	0.21	0.18	0.23	0.04
Child characteristics						
Child is female	0.49	0.49	0.48	0.49	0.48	0.47
Age at assessment in years	6.0	7.1	7.1	6.2	7.2	8.0
(SD)	(0.1)	(0.4)	(0.4)	(0.6)	(0.2)	(0.6)
Demographic characteristics						
Two bio. parents	0.83	0.78	0.72	0.79	0.70	0.96
Single parent	0.12	0.17	0.21	0.18	0.23	0.04
Stepfamily	0.04	0.05	0.07	0.03	0.08	-
Foreign born parent(s)	0.07	0.31	0.27	0.24	0.16	-
Foreign language at home	0.26	0.27	0.26	0.25	0.10	-
JCPS survey wave						
2010	-	-	-	-	-	0.13
2011	-	-	-	-	-	0.16
2012	-	-	-	-	-	0.12
2013	-	-	-	-	-	0.17
2014	-	-	-	-	-	0.17
2016	-	-	-	-	-	0.16
2018	-	-	-	-	-	0.10
N	13,297	5,365	10,250	5,599	13,355	820

Note. Children's achievement and household income quintile groups are not presented because they are standardized to 0.00 (SD=1.00) and 0.20 respectively in all countries. All ECLS-K sample sizes are rounded to the nearest 50 in accordance with NCES statistical disclosure rules.

ONLINE APPENDICES

Appendix A. Achievement measures

Language/literacy test scores

France: DEPP Early Reading (prelecture) test at the beginning of primary. The score is the sum of the correct answers to the four sub-tests composed of the following tasks: 1) circling the word presented orally from a list of four written options; 2) circling a meaningless “pseudoword” presented orally from a list of four written options; 3) circling the specified letter "x" (written) among a series of letters; 4) circling the specified letter "x" (said orally) among a series of letters.

Germany: Modified Peabody Picture Vocabulary Test (PPVT) administered in Grade 1 (Berendes et al., 2013) which measures receptive vocabulary (identification of the picture corresponding to a word presented orally/by a CD player from a set of four options). Test results were IRT-scaled by the NEPS data centre.

United States: ECLS-K:2011 Spring 1st grade Reading Test score (IRT scaled). The ECLS-K Reading Test administered in 1st grade was based largely on the National Assessment of Educational Progress (NAEP) Reading Frameworks for 2009 (Najarian et al., 2018). The test included items on basic literacy skills (e.g., print familiarity, word recognition), vocabulary knowledge, and reading comprehension (Tourangeau et al., 2019).

Netherlands: “When the children were [approximately] 6 years old (...), the children were invited to visit the Generation R research centre, where their vocabulary comprehension was assessed using a subtest of a Dutch battery: Taaltest voor Kinderen (TvK). This test battery is composed of subtests that provide information about expressive and receptive vocabulary skills

in children aged four to 6 years. In the receptive subset, each item of the test consists of two pictures, and the child has to choose the alternative that matches the given words. Due to the length of the original test and the need to minimise the burden on the children, we selected 27 difficult items from the full battery of 40 items. We added together the total correct answers for each child and divided this sum by the total number of items answered, yielding a percentage correct score” (Ghassabian et al., 2014: 72).

United Kingdom: British Ability Score II (BAS II) Word Reading test (IRT scaled). Children read aloud a series of words (10 words per block) presented on a card by the MCS interviewer. The Word Reading test captured students word decoding ability such as the recognition and oral reading of single words as well as vocabulary knowledge (Elliott et al., 1996).

Japan: The JCPS Japanese language tests consisted of vocabulary and grammar as well as reading and writing of kanji characters. Although the test items for Grades 1 and 2 differ, every item of the tests is vertically equated across grades using item response theory (IRT), and the estimated latent Japanese language theta scores were used for analysis (Yamaguchi et al., 2019). The JCPS tests were mailed to consenting households and were then mailed back. The instructions asked that the child answer the questions by him/herself and immediately seal the completed questionnaire using the seal enclosed in the envelope and then hand it to his/her parent.

Comparability issues

The language/literacy test instruments described above clearly differ in the specific item questions they contain but also potentially in the skill sub-domains which they are intended to measure. For example, the German and Dutch tests are purely measures of receptive vocabulary

(ability to identify the correct picture corresponding to a spoken word) and do not assess reading skills such as recognition of written letters or words. The key issue for the purposes of this study is whether instrument differences bias estimates of the *SES gradients* in achievement test scores. Domain differences in the nature of skills assessed will only lead to biases if those domains differ in the extent to which they are socially graded; for example, if knowledge of written letters/words is more strongly associated with parental education than is (oral) receptive vocabulary. A separate consideration is the reliability or accuracy of tests in measuring the target unobserved underlying construct. Less reliable (more “noisy”) tests will lead to attenuation bias and greater underestimation of the SES gradient.

To address these issues, we first note that scores on a number of the test instruments have been used successfully in previous peer-reviewed cross-national studies, sometimes even using the same samples as in this study. For example, Passaretta et al. (2022) conduct comparative analyses using the same variables as this study from the UK MCS and the Germany NEPS, as well as a similar measure of language/emergent literacy from a Dutch sample (the COOL study, rather than Generation-R as in this study). Linberg et al. (2019) compare results using the same measures as this study from the German NEPS and the US ECLS-K:2011, although their score on the ECLS-K Reading test was administered when children were one year younger (in Spring Kindergarten rather than 1st grade). Bradbury et al. (2019) use an expressive vocabulary measure from an earlier wave of the MCS (at age 5) and compare this with an ECLS-K Reading test score administered in an older cohort (the ECLS-K:1998) in Fall Kindergarten. They argue that the inclusion of items related to letters and print in the latter is unlikely to substantially affect estimates of the test score gaps. Indeed, in one US cohort study —the ECLS Birth Cohort—test developers collapsed the separate measures of children’s vocabulary and literacy into a single

scale, explaining that “it was determined that separate language and literacy scores were no longer appropriate” (Najarian et al., 2010:76–77).

As a further piece of evidence in support of the similarity of SES gradients in language and reading skills in early-to-mid childhood, we were able to compare results using alternative measures from the UK MCS. As noted above, the MCS administered the BAS Naming Vocabulary scale, a test of expressive vocabulary (a picture-based test that did not involve written words or letters) when children were age 5. We opted not to use it in our main analysis because children in the other five countries were aged at least 6 when assessed and the age 7 BAS Word Reading test aligns better cross-nationally in terms of child age. Table A1 below reproduces our main results from Table D1 with a row added for results based in the MCS age 5 expressive language score. It is clear that despite the difference in competencies measured as age 7 and age 5 (reading of words versus oral naming of pictured objects respectively) and the two-year time difference, the SES gradients estimated for the UK are virtually identical on the two measures. This gives us some confidence that the gradients estimated for the other countries would not be sensitive to differences in the sub-domains of language and literacy skills assessed, or in small differences in the timing of measurement.

Nevertheless, to some extent measurement differences are an inherent feature of cross-national research that apply even when a single common instrument is translated into different languages, as in the PISA study (Arffman, 2010). It is necessary to bear this in mind when interpreting any comparative study and to avoid over-interpreting cross-national differences that are small in magnitude.

Although differential test reliabilities are potentially an issue, it is important to realise that plausible differences in reliabilities often only lead to relatively small biases in practice.

Achievement test reliabilities are typically thought to range between 0.70 and 0.95 (Reardon, 2011: Table 5.A2), giving a ratio of a hypothetically “high” reliability instrument to a “low” one of 1.36. The ratio of the highest (Germany) to the lowest (Japan) partial eta-squared estimates among our 6 countries (shown in Table D1) is $19.5 / 4.6 = 4.24$. Even the ratio between the highest and second highest (US) partial eta-squareds is $19.5 / 12.4 = 1.57$. The magnitudes involved, therefore, suggest that differential measurement reliability could not account for the pattern of cross-country differences found in practice, although it is possible that some estimates are biased downwards slightly more than others.

Mathematics test scores

France: DEPP Mathematics test, administered at the beginning of primary school. The final score is a sum score of the correct answers to several exercises designed as follows: 1)

Completion tests: students had to add in the boxes provided for this purpose: 3, 17, 29, 70 (items 1 to 4); 2) Quantity comparison tests, in which two-point alignments were presented. These two alignments included either the same number (items 5 to 8) or different numbers of tokens (items 6, 7 and 9). In addition, the length of the rows was either congruent with the number (item 6; item 9: the longest row contains the + of items) or not congruent with the number (item 7; item 8: the longest row does not necessarily contain tokens); 3) Simple arithmetic problems (with one operation) in which the children had to mark the result by ticking each of the 6 numbers presented; 4) An enumeration test in which they must count 17 objects and select the number obtained from 6 presented (both as dominoes and in writing Arabic numerals).

Germany: NEPS Grade 1 Mathematics test. Constructed by the NEPS to cover content-related (i.e., quantity, space and shape, change and relationship, data and change) and process-related components (i.e., applying technical skills, representing, modelling, communicating, problem

solving; Schnittjer et al., 2020). The test consisted of 22 items and used a picture-based answer format. Test results are IRT-scaled by the NEPS data centre and available in the Scientific Use Files.

United Kingdom: Adapted version of the National Foundation for Educational Research (NFER) Progress in Maths test (ability score). The test assessed mathematical skills and knowledge by asking children 20 questions covering such topics as numbers, spaces, measurement, and data handling. The test was read aloud to children at their homes, and they were asked to complete a series of calculations in a paper and pencil exercise. All children had to complete an initial test and were then routed to an easier, medium, or harder section on the basis of their initial score (Chaplin Gray et al., 2010).

United States: ECLS-K:2011 Mathematics test (IRT-scaled). The assessment framework was based on that developed for the National Assessment of Educational Progress and for the Principles and Standards for School Mathematics guidelines of the National Council of Teachers of Mathematics. The assessment was designed to measure skills in conceptual knowledge, procedural knowledge, and problem-solving. The test consisted of questions on number sense, properties, and operations; measurement; geometry and spatial sense; data analysis, statistics, and probability; and patterns, algebra, and functions. A set of routing items was administered to all students, and then the students' scores on these items determined which second-stage test (low, middle, or high difficulty) they received (Najarian et al., 2020).

Japan: The JCPS mathematics tests consisted of calculations and questions expressed in words concerning numbers and the manipulation of figures. Although the test items for Grades 1 and 2 differ, every item of the tests is vertically equated across grades using the item response theory (IRT), and the estimated latent mathematics theta scores were used for analysis (Yamaguchi et

al. 2019). The JCPS tests were mailed to consenting households and were then mailed back. The instructions asked that the child answer the questions by him/herself and immediately seal the completed questionnaire using the seal enclosed in the envelope and then hand it to his/her parent.

Table A1. Percent of variation in literacy scores at age 6-8 accounted for by parental education and income group (partial eta-squared), with alternative measures for the UK

	A. Joint contribution (total SES gradient)	Gross contributions:		Net contributions:		F. Shared contribution
		B. Education	C. Income	D. Education	E. Income	
France	6.84 (0.43)	5.79 (0.40)	4.63 (0.38)	2.21 (0.26)	1.05 (0.19)	3.58 (0.24)
Germany	19.53 (1.03)	16.90 (1.03)	12.46 (0.88)	7.06 (0.71)	2.62 (0.43)	9.84 (0.62)
US	12.36 (0.64)	9.76 (0.57)	9.38 (0.58)	2.98 (0.33)	2.60 (0.31)	6.78 (0.37)
Netherlands	11.46 (0.85)	8.72 (0.83)	9.36 (0.79)	2.10 (0.47)	2.74 (0.50)	6.61 (0.52)
UK (age 7 reading)	10.07 (0.48)	7.69 (0.43)	7.73 (0.44)	2.34 (0.25)	2.38 (0.25)	5.35 (0.27)
UK (age 5 vocabulary)	9.45 (0.45)	6.82 (0.41)	7.77 (0.42)	1.68 (0.21)	2.63 (0.26)	5.14 (0.27)
Japan	4.58 (1.32)	3.25 (1.09)	1.41 (0.72)	3.17 (1.09)	1.33 (0.72)	0.08 (0.31)

Notes: Columns sum as follows: A = B + E = C + D = D + E + F. Standard errors in parentheses.

Additional references

- Arffman, I. (2010). Equivalence of translations in international reading literacy studies. *Scandinavian Journal of Educational Research* 54(1), 37-59. <https://doi.org/10.1080/00313830903488460>
- Berendes, K., Weinert, S., Zimmermann, S., & Artelt, C. (2013). Assessing language indicators across the lifespan within the German National Educational Panel Study (NEPS). *Journal for Educational Research Online*, 5(2), 15–49. <https://doi.org/10.1080/00313830903488460>

- Bradbury, B., Waldfogel, J., & Washbrook, E. (2019). Income-related gaps in early child cognitive development: Why are they larger in the United States than in the United Kingdom, Australia, and Canada? *Demography*, *56*(1), 367–390. <https://doi.org/10.1007/s13524-018-0738-8>
- Chaplin Gray, J., Gatenby, R., Simmonds, N., & Huang, Y. (2010). *Millennium Cohort Study Sweep 4: Technical Report (Second Edition)*. London: Centre for Longitudinal Studies.
- Elliott, C. D., Smith, P., & McCulloch, K. (1996). *British Ability Scales II*. Windsor, Berkshire. NFER-NELSON Publishing Company.
- Ghassabian A., Rescorla L., Henrichs J., Jaddoe V.W., Verhulst F.C., & Tiemeier, H. (2014). Early lexical development and risk of verbal and nonverbal cognitive delay at school age. *Acta Paediatrica*, *103*, 70–80. <https://doi.org/10.1111/apa.12449>
- Linberg, T., Schneider, T., Waldfogel, J., & Wang, Y. (2019). Socioeconomic status gaps in child cognitive development in Germany and the United States. *Social Science Research*, *79*, 1–31. <https://doi.org/10.1016/j.ssresearch.2018.11.002>
- Najarian, M., Snow, K., Lennon, J., & Kinsey, S. (2010). *Early Childhood Longitudinal Study, Birth Cohort (ECLS-B), Preschool–kindergarten 2007 psychometric report (NCES 2010-009)*. National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education. <https://nces.ed.gov/pubs2010/2010009.pdf>
- Najarian, M., Tourangeau, K., Nord, C., Wallner-Allen, K., & Mulligan, G. M. (2018). *Early Childhood Longitudinal Study, Kindergarten Class of 2010–11: First- and second-grade psychometric report (NCES 2018-183)*. Washington, DC. National Center for Education Statistics. <https://nces.ed.gov/pubs2018/2018183.pdf>
- Najarian, M., Tourangeau, K., Nord, C., Wallner-Allen, K., Vaden-Kiernan, N., & Mulligan, G. M. (2020). *Early Childhood Longitudinal Study, Kindergarten Class of 2010–11: Third-grade, fourth-grade, and fifth-grade psychometric report (NCES 2020-123)*. Washington, DC. National Center for Education Statistics. <https://nces.ed.gov/pubs2020/2020123.pdf>

- Passaretta, G., Skopek, J., & van Huizen, T. (2022). Is social inequality in school-age achievement generated before or during schooling? A European perspective. *European Sociological Review*, jcac005, <https://doi.org/10.1093/esr/jcac005>
- Reardon, S. F. (2011). Online Appendix to The widening academic-achievement gap between the rich and the poor: New evidence and possible explanations. In G. J. Duncan & R. J. Murnane (Eds.), *Whither opportunity? Rising inequality, schools, and children's life chances*. Russell Sage Foundation. https://www.russellsage.org/sites/default/files/duncan_murnane_online_appendix.pdf
- Schnittjer, I., Gerken, A.-L., & Petersen, L.A. (2020). *NEPS Technical Report for Mathematics – Scaling Results of Starting Cohort 2 in Fourth Grade* (NEPS Survey Paper No. 69). Bamberg.
- Tourangeau, K., Nord, C., Lê, T., Wallner-Allen, K., Vaden-Kiernan, N., Blaker, L., & Najarian, M. (2019). *Early Childhood Longitudinal Study, Kindergarten Class of 2010–11 (ECLS-K:2011) User's Manual for the ECLS-K:2011 Kindergarten–Fifth Grade Data File and Electronic Codebook, Public Version (NCES 2019-051)*. Washington, DC. National Center for Education Statistics. <https://nces.ed.gov/pubs2019/2019051.pdf>
- Yamaguchi, K., Shikishima, C., Hoshino, T., Shigemasu, K., & Akabayashi, H. (2019). Vertical scaling of academic ability tests for elementary school first year students through junior high school third year students (in Japanese). *The Japanese Journal of Psychology*, 90, 408–418. <https://doi.org/10.4992/jjpsy.90.18221>

Appendix B. Income measures

Table B1 below provides information on the raw income variables provided within the national datasets. The extent to which taxes and transfer payments were included in the definition of income varied across surveys. For example, the pre-tax measure used in the French survey specified that social security contributions be deducted; the post-tax measure used in the Netherlands survey specified that child allowances be excluded. Our assumption is that taxes and transfers will affect the variance of the income distribution but not the ranking position of households.

Continuous imputed income variables were generated for all countries as part of the core multiple imputation (MI) process. The MI model included all analysis variables plus sets of auxiliary variables that included measures of parental employment, parental occupation/social class, receipt of welfare benefit and income from other survey waves, depending on data availability. The MI equation for income was specified in natural logs for all surveys, to better approximate a normal distribution.

For surveys with partly or wholly banded income data, an interval regression model was used for the MI prediction equation for income. This involved specifying a lower and an upper bound value for each observation: where the exact income value was known the two bounds were identical, otherwise they were the boundary values of the selected response option. Post-imputation, continuous income values were generated for all banded and missing cases by predicting from the interval regression model. This process ensures that the exact value predicted for an individual household will always lie within the specified boundaries of the selected response category. Where responses were banded or missing, this exact value will vary across imputations, hence it is not possible to report means and standard deviations of continuous income for the single observed unimputed sample of cases in the majority of countries.

The imputed continuous values were equivalized by dividing through by the square root of household size and then categorized into quintile groups, with survey weights applied when defining the quintile boundaries. When income measures from multiple waves were averaged (to approximate a measure of permanent income, used in sensitivity analyses only), the imputed continuous income values were deflated using a national price index prior to equivalization, averaging and conversion to quintile groups.

Table B1. Survey income measures

Country	Net or gross?	Missing data pre-imputed? ^a	Banded response categories?	Question wording	Supplemental waves ^b
France	Gross	No	Partly ^c	<p>[1] “Amount of money family has a month: wages, salaries and bonuses, income from a self-employed professional activity, long-term unemployment benefits, unemployment benefits, pensions, sickness or disability benefits, family benefits and scholarships (family allowances, single parent allowance, study grant), rents (if you have real estate or land that you rent), interest, savings income, dividends, alimony.”</p> <p><i>If [1] was not answered, [2] was asked,</i></p> <p>[2] “Family monthly income net of social contributions before taxes – in bands”, with 15 options ranging from less than 400 euros to 10,000 euros or more.</p>	Age 10
Germany	Net	No	Partly ^c	<p>[1] “In many areas, childcare and vocational training for children can be costly. Now, we would like to look at all of the income from your entire household: What is the current monthly household income from all the members of the household? Please give the net amount, after deduction of all taxes and social security contributions. Please include regular payments such as pensions, rent allowance, parental and child allowance, student loans/grants, alimony payments, unemployment benefits, etc.”</p> <p><i>If [1] was not answered, [2a] was asked, with respondents then routed into [2b] on the basis of their response:</i></p> <p>[2a] “It would help us if you could at least roughly assign yourself to one of the following categories. Is your monthly net income less than 2,000 euros, 2,000 to less than 4,000 euros or 4,000 euros and more?”</p> <p>[2b] Select from one of 9 narrower bands ranging from less than 1000 euros to more than 6000 euros.</p>	Grade 2, Grade 3

Country	Net or gross?	Missing data pre-imputed? ^a	Banded response categories?	Question wording	Supplemental waves ^b
US	Gross	Yes	Yes	<p>“{In studies like this, households are sometimes grouped according to income.} What was the total income of all persons in your household over the past year, including salaries or other earnings, interest, retirement, and so on for all household members?”</p> <p><i>Response options:</i> 18 bands with range: \$5000 or less to \$200,001 or more.</p>	Spring Kindergarten
Netherlands	Net	No	Yes	<p>“What is the net income of your household per month (your income plus that of your partner, if any)? By this, we mean income from work, benefits and or assets that you receive ‘clean’ every month. The income of live-in children or other persons must only be counted if it contributes to the household (room and board). You do not need to include income such as vacation allowance, child allowance and rent subsidy. If you receive your income on an annual basis, for example if you are self-employed, please divide that income by twelve.”</p> <p><i>Response options</i> 11 bands with ranges: Less than 800 euros per month to more than 5600 euros per month</p>	Age 0, Age 3
UK	Net	Yes	<p>In survey data: Yes;</p> <p>In pre-imputed data: No</p>	<p>“This card shows incomes in weekly, monthly and annual amounts. Which of the groups on this card represents you [^and your husband/wife]'s total take-home income from all these sources and earnings, after tax and other deductions. Just tell me the number beside the row that applies to your joint incomes.”</p> <p><i>Response options</i> 19 bands with different thresholds depending on whether respondent has a co-resident partner. Bands for single-parent households range from Less than £20 per week to £1270 per week or more; bands for two-parent households range from Less than £30 per week to £1920 per week or more.</p>	Age 3, Age 5

Country	Net or gross?	Missing data pre-imputed? ^a	Banded response categories?	Question wording	Supplemental waves ^b
Japan	Net	Yes	No	<p>“About how much was your household’s annual take-home income (total take-home income of all family members with the same household finances, after tax and social insurance deductions) last year (Jan.-Dec.)? Do not include any income from private insurance receipts or the sale of assets (financial assets or real assets).”</p> <p>Each household answered in units of 10,000 yen and since it is an open-ended question, no imputation is used.</p>	Up to 4 survey waves between 2009 and 2018 (all waves in which household participated)

^a Imputed values for missing income data were generated by the survey providers; the derived variables provided in the dataset were used in our analysis.

^b Income measures taken from additional waves beyond the target wave (as shown in Table 2), used in the multiple imputation model and in the calculation of averaged income quintiles for sensitivity analysis.

^c Respondents were first asked to give an exact continuous income figure. Only if respondents were unable to answer this question were they routed to an alternative question which asked them to select from banded categories.

Appendix C. Missing data and imputation

Table C1. Missing data

	FR	GE	US	NL	UK	JP
Imputed sample N	13,759	5,571	10,750	5,599	13,798	820
Literacy sample N	13,297	5,365	10,250	5,599	13,355	820
(%)	(96.6%)	(96.3%)	(95.2%)	(100%)	(96.8%)	(100%)
Mathematics sample N	13,335	5,378	10,250	-	13,517	820
(%)	(96.9%)	(96.5%)	(95.1%)		(98.0%)	(100%)
Percent imputed within literacy sample:						
Mother's Education	4.7	2.2	0 ^a	15.0	0.6	0.7
Father's Education	6.2	3.8	0 ^a	19.6	11.8	0.6
Income	5.8	12.9	0 ^a	19.6	0.1 ^a	4.9
Child's gender	0	0	0	0	0	0
Age at assessment	0	1.4	0	0	0	3.5
Foreign born parents	1.5	0	<0.1	3.6	1.8	-
Foreign language	10.3	14.7	<0.1	38.5	0	-
Family structure	0.9	4.5	0	46.0	0	0

^a Derived variables supplied by the data provider with missing values already imputed.

All ECLS-K sample sizes are rounded to the nearest 50 in accordance with NCES statistical disclosure rules.

Imputation was conducted on the sample of cases with a valid survey weight supplied by the data providers as the target wave, i.e. the sample who participated in the survey in any way at that time point. Due to lack of appropriate survey weights for the Dutch and Japanese target samples, imputation for the Dutch sample was conducted on the sample of cases with valid achievement score data and imputation for the Japanese sample was conducted for children who were assessed in both JCPS 2013 and 2014 (e.g., children who were grade 1 in 2013 and 2 in 2014). Literacy and

mathematics scores were included in the joint multiple imputation model for all variables to improve the precision of prediction. Cases with missing values on the dependent variables were then excluded from the analytical models of interest (von Hippel, 2007). Our method precluded the estimation of comparable models on a non-imputed, complete case, sample for countries where income data was banded (see Appendix B) because quintile groups were defined based on continuous predictions from the MI model. Hence quintile group membership varied across imputed datasets even when household income band was observed in the data.

Additional reference

von Hippel, P. T. (2007). Regression with missing Ys: An improved strategy for analyzing multiply imputed data. *Sociological Methodology*, 37, 83–117. <https://doi.org/10.1111/j.1467-9531.2007.00180.x>

Appendix D. Supplementary tables

Table D1. Percent of variation in literacy scores at age 6-8 accounted for by parental education and income group (partial eta-squared)

	A. Joint contribution (total SES gradient)	Gross contributions:		Net contributions:		
		B. Education	C. Income	D. Education	E. Income	F. Shared contribution
France	6.84 (0.43)	5.79 ^J (0.40)	4.63 ^J (0.38)	2.21 (0.26)	1.05 (0.19)	3.58 ^J (0.24)
Germany	19.53 ^{F,J,N,K,S} (1.03)	16.90 ^{F,J,N,K,S} (1.03)	12.46 ^{F,J,N,K,S} (0.88)	7.06 ^{F,J,N,K,S} (0.71)	2.62 ^F (0.43)	9.84 ^{F,J,N,K,S} (0.62)
US	12.36 ^{F,J,K} (0.64)	9.76 ^{F,J,K} (0.57)	9.38 ^{F,J,K} (0.58)	2.98 (0.33)	2.60 ^F (0.31)	6.78 ^{F,J,K} (0.37)
Netherlands	11.46 ^{F,J} (0.85)	8.72 ^{F,J} (0.83)	9.36 ^{F,J} (0.79)	2.10 (0.47)	2.74 ^F (0.50)	6.61 ^{F,J,K} (0.52)
UK	10.07 ^{F,J} (0.48)	7.69 ^{F,J} (0.43)	7.73 ^{F,J} (0.44)	2.34 (0.25)	2.38 ^F (0.25)	5.35 ^{F,J} (0.27)
Japan	4.58 (1.32)	3.25 (1.09)	1.41 (0.72)	3.17 (1.09)	1.33 (0.72)	0.08 (0.31)

Notes: Columns sum as follows: A = B + E = C + D = D + E + F. Standard errors in parentheses.

Superscripts indicate that partial eta-squared is significantly greater than in country i ($p < .05$), where i , takes values F (France), G (Germany), S (US), N (Netherlands), K (UK), J (Japan).

Table D2. Country contexts in 2005

	France	Germany	United States	Netherlands	United Kingdom	Japan	OECD average
Income inequality (Gini)	0.281	0.298	0.381	0.271	0.335	0.321	0.311
Age at first tracking	15 (grade 9)	10 (grade 4) ^a	18 (grade 12)	12 (grade 6)	16 (grade 11)	15 (grade 9)	-
ECEC spending (% GDP)	1.20	0.37	0.33	0.43	0.75	0.33	0.49
Non-ECEC family spending (% GDP)	1.73	1.68	0.37	1.11	2.09	0.38	1.37

Sources: OECD (2009) *Society at a Glance* (Gini coefficients); Strello et al. (2021) (age at first tracking); OECD Family Database (ECEC and family spending). Gini coefficients are for disposable income. Social spending figures are taken from 2005, Gini coefficients from the mid-2000s, in order to align approximately with analysis cohort birth years. ^a Tracking takes place at age 12 in two states, Berlin and Brandenburg.

Additional references

OECD (2009). *Society at a glance 2009*. OECD Publishing.

Strello, A., Strietholt, R., Steinmann, I., & Siepmann, C. (2021). Early tracking and different types of inequalities in achievement: difference-in-differences evidence from 20 years of large-scale assessments. *Educational Assessment, Evaluation and Accountability*, 33(1), 139-167.
<https://doi.org/10.1007/s11092-020-09346-4>

Appendix E. Extensions and robustness checks

We explored the contribution of demographic composition to the social gradients by adding indicators, where available, for family structure, presence of a foreign-born parent and whether a foreign language is spoken in home to the set of baseline controls. We then re-calculated the contribution of parental education and income to the achievement variance, net of demographic differences. The results, provided in Appendix Tables E1 to E3, show that the pattern of cross-country differences from the original specification remains largely intact. The average percent of variation explained by parental education and income across the six countries falls from 10.6% to 7.0%, indicating that demographic differences contribute in a non-trivial way to the social gradient. They also help to account, in part, for the variation in the gradient across countries. Controlling for demographic composition reduces the social gradient by most in Germany and least in France and Japan, so that country differences in the remaining social gradients become more compressed. Nevertheless, marked differences remain with, for example, the percent of variance explained jointly by education and income in Germany still 2.7 and 7.6 percentage points greater than in the US and Japan respectively, down from 7.2 and 15.5 percentage points when demographic characteristics are not controlled (Appendix Table E1). Adjusting for demographic composition has a particularly marked effect in the Netherlands, driven entirely by the controls for foreign-born parent and home language (Appendix Table E2). The remaining Dutch SES gradient drops below that recorded for the UK and approaches the size of the gradient for France, an adjustment likely related to the nature of the Dutch sample, which is

drawn from the city of Rotterdam, a city that is more demographically diverse than the Netherlands as a whole.

Our main specification uses the “dominance approach” to characterizing parental education, in which the education level of the less-educated parent (if they are present) is assumed to contribute nothing to the children’s achievement. We tested the sensitivity of results to this assumption by adapting the model with baseline demographic controls, described above, to include a more fine-grained measure of parental education. Specifically, we replaced the indicators for highest parental qualification (two dummies) with indicators of the educational attainment of the mother/main carer and of the resident father/partner (four dummies) if any. The increment in achievement variance explained was small and relatively similar in all countries, ranging from 0.2 and 0.3 percentage points in Japan and the US, respectively, to 0.6 percentage points in Germany and 0.7 in the Netherlands (Appendix Table E4). Hence, we find little evidence that a simple household-level measure of parental education leads to significant distortions in the magnitude of the social gradient or the way it differs across countries.

We were conscious household income measured in a single year is liable to measurement error and will pick up transitory fluctuations that tend to bias downwards the estimated contribution of income to explained variance in achievement. To give some sense of the potential magnitude of this bias, wherever possible we calculated a measure of average income (in constant prices) over multiple waves and used this to define average income quintile groups in place of the single-year quintile group measure (results available on request). The number and timing of these additional income measures could not be harmonised across datasets (varying between 2 and 4), so results are only indicative. Perhaps surprisingly, the gross contribution of income changed very little when calculated using this averaged definition of income and even fell very slightly in several

countries (results available on request). The largest effect was seen for the UK, where incomes from the age 7 survey wave were averaged with those from the age 3 and age 5 waves. This resulted in a rise in the estimated gross contribution of income by 1.2 percentage points (from 7.7 to 8.9) and a fall in the net contribution of education of 0.6 percentage points, leading to an increase of just 0.6 percentage points (a 6% increase) in the overall percentage of achievement variance explained. We tentatively conclude, therefore, that the finding that parental education is a stronger driver of early achievement inequalities is unlikely to be purely a measurement artefact.

Finally, we repeated our main analyses using mathematics, rather than literacy, test scores for the five countries in which they were available (with the Netherlands omitted). In some respects, patterns were broadly similar, in that the social gradients were comparatively weak in Japan and France and high in Germany (Appendix Figures E1 and E2; Table E5). Country differences, however, were less marked in mathematics than in reading. The percent of variance explained jointly by education and income was higher in mathematics than in literacy in the US and Japan, but lower in maths than in literacy in Germany and the UK. As a result, contrary to the case for literacy, differences between Germany and the US, and between the UK and Japan, were not significant. The more muted differences in the SES gradient between countries in mathematics indicate that interactions between parental SES and the macro context are not uniform; the evidence presented here suggests the impact of parental SES on the development of children's literacy skills differs more across countries than its impact on numeracy skills. Nevertheless, the pattern of results is consistent in showing a clear distinction between the high inequality

countries of Germany and the US and the lower inequality countries of the UK, France and Japan.

Table E1. Percent of variation in literacy scores at age 6-8 accounted for by parental education and income group (partial eta-squared), with and without controls for demographic characteristics

	Total SES gradient (%)			Gross contribution of education (%)			Gross contribution of income (%)		
	Demographic controls:			Demographic controls:			Demographic controls:		
	No	Yes	Change	No	Yes	Change	No	Yes	Change
France	6.8	5.8	-1.0	5.8	5.4	-0.4	4.6	3.6	-1.0
Germany	19.5	11.0	-8.5	16.9	9.1	-7.8	12.4	6.6	-5.8
US	12.3	8.3	-4.1	9.8	6.5	-3.3	9.4	5.6	-3.8
Netherlands	11.4	6.0	-5.4	8.7	4.7	-4.1	9.3	4.0	-5.3
UK	10.0	7.9	-2.1	7.7	5.6	-2.1	7.7	6.0	-1.7
Japan	4.0	3.4	-0.7	3.1	2.2	-0.8	1.0	1.1	0.1

Notes: Numbers show the percent of the variance contributed jointly by parental education and income group over an initial set of control variables (i.e. $R^2[M4] - R^2[M1]$). Models with demographic controls include indicators for family structure, presence of a foreign-born parent and foreign language spoken in the home (only a single-parent indicator is included for Japan). Slight discrepancies in the baseline estimates compared to those reported in the main text are due to bootstrapping of the latter to derive standard errors.

Table E2. Baseline regression models (M1), with and without demographic controls

	France		Germany		United States	
	(1)	(2)	(1)	(2)	(1)	(2)
Age at assessment	-0.057*** (0.006)	-0.051*** (0.005)	0.024*** (0.005)	0.024*** (0.003)	0.021*** (0.004)	0.017*** (0.002)
Child is female	0.188*** (0.018)	0.185*** (0.017)	-0.041 (0.040)	-0.056* (0.024)	0.217*** (0.023)	0.227*** (0.019)
Foreign born		-0.239*** (0.036)		-0.245*** (0.046)		-0.024 (0.033)
Parents						
Foreign language at Home		-0.051* (0.023)		-0.656*** (0.051)		-0.292*** (0.033)
Single parents		-0.166*** (0.027)		-0.111** (0.038)		-0.387*** (0.025)
Stepfamilies		-0.197*** (0.044)		-0.229*** (0.058)		-0.333*** (0.040)
Constant	4.040*** (0.437)	3.678*** (0.363)	-2.027*** (0.443)	-1.596*** (0.217)	-1.862*** (0.334)	-1.312*** (0.192)
R-squared	.0195	.0316	.0147	.2069	.0189	.062
Observations	13297	13297	5365	5365	10250	10250

	Netherlands		United Kingdom		Japan	
	(1)	(2)	(1)	(2)	(1)	(2)
Age at assessment	0.025*** (0.002)	0.032*** (0.002)	0.038*** (0.003)	0.044*** (0.003)	0.027*** (0.006)	0.029*** (0.005)
Child is female	0.111*** (0.028)	0.106*** (0.025)	0.174*** (0.019)	0.156*** (0.017)	0.027 (0.084)	0.142* (0.070)
Foreign born		-0.130** (0.048)		0.217*** (0.028)		
Parents						
Foreign language at Home		-0.381*** (0.050)		-0.113*** (0.032)		
Single parents		0.000 (0.049)		-0.341*** (0.021)		0.159 (0.187)
Stepfamilies		-0.000 (0.049)		-0.331*** (0.035)		
Survey wave	-	-	-	-	X	X
Constant	-1.966*** (0.138)	-2.157*** (0.155)	-3.376*** (0.306)	-3.864*** (0.250)	-2.936*** (0.611)	-3.050*** (0.507)
R-squared	.0329	.1026	0.0203	.0503	.0776	.0779
Observations	5599	5599	13355	13355	820	820

Notes: Reference categories: High education, 5th income quintile, two biological parents. For Japan, we cannot distinguish between biological parents and stepparents. *** $p < .001$, ** $p < .01$, * $p < .05$.

Table E3a. Regressions of literacy scores at age 6-8 on parental education and income group, with and without demographic controls

	France		Germany		United States	
	(1)	(2)	(1)	(2)	(1)	(2)
Low education	-0.444*** (0.027)	-0.432*** (0.027)	-0.899*** (0.067)	-0.671*** (0.047)	-0.520*** (0.036)	-0.546*** (0.028)
Medium education	-0.181*** (0.022)	-0.174*** (0.023)	-0.313*** (0.041)	-0.279*** (0.027)	-0.238*** (0.029)	-0.258*** (0.024)
1 st Income quintile	-0.346*** (0.035)	-0.318*** (0.035)	-0.529*** (0.083)	-0.500*** (0.052)	-0.518*** (0.043)	-0.469*** (0.036)
2 nd Income quintile	-0.176*** (0.031)	-0.178*** (0.031)	-0.289*** (0.056)	-0.207*** (0.038)	-0.317*** (0.039)	-0.272*** (0.034)
3 rd Income quintile	-0.116*** (0.029)	-0.115*** (0.030)	-0.130* (0.052)	-0.131*** (0.035)	-0.156*** (0.038)	-0.125*** (0.031)
4 th Income quintile	-0.062* (0.026)	-0.062* (0.028)	-0.041 (0.045)	-0.068* (0.033)	-0.034 (0.033)	-0.029 (0.031)
Age at assessment	-0.042*** (0.006)	-0.039*** (0.005)	0.036*** (0.004)	0.032*** (0.002)	0.021*** (0.003)	0.019*** (0.002)
Child is female	0.190*** (0.017)	0.185*** (0.016)	-0.001 (0.034)	-0.041 (0.022)	0.220*** (0.025)	0.219*** (0.018)
Foreign born Parents		-0.121*** (0.035)		-0.163*** (0.043)		0.023 (0.031)
Foreign language at Home		0.053* (0.023)		-0.516*** (0.049)		-0.066* (0.032)
Single parents		0.026 (0.028)		0.200*** (0.040)		-0.059* (0.026)
Stepfamilies		-0.107* (0.043)		-0.113* (0.055)		-0.098* (0.039)
Constant	3.326*** (0.417)	3.121*** (0.354)	-2.496*** (0.372)	-2.088*** (0.207)	-1.486*** (0.289)	-1.267*** (0.183)
R-squared	0.088	0.089	0.209	0.317	0.142	0.145
Observations	13297	13297	5365	5365	10250	10250

Notes: Reference categories: High education, 5th income quintile, two biological parents. *** $p < .001$, ** $p < .01$, * $p < .05$.

Table E3b. Regressions of literacy scores at age 6-8 on parental education and income group, with and without demographic controls

	Netherlands		United Kingdom		Japan	
	(1)	(2)	(1)	(2)	(1)	(2)
Low education	-0.491*** (0.068)	-0.499*** (0.061)	-0.425*** (0.031)	-0.395*** (0.024)	-0.411*** (0.107)	-0.375*** (0.092)
Medium education	-0.253*** (0.042)	-0.250*** (0.035)	-0.289*** (0.027)	-0.233*** (0.023)	-0.344*** (0.103)	-0.274** (0.084)
1 st Income quintile	-0.540*** (0.052)	-0.412*** (0.057)	-0.509*** (0.037)	-0.567*** (0.032)	-0.030 (0.148)	-0.200 (0.127)
2 nd Income quintile	-0.306*** (0.050)	-0.251*** (0.049)	-0.404*** (0.034)	-0.414*** (0.029)	0.035 (0.132)	-0.061 (0.109)
3 rd Income quintile	-0.203*** (0.044)	-0.154*** (0.043)	-0.236*** (0.031)	-0.233*** (0.028)	-0.184 (0.138)	-0.231* (0.110)
4 th Income quintile	-0.121** (0.039)	-0.090* (0.042)	-0.141*** (0.030)	-0.134*** (0.027)	-0.195 (0.130)	-0.106 (0.108)
Age at assessment	0.039*** (0.002)	0.038*** (0.002)	0.041*** (0.003)	0.045*** (0.003)	0.027*** (0.006)	0.029*** (0.005)
Child is female	0.114*** (0.027)	0.111*** (0.024)	0.176** (0.017)	0.160** (0.016)	0.038 (0.084)	0.144* (0.070)
Foreign born				0.220*** (0.027)		
Parents		-0.078 (0.045)		0.109*** (0.032)		
Foreign language at Home		-0.217*** (0.050)				
Single parents		0.226*** (0.054)		-0.006 (0.023)		0.343 (0.195)
Stepfamilies		-0.114 (0.146)		-0.120*** (0.035)		
Survey wave	-	-	-	-	X	X
Constant	-2.523*** (0.144)	-2.437*** (0.153)	-3.098*** (0.282)	-3.532*** (0.240)	-2.603*** (0.595)	-2.469*** (0.504)
R-squared	0.147	0.163	0.121	0.130	0.118	0.116
Observations	5599	5599	13355	13355	820	820

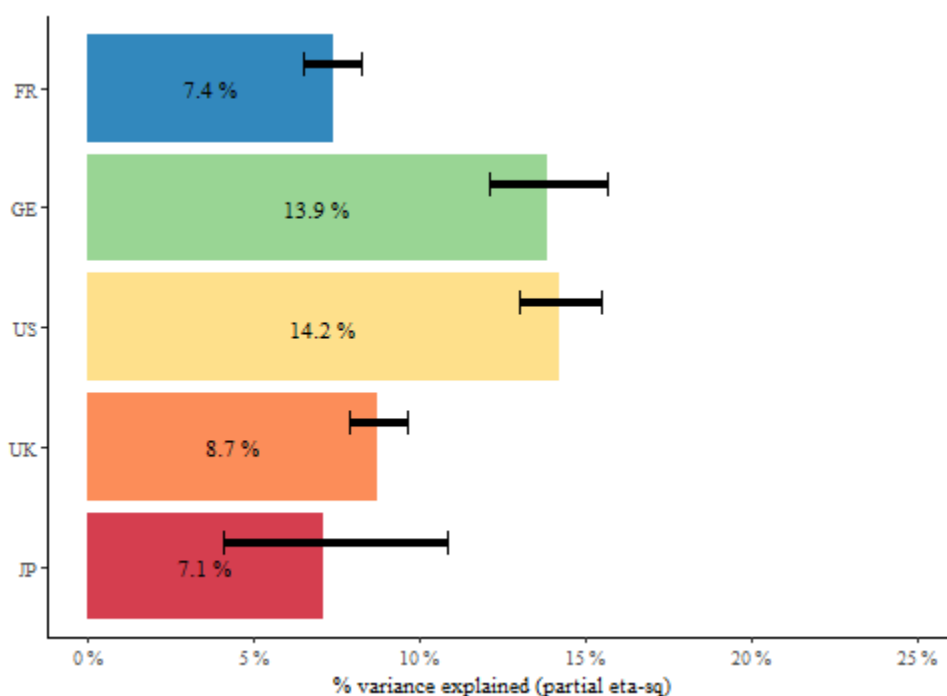
Notes: Reference categories: High education, 5th income quintile, two biological parents. For Japan, we cannot distinguish between biological parents and stepparents. *** $p < .001$, ** $p < .01$, * $p < .05$.

Table E4. Percent of variation in literacy scores at age 6-8 accounted for by parental education and income group (partial eta-squared), with household and individual-level measures of parental education

	Total SES gradient (%)			Gross contribution of education (%)			Gross contribution of income (%)		
	Education indicators:			Education indicators:			Education indicators:		
	HH	Ind	Change	HH	Ind	Change	HH	Ind	Change
France	5.8	6.1	+0.3	4.9	5.4	+0.5	3.3	3.3	-
Germany	11.0	11.6	+0.6	9.1	9.9	+0.8	6.6	6.6	-
US	8.3	8.6	+0.3	6.5	6.9	+0.5	5.6	5.6	-
Netherlands	6.0	6.7	+0.7	4.7	5.9	+1.2	4.0	4.0	-
UK	7.9	8.4	+0.5	5.6	6.4	+0.8	6.0	6.0	-
Japan	3.4	3.6	+0.2	2.2	2.5	+0.3	1.1	1.1	-

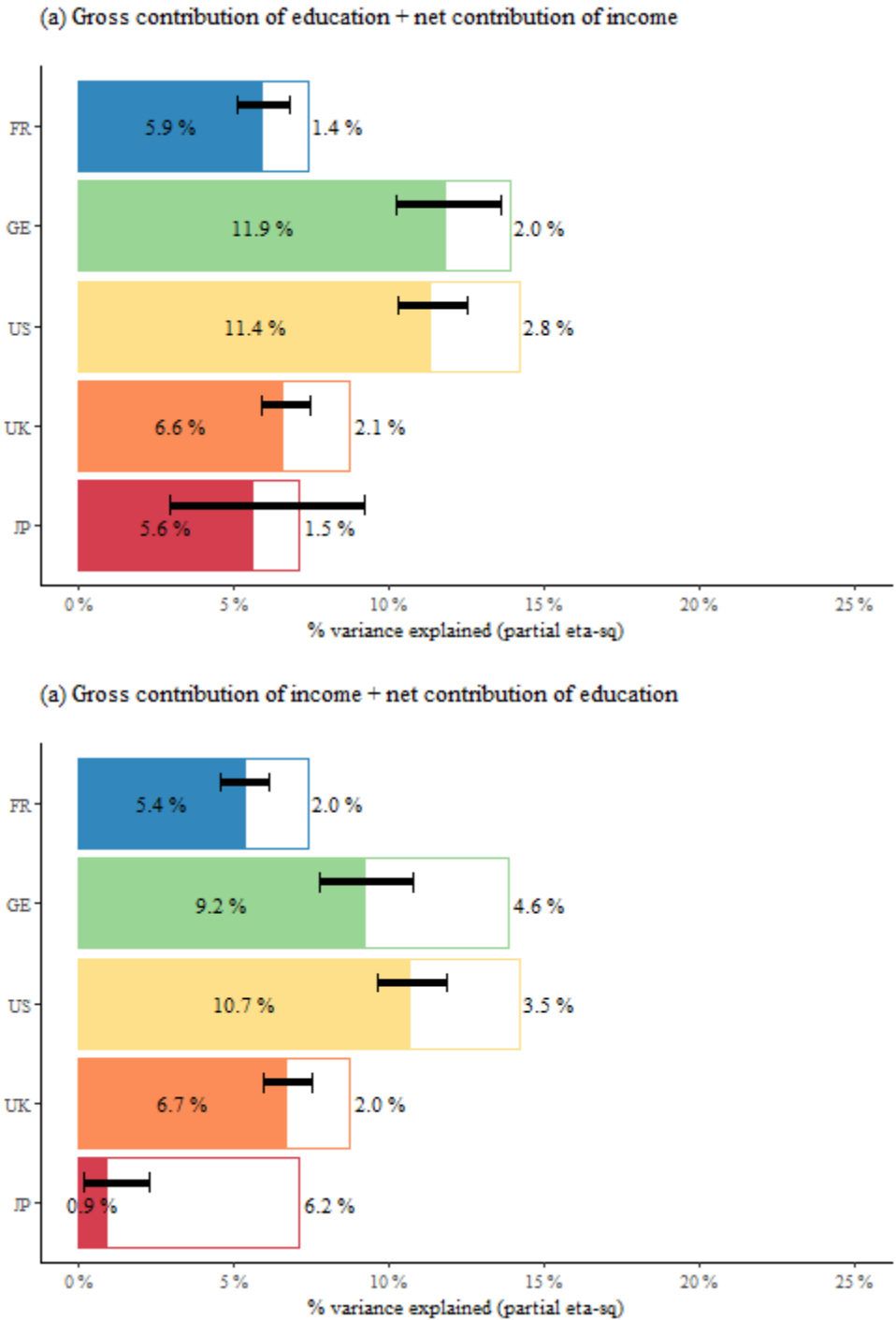
Notes: Numbers show the percent of the variance contributed jointly by parental education and income group over an initial set of control variables (i.e. $R^2[M4] - R^2[M1]$). All models include controls for family structure, presence of a foreign-born parent and foreign language spoken in the home (only a single-parent indicator is included for Japan). The household-level measure of education uses the highest education attained by a resident parent. The individual-level measure uses separate variables for the education level of the mother/main carer and resident father/partner.

Figure E1. Percent of variance in mathematics scores at ages 6-8 accounted for by SES: joint contribution of parental education and income group



Note: See notes to Figure 1.

Figure E2. Alternative decompositions of the percent of variance in mathematics scores at age 6-8 accounted for by parental SES



Note: See notes to Figure 2.

Table E5. Percent of variation in mathematics scores at age 6-8 accounted for by parental education and income group (partial eta-squared)

	A. Joint contribution (total SES gradient)	Gross contributions:		Net contributions:		F. Shared contribution
		B. Education	C. Income	D. Education	E. Income	
France	7.38 (0.46)	5.93 (0.42)	5.37 ^J (0.39)	2.01 (0.25)	1.45 (0.21)	3.92 ^J (0.26)
Germany	13.86 ^{F,K,J} (0.91)	11.86 ^{F, K,J} (0.87)	9.23 ^{F, K,J} (0.76)	4.63 ^{F, K} (0.56)	2.01 (0.35)	7.22 ^{F,K,J} (0.54)
US	14.19 ^{F,K,J} (0.64)	11.37 ^{F,K,J} (0.59)	10.72 ^{F,K,J} (0.57)	3.48 ^{F,K} (0.33)	2.82 ^F (0.30)	7.90 ^{F,K,J} (0.38)
UK	8.71 ^F (0.46)	6.63 (0.40)	6.72 ^{F,J} (0.42)	1.98 (0.22)	2.08 ^F (0.24)	4.64 ^J (0.26)
Japan	7.10 (1.71)	5.64 (1.55)	0.93 (0.55)	6.18 ^{F,K} (1.63)	1.46 (0.73)	-0.54 (0.41)

Notes: Columns sum as follows: A = B + E = C + D = D + E + F. Standard errors in parentheses.

Subscripts indicate that partial eta-squared is significantly greater than in country i ($p < .05$), where i , takes values F (France), G (Germany), S (US), K (UK), J (Japan).