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STATE-OF-THE-ART REVIEW

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Inadequacies in the SES–Achievement model: Evidence from PISA and other studies

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Abstract

Students' socioeconomic status (SES) is central to much research and policy deliberation on educational inequalities. However, the SES model is under severe stress for several reasons. SES is an ill-defined concept, unlike parental education or family income. SES measures are frequently based on proxy reports from students; these are generally unreliable, sometimes endogenous to student achievement, only low to moderately intercorrelated, and exhibit low comparability across countries and over time. There are many explanations for SES inequalities in education, none of which achieves consensus among research and policy communities. SES has only moderate effects on student achievement, and its effects are especially weak when considering prior achievement, an important and relevant predictor. SES effects are substantially reduced when considering parent ability, which is causally prior to family SES. The alternative cognitive ability/genetic transmission model has far greater explanatory power; it provides logical and compelling explanations for a wide range of empirical findings from student achievement studies. The inadequacies of the SES model are hindering knowledge accumulation about student performance and the development of successful policies.

KEYWORDS
assessment, educational psychology, socioeconomic circumstances

Context and implications

Rationale for this study

This review was written in response to the disconnect between the literature surrounding student achievement studies, and the cognitive psychology and behavioural genetic academic literatures. It is well-established that student achievement is closely related to cognitive ability and both have sizable genetic components, findings largely ignored in achievement studies. This review's aim is for more considered responses to socioeconomic inequalities in student achievement by both researchers and policymakers.

Why the new findings matter

The review provides overwhelming evidence that much of the current thinking about SES and student achievement is mistaken.

Implications for researchers and policymakers

The current emphasis on SES is misleading and wastes considerable human and financial resources that could much better be utilized. The focus should be on student performance ensuring that low achievers have rewarding educational and occupational careers, and raising the overall skill levels of students, not on the nebulous, difficult to measure, concept of SES, which is only moderately associated with achievement.

INTRODUCTION

Students' socioeconomic status (SES) is the most prominent explanatory concept in studies of student achievement, and education more generally. It is central to the model which assumes that educational inequalities are primarily due to students' SES or aspects of SES, such as parents' education, occupational class, family income and wealth. The SES model has generated thousands of publications on the extent of socioeconomic inequalities in education; theoretical accounts for its relationships with education; its measurement; the role of schools, teachers and other factors as mediators of SES effects; and policies aiming at reducing educational inequalities. SES figures prominently in reports on education by national and international agencies, research organisations and non-government stakeholders.

Over the last 50 years, there have been numerous technical advances in psychometrics, sampling, survey design, measurement and statistics. Today, there is no shortage of high quality, national and international studies, and system-wide longitudinal studies producing individual-level data that can be analysed efficiently on easily affordable computers. In contrast, there has been, arguably, little progress in understanding socioeconomic inequalities in education since Jencks et al. (1972). The very concept of SES is as vague as it was in the early 1970s. There is a plethora of theoretical accounts for SES effects, none of which reach consensus among researchers, but instead serve as justifications for further research. The variables that typically measure SES are often unreliable and are not highly intercorrelated, undermining the presumption that SES is a valid and reliable concept. SES effects on student achievement are surprisingly moderate and are probably declining. They are weak when considering cognitive ability and especially weak when considering prior achievement. Furthermore, there is little evidence that policies designed to reduce SES inequalities in student achievement have been successful. Policies falling short of their objectives often lead to calls for increased funding rather than examination of the policies' fundamental assumptions.

In this review, we provide evidence that the SES model is failing. There are serious problems with many aspects of the SES model: conceptualisation, measurement, theory and its inability to account for empirical phenomena. The SES model produces misleading results. SES is an inadequate control for the estimation of school, teacher (or classroom) and programme effects. The alternative cognitive ability/genetic transmission model accounts for the SES–achievement relationship and a range of related empirical phenomena that cannot be accounted for by the SES model.

The core components of the cognitive ability/genetic transmission model are: causal relationships between parents' cognitive abilities and their socioeconomic characteristics; the genetic transmission of cognitive ability and other achievement-relevant traits (e.g., motivation, conscientiousness) from parents to their children; and strong effects of cognitive ability and, to a lesser extent, other achievement-relevant traits on student achievement.

The cognitive ability/genetic transmission model does not imply that schools and education systems are irrelevant. Students' knowledge and skills are almost entirely the product of students learning from teachers in schools. The cognitive ability/genetic transmission rests on empirically credible assumptions about the sources of variation in student performance and implies more nuanced policies with achievable goals. For example, the elimination of socioeconomic inequalities in student achievement is not a realistic goal, but maximising the academic performance of students facing social impediments or from disadvantaged backgrounds, increasing the general performance of all students, and ensuring low achievers do not fall too far behind are worthwhile and realisable goals.

It could be argued that the SES and the cognitive ability/genetic transmission models are not fundamentally different. There are many studies that include measures of SES and cognitive ability in the same analysis. However, the two models rest on very different assumptions. The SES approach assumes that the effects of SES represent purely sociological processes, for example parenting, economic and cultural resources, and schools. In contrast, the cognitive ability/genetic transmission approach assumes that SES effects include the genetic transmission of achievement related traits, as well as family and school effects. Estimating the 'true' effects of SES involves considering both cognitive ability and genetics.

The next section of this review outlines the OECD's Programme for International Student Assessment (PISA) as an internationally prominent exemplar of the SES model. It is arguably one of the most influential forces in global education (Zhao, 2020). The following four sections discuss the concept of SES, its measurement, theoretical explanations for SES inequalities in student achievement, and the seldom acknowledged explanatory weaknesses of the SES model. A further section discusses the cognitive ability/genetic transmission model. The final section shows that the cognitive ability/genetic transmission model accounts for the observed SES–achievement relationships and a range of relevant empirical phenomena that the SES model cannot account for.

THE OECD'S PISA STUDY

The OECD's PISA study aims to assess the skills of 15-year-old students necessary for their adult lives (Schleicher, 2007). The first PISA round of data collection was in 2000. PISA assesses student performance in representative samples of 15-year-olds in participating countries using standardised tests in the core domains of reading, mathematics and science. In each triennial round of PISA, one core domain is the major domain for which each student is tested, with a larger number of test items covering several subdomains: reading in 2000, mathematics in 2003, science in 2006, reading again in 2009 and so forth.

PISA is based on a dynamic model of lifelong learning. It seeks to assess what students can do with the skills they have learned. Unlike most other achievement studies, the PISA tests are not based on national curriculums (Koretz, 2009). Performance in PISA at age 15 has strong associations with school grades and subsequent educational outcomes (e.g., school completion, university and college), and more moderate relationships with early labour market outcomes (Fischbach et al., 2013, pp. 141–165; Knighton & Bussière, 2006; OECD, 2010b, 2018).

The number of participating countries in PISA has steadily increased since 2000. For PISA 2018, all 37 OECD countries participated, along with 42 partner countries or regions. Approximately 600,000 students completed the assessment, representative of about 32 million 15-year-olds globally (OECD, 2019b, pp. 34–35).

Policy impact

In terms of policy, PISA has had substantial impacts on national-level policies around student assessment, curriculum standards and reforms, and perhaps education funding. One of the best-known instances was Germany, where disappointing results for PISA 2003—the 'PISA shock' (Breakspear, 2014, p. 5)—led to a series of reform measures: the introduction of national rather than regional standards and greater support for disadvantaged students (Ertl, 2006). In Denmark, there was widespread debate and concern over why its well-funded school system produced only middling outcomes in PISA, prompting reforms in student evaluation, the curriculum and greater supports for disadvantaged and immigrant-family students (Egelund, 2008). Japan's decline in PISA performance between 2000 and 2003 led its Ministry of Education to reverse some newly implemented curriculum policies (Takayama, 2008). In Switzerland, disappointing PISA results led to significant educational reforms (Bieber & Martens, 2011). PISA results may have acted to confirm and reinforce existing institutional arrangements and policies in Finland and New Zealand, which have been consistently strong performers (Dobbins, 2010; Dobbins & Martens, 2012; Grek, 2009).[1] The USA's muted responses to disappointing PISA scores were attributed to the significant domestic evaluation programmes already in place which had forewarned the public and policymakers of poor national outcomes (Bieber & Martens, 2011). Grek (2009) argued that PISA had become a powerful and influential indirect tool; national results are used to legitimise policy reforms, with major effects on the curricula and pedagogy. Within Europe, PISA has become a major resource for government: 'it provides knowledge and information about systems, and implants constant comparison … without the need for new or explicit forms of regulation in education' (Grek, 2009, p. 35). Generally, politicians, bureaucrats, academics, and educational journalists and commentators are aware of their country's standing in PISA and other large-scale international assessments.

PISA sample and achievement measures

Within countries, the core PISA sample is drawn by first randomly selecting 150 schools with probabilities proportional to size and second, randomly selecting 42 students from selected schools (OECD, 2020, Chapter 4). Some countries draw larger samples for various reasons: to have representative samples of states or provinces, to select greater proportions of disadvantaged students, or to form the base for a longitudinal study. The application of weights provided with the data generates representative samples of 15-year-olds for each participating country.

PISA uses an Item Response Theory (IRT) model which assumes that the probability of a student correctly answering a test item is a function of a latent student ability dimension (for that domain) and item difficulty (Hambleton et al., 1991). This allows for very flexible test designs since test items can be considered as a sample from the population of test items, each with estimable parameters. The PISA rotated design means that students are asked to answer only a subset of items, and their responses to other items are predicted by their responses to the responded items and the items' difficulties. An innovation of PISA 2018 was multistage adaptive testing where the test items presented to students are largely based on their responses to previous items (OECD, 2020, chapter 9).

Students' scores are not the sum of correct responses but a set of 5 or 10 'plausible values'. Plausible values represent the range of abilities that students might reasonably have given their responses to the test items administered to them (Wu, 2005). Plausible values are estimated from multidimensional IRT models with correlated latent dimensions for reading, mathematics and science. Plausible values provide better estimates for population parameters, for example means and variances of countries and subpopulations (von Davier et al., 2009). Plausible values are not appropriate for comparisons of individual students (Wu, 2005).

PISA and the SES model

PISA is a prime example of the predominance of the 'SES model' in education. It assumes that student performance is a function of students' SES together with demographic characteristics (e.g., gender, immigrant status) with contributions from schools, teachers and programmes. SES is understood as the primary influence and its effects can be attributed to family and school factors. It is also assumed that school systems and the organisation of learning within schools can affect the SES–achievement relationship. According to the OECD's (2018, p. 13) report on social mobility, based largely on PISA data, 'socio-economic status has a large influence on students' performance in science, reading and mathematics'. The OECD maintains that its SES measure, Economic, Social and Cultural Status (ESCS), is a powerful, but not determining, influence on student achievement (OECD, 2016a, p. 217). Therefore, there is room for system and school-level policies and practices to improve social equity (OECD, 2013, p. 104).

The PISA approach does not seriously engage with the proposition that students' test scores are, at least in part, manifestations of their general cognitive ability with genetic transmission from parents to children. The OECD's PISA study is essentially a blank slate approach. The OECD and its numerous experts appear unaware of, or decided to ignore, Rowe's (1994) *The Limits of Family Influence*, Harris's (2009) *The Nurture Assumption*, Pinker's (2011) *The Blank Slate* and Asbury and Plomin's (2014) *G is for Genes: The Impact of Genetics on Education and Achievement* and the associated large academic literatures. An exception from the OECD (2018, p. 156) is a text box of less than a page entitled 'Can genes predict educational attainment?', which after citing several dated studies leaves the question open (OECD, 2018, p. 156). In contrast to PISA, the educational production function literature in economics specifically includes innate ability together with inputs from home and school (Hanushek, 1979; Todd & Wolpin, 2003).

Every PISA cycle reports the effects of ESCS on student achievement (OECD, 2001, p. 308; 2004, p. 399; 2007, p. 184; 2010c, p. 55; 2013, p. 36; 2016a, p. 46; 2019b, p. 17). Jurisdictions in which ESCS effects are weak and the mean achievement levels are above average, are understood as exemplars of good educational institutional arrangements and policy, whereas jurisdictions in which ESCS effects are relatively strong are criticised and advised to pursue reforms. ESCS is also used as a control variable to examine differences in student performance from a range of likely influences: immigrant status, family structure, school, location, parents' work status, opportunity to learn, teacher quantity and quality, disciplinary climate and other factors (OECD, 2013; 2016a, pp. 248–250; 2019b).

SES is prominent in the academic literature on PISA. According to Hopfenbeck et al. (2018) a substantial number (109) of the articles classified as secondary data analyses of PISA (430) explored educational inequalities relating to SES. In a systematic review, Early et al. (2019) reviewed 23 UK studies on PISA published between 2000 and 2017 of which 19 included single, composite or school-level measures of SES or social class.

The PISA ESCS measure of SES

ESCS is a composite score constructed from principal component analysis of three indicators: highest level of parental education (PARED) and occupational status (HISEI), and home possessions (HOMEPOS) (Avvisati, 2020, p. 8). These three indicators conform to the common idea that SES has three components: education, occupation and income. PARED was derived using the ordinal International Standard Classification of Education (ISCED) categorisations (e.g., primary, lower secondary, upper secondary, etc.). HISEI was derived by mapping students' reports of their parents' occupations onto the international socio-economic index (ISEI) of occupational status (see section Parents' occupation below).

Since direct income measures could not be collected from students, they are instead asked about household possessions. The HOMEPOS index comprises all the household possessions items (25 items in 2015) that index wealth or economic resources (12 items, e.g., television, room with a shower, car), cultural resources (5 items, e.g., quality and quantity of books, art, musical instruments), educational resources (7 items, e.g., study desk, quiet room to study) and ICT resources (5 items, e.g., computers, e-readers). It also includes books in home (OECD, 2016b, p. 300). There are items common to both the wealth and ICT indices.

In summary, ESCS is a composite constructed from the highest level of education attained by parents, the highest occupational status of the parents, and about 25 measures of economic, cultural and educational resources, and since 2003 'books in the home'. Changes to the ESCS measure between PISA waves had undermined its comparability, so it was reconstructed to produce more comparable measures for all PISA waves (OECD, 2014, p. 353).

Large-scale achievement studies do not routinely collect data on family income. However, since 2006 there has been a national PISA option of a parent questionnaire, which may include a standard question on family income. However, the PISA family income data has only been used in a few studies (e.g. Chmielewski & Reardon, 2016; Marks & Pokropek, 2019; OECD, 2017a, p. 175). The income data is only for one year whereas economists prefer to collect income data over several years to measure families' permanent incomes as this is a better indicator of families' economic standing (see Muller, 2010). Accurate data on wealth are even more difficult to gather, requiring detailed information on assets and liabilities. Achievement studies such as PISA, as noted above, rely on household possessions as a proxy for income and wealth.

The OECD (2011) developed the concept 'resilient students' defined as students that overcame disadvantaged socioeconomic origins in their own country and score within the top achievement quartile across all countries/economies. Subsequent reports compare the percentage of resilient students across countries as another indicator of the performance of education systems. The proportions of resilient students are understood as products of the policies and institutional arrangements of education systems.

PISA routinely constructs school-level SES measures by calculating the average ESCS of each school, referred to as schools' socioeconomic background and more recently schools' socioeconomic profile. This measure is used to estimate the proportion of students that attend schools with average school-ESCS scores in the bottom quartile (OECD, 2019b, p. 55).

THE CONCEPT OF SES

Everyone seems to know what SES is, but the concept remains nebulous. SES is generally understood as something to do with social advantage and disadvantage, or socioeconomic standing (APA, 2018). There is no consensus on the operational definition of the concept (Broer et al., 2019, p. 8). The absence of a generally accepted operational definition for SES has generated a great variety of SES measures used in studies of student achievement and other outcomes. White (1982, p. 462) notes it was not uncommon for SES to be defined tautologically by its constituent variables.

Buchmann (2002, p. 150) and Bradley and Corwyn (2002) endeavoured to provide SES with theoretical legitimacy by invoking well-known theoretical concepts, the Marxist concept of capital, human capital from human capital theory (Becker, 1975), cultural capital (Bourdieu & Passeron, 1990) and social capital (Coleman, 1988). These concepts are not directly relevant to SES measures in large-scale student achievement studies.

The Marxist concept of capital, which refers to anything that can be economically productive (e.g., land, machinery, factories, businesses), is not equivalent to family income or wealth. Human capital theory is about the credentials, skills and attributes workers bring to the labour market to sell their labour to employers, not the relationship between parental education and student achievement. Cultural capital theory was developed specifically to explain the reproduction of educational, and thus societal, inequalities. It involves the positive unconscious responses of teachers and other educational 'gatekeepers' to the elite cultural cues transmitted by socioeconomically privileged students. Since achievement studies are invariably based on multiple choice or short answer questions assessed by markers that have no additional information about the students, it is not clear how cultural capital would operate in this context. Social capital focuses on the family and social networks that facilitate students' education. However, its prominence in the literature is not because of SES, but from explaining, differences in achievement between US Catholic and public schools, and ethnic groups (Coleman, 1987; Coleman & Hoffer, 1987).

THE MEASUREMENT OF SES

There is some consensus that SES has three main components: parental occupation and education and family income (Avvisati, 2020; Hoffman, 2003). However, in large-scale assessments it is not possible to collect data on all three components and there are concerns about the accuracy of information collected from students (Broer et al., 2019, p. 8).

SES can be measured by single indicators of SES such as father's and mother's educational attainment, father's and mother's occupational status, family income or family wealth (Bradley & Corwyn, 2002; Buchmann, 2002). There is some tendency for economists to focus on income, sociologists on social class and occupational status, and researchers in education and psychology on parents' education. However, there is much variation in the measures used both within and between disciplines, and all researchers are restricted by the measures available in their data. Parents' education is probably the most common SES measure used in national and international achievement studies followed by father's occupation. Mother's occupation is less commonly used, given the generally lower historic formal workforce participation of mothers compared to fathers.

Multiple measures of SES include two or more indicators in the same analysis and composite SES measures combine two or more indicators into a single variable. Composite measures are preferred because they have stronger associations with educational outcomes, they are simple to use, and single indicator SES measures (e.g., mother's education) are unlikely to index all aspects of SES (Braveman et al., 2005; Buchmann, 2002; NCES, 2012). However, the cost of composite SES measures is conceptual clarity. It is not clear what the effects of composite SES measures mean, especially cross-nationally or over time.

The following section discusses issues surrounding the measurement of SES, frequently referencing the PISA study. It demonstrates that for a variety of reasons, SES measures collected from students are highly problematic.

Parents' education

St John (1970) was perhaps the first to question the reliability and validity of pupils' reports of their parents' education because of high levels of non-response, low correlations with other measures of socioeconomic status, the tendency for pupils to upgrade their parents' levels of education, and differential reporting across racial groups. Looker's (1989, p. 275) meta-analysis concluded that children's reports of parental education were unreliable, because of high levels of non-response and low correlations between children and parent reports. Lien et al. (2001) describes the strength of agreement between the adolescents' and parents' reports of parental education as low, with kappa[2] statistics of 0.30 for father's education and 0.37 for mother's education. For four countries, Engzell and Jonsson (2015) report only moderate correlations between 0.46 and 0.61 for parent and child reports on parents' education.

For PISA, the median correlations for parents' and their 15-year-old child's reports of parents' education converted into continuous measures are unimpressive: 0.63 for mothers and 0.64 for fathers (Schulz, 2005, table 5). A later study also found only moderate agreement between 15-year-old students and their parents' reports, with the average kappa statistic of only 0.49, and much variation between countries ranging from 0.36 for Denmark to 0.76 for Turkey (Jerrim & Micklewright, 2014, p. 772). Correcting for reliability would dramatically increase the effects of parental education in Denmark, but much less so for Turkey. The sizeable variation between countries in the correspondence between parents' and their children's reports undermines cross-national comparisons of the effects of parents' education, and thus ESCS on PISA test scores.

Furthermore, agreement between students and their parents' education is, in part, a function of, or endogenous to, students' test scores. Higher-achieving students provide more accurate reports. For Germany, Kreuter et al. (2010) found that students with higher math scores tend to provide reports that are more consistent with that of their parents, and note that differential measurement error undermines within and between country comparisons. Jerrim and Mickelwright (2014, p. 774) also found that students who agree with their parents on their parents' education level, score, on average, about 0.2 of a national standard deviation higher on the PISA reading test.

Parents' occupation

In PISA, students are asked the occupations of each parent and the information is coded according to the International Classification of Occupations (ISCO), and then converted to

ISEI scores (OECD, 2017b, pp. 298–299). ISEI is a worldwide scale that scores occupations based on the educational levels and incomes of the incumbents of narrowly defined occupational groups. ISEI scores are constructed by conceiving occupation as the mechanism that transfers educational credentials into earnings. It is constructed by optimal scaling of ISCO occupational unit groups (Ganzeboom & Treiman, 1996, p. 212; Ganzeboom & Treiman, 2010).

Students' reports of parents' occupations are more accurate than their reports of parental education, but there is a far from perfect correspondence. In a PISA field trial, the correlations between child and parents' reports of the parents' occupation converted to ISEI scores ranged from 0.70 to 0.86 across countries (Adams & Wu, 2002, p. 221). Schulz (2005, table 4) reported median ISEI correlations constructed from parents' and children's reports around 0.8 with one country falling below 0.6. Jerrim and Mickelwright (2014, pp. 772–773) reported kappa statistics ranging from 0.58 to 0.86 for ISEI across countries in PISA with an average of 0.63 (compared to 0.49 for parents' education). Only about 70% of 15-year-old students agreed with their parent on the occupational category of that parent's occupation when presented with a choice of five categories.

Books in the home

'Books in the home' is a component of ESCS and has been used to measure scholarly culture and cultural capital (Evans et al., 2014; Sieben & Lechner, 2019). It has been used extensively in academic research for a very long time, and tends to show comparable or stronger effects on achievement than parents' education and occupation (see Engzell, 2019). It was used extensively by Chmielewski (2019) in her paper on increasing SES gaps in student achievement.

Books in the home is even more problematic than parents' education. Jerrim and Mickelwright (2014, p. 772) reported kappa statistics less than 0.2 between parents and their 15-year-old children's reports on the number of books in the home, indicating only 'slight' agreement. They (2014, p. 774) also found that students who agree with parents' estimates, score higher in PISA reading, with the extreme case of England, where children who agree with their parents' estimate, score, on average, 0.35 standard deviations higher than those who disagree. Engzell (2019) concluded that books in the home is endogenous to student achievement because low achievers accrue fewer books of their own and are also prone to underestimate the number of books in the home. He concludes that the endogeneity of the books in the home measure distorts cross-country patterns and invalidates many common study designs.

Household wealth and possessions in the home

The OECD argues that household assets are a valid measure of wealth. According to the PISA 2014 technical report 'Household assets are believed to capture wealth better than income because they reflect a more stable source of wealth' (OECD, 2014, p. 316). This is a highly questionable claim given that the household items listed in the questionnaire includes possessions that in Western countries are almost universal (e.g., cars, bathrooms, mobile phones, computers, dictionaries, desks for study) so would be only weakly correlated with direct measures of income and wealth. The 'cars' item lacks face validity. Wealthy families living in high density city centres (e.g., London, New York, Paris) are less likely to have cars than poorer suburban, regional or rural families. Analysing household assets in several cross-national studies, including PISA, Traynor and Raykov (2013) conclude that between one-third and one-half of the wealth score variability is attributable to measurement error. Although the OECD (2020, Annex E) study updates the country-specific home possession items, it is not possible to confidently assert that PISA household possession indices measure wealth.

Intercorrelations of SES components

Although the ESCS composite SES measure is used frequently, its constituent variables are not highly intercorrelated. Among OECD countries, in the PISA 2000 data the correlations of wealth (the home possessions index), educational resources and cultural possessions with mother's and father's education and occupation were all below 0.3. Among ESCS constituent variables, the strongest correlation was between father's education and occupation at 0.46 (Marks, 2011, p. 227). Analysing Irish 2006 PISA data, Gilleece et al. (2010, p. 479) note that ESCS components are not strongly interrelated: 13 of the 15 intercorrelations were between 0.18 to 0.37.

Since the ESCS indicators are, at best, only moderately intercorrelated, ESCS does not have high reliability. Rutkowski and Rutkowski (2018, p. 360) estimated ESCS reliabilities ranging from 0.6 to 0.8. This means that between 20% and 40% of the variance in ESCS is error variance. Therefore, ESCS is an unreliable measure of an ill-defined concept.

Cross-national comparability

Caro et al. (2014) examined the cultural, social and economic capital constructs in PISA and PIRLS[3] data using exploratory structural equation modelling. They found that the constructs are not reflected equally across countries. Only for a few pairs of countries were the sociological constructs somewhat comparable (2014, p. 447). Similarly, Rutkowski and Rutkowski (2013, p. 259) conclude that the home possessions index has ‘highly variable reliability by country, poor model-to-data consistency on a number of subscales, and evidence of poor cultural comparability’. Pokropek et al. (2017) constructed a consistency measure of a PISA 15-item home possessions index from 33 OECD countries based on PISA 2012. Australia, Canada, Japan, Turkey and, especially, Mexico exhibited low comparability with other OECD countries. A subsequent analysis assessing consistency between countries and over time found even less consistency. They (2017, p. 254) concluded ‘in almost all of the countries examined, more than half of the home possessions items did not show sufficient fit indexes to be considered comparable both across time and across countries’. Problematic items included those relating to the possession of art and literature—items intended to capture cultural resources—and items about computer software.

One apparent explanation for the low comparability over time of the home possessions index is that some countries became richer between 2000 and 2015 (e.g., Portugal, Spain, Chile, Hungary, Poland and Greece) so there was less differentiation between households in their possessions. However, comparability was also low in economically stable Canada and France. So, comparisons of home possessions construct scores and their effects on achievement across nations and over time are very likely to be misleading.

Obscuring possible social processes

Rindermann and Baumeister (2015) point out that composite measures of SES do not allow for understanding possible causal mechanisms behind the positive correlations between

SES and achievement. It is easier to interpret the effects of family income, mother's education or father's occupation on student achievement than the effects of the amorphous ESCS measure without a meaningful metric. Similarly, O'Connell (2019) found differences in the relative effects of parental education and possessions across countries—parental education had stronger effects in wealthier countries and vice versa for poorer countries—concluding that composite measures of SES hide potentially interesting country differences. Furthermore, concepts such as cultural capital and educational resources in the home, are supposed to *explain* SES differences in student achievement rather than contribute to the measurement of SES.

THEORETICAL ACCOUNTS FOR THE SES EFFECTS ON ACHIEVEMENT

There are many theoretical explanations for the relationship between SES and student achievement. Bradley and Corwyn (2002) surmise that explanations for SES effects on children involve differences in access to material and social resources, or reactions to stress-inducing conditions by both children and their parents. Buchmann (2002) posits three processes responsible for the SES–education relationship—financial capital, cultural status and social connections—corresponding to the theoretical concepts of economic capital, cultural capital and social capital. Shavit et al. (2007) list economic resources, cultural resources, significant others' influences (teachers, peers and parents), educational differentiation (between-school tracks and within-school streams, sets or programmes) and rational choice on the costs and benefits of schooling.[4]

The effects of parental occupation or social class on education have been attributed variously to: working class oppositional culture (Willis, 1977), parental attitudes to the value of education (Chen & Uttal, 1988; Hyman, 1966), codes of speech (Bernstein, 1971), parenting styles (Baumrind, 1966, 1989), middle- and working-class cultures (Lareau, 2002), and the richness and complexity of the language used by parents to their children (Hart & Risley, 1995).

Explanations for the effects of parental education include the family's educational resources, home literacy environments (Park, 2008; but see Puglisi et al., 2017), scholarly culture measured by books in the home (Evans et al., 2014) and the frequency of reading to children (Kalb & van Ours, 2014). Brown and Iyengar (2008) account for the effects of parental education on achievement by parental beliefs and attitudes concerning the value and utility of education, stimulating home behaviours and, notably, the transmission of cognitive competencies.

Explanations for income effects focus on the ability of families to utilise resources to improve their children's outcomes (Chmielewski & Reardon, 2016). Obviously, richer and wealthier families can access higher-quality childcare, kindergartens and schools than poorer families. In addition, low-income parents, under severe financial pressure, experience greater psychological stress, which may undermine their parenting (Mayer, 1997, p. 45). Yeung and Conley (2008) suggest wealth effects on achievement can be accounted for, at least in part, by a higher-quality home environment and better parenting behaviour. Analysing PISA data, Pokropek et al. (2015) conclude that the root of socioeconomic inequalities in student achievement across the world is access to cultural and educational resources.

Schools also figure in explanations for socioeconomic differences in achievement. One prominent explanation involves between- and within-school tracking (van Domina et al., 2017; van de Werfhorst & Mijs, 2010). The OECD (2019b, p. 44) favours comprehensive systems asserting that educational differentiation exacerbates SES inequalities. Other aspects of schools postulated as important to SES inequalities in achievement include school quality (Rouse & Barrow, 2006), teacher quality (Chiu, 2015), school effectiveness (Hobbs, 2016), school climate (Berkowitz et al., 2017) and school resources (Greenwald et al., 1996; but see Hanushek, 1997).

For SES inequalities in PISA, Martins and Veiga (2010) distinguished countries where individual-level social background factors account for SES inequalities in contrast to countries where school contextual effects (i.e., school SES) predominate. It is not coincidental that the second group of countries mainly have tracked school systems where students are allocated to different types of schools based largely on their prior performance.

No theoretical explanation has achieved consensus among researchers as the explanation most congruent with the range of relevant and available empirical evidence. Almost all have some empirical support, but there are many empirical findings not consistent with the theories. Furthermore, these theoretical explanations assume that SES effects are much stronger than they are. The theories cannot explain the much stronger effects of ability and prior achievement, the substantial genetic components to student achievement. Low-achieving high-SES students and high-achieving low-SES students are two sizeable groups routinely ignored in theoretical discussions on the relationship between SES and student performance.

Once the true effects of SES on achievement have been estimated—that is, its effects net of parents' and their children's abilities—then it could be established what are the primary social mechanisms involved; for example: private schools, tracking and streaming, teachers, home literacy environments and early childhood education.

EXPLANATORY WEAKNESS OF SES

Only moderate SES–achievement correlations

Despite the high-profile SES enjoys in both the research and policy communities, it does not have strong relationships with student achievement. Sirin's (2005, p. 437) meta-analysis found that the average effect size (the adjusted correlation coefficient) for the bivariate relationship between SES measures and student achievement was 0.30, equivalent to explaining 9% of the variance. The most recent meta-analysis concluded that the SES–achievement relationship is surprisingly modest, with an average SES–achievement correlation of 0.22, explaining less than 5% of the variance (Harwell et al., 2017).

ESCS has stronger correlations with student achievement ($r \approx 0.40$) than the composite home possessions index ($r \approx 0.36$), occupational status ($r \approx 0.33$) and parents' education ($r \approx 0.29$) (Lee et al., 2019). In the two most recent PISA rounds, the OECD's composite ESCS measure accounts for, on average, 12–13% of the variation in students' PISA scores across OECD countries (OECD, 2016a, p. 402; OECD, 2019b, p. 18). Although the PISA SES measure comprises many constituent variables, it explains less than 15% of the variation in student achievement in most OECD countries. But this is a vast overstatement of SES's explanatory power, as discussed below.

SES effects are confounded by parental ability

The associations between parents' socioeconomic characteristics and their children's scores in achievement tests cannot naively be interpreted as the effects of parenting, socialisation, and economic and cultural resources since they are confounded by parents' cognitive abilities and genetic transmission from parents to their children. Ability measured during childhood or adolescence is strongly correlated with family SES during adulthood

($r \approx 0.5$), highest level of education reached ($r \approx 0.6$), occupational status ($r \approx 0.5$) and to a lesser extent income ($r \approx 0.2$) (See section, 'Cognitive ability is strongly associated with adult socioeconomic attainments'). Therefore, to an unknown extent, part of the effects of SES can be accounted for by parents' abilities and their genetic transmission. This serious threat to the validity of standard analyses from genetic confounding is almost universally ignored (Freese, 2008; Harden, 2021; Murray, 2020, p. 237).

The effects of SES measures on achievement, net of mother's ability, are weak. Currie and Thomas (1999, p. 302) reported a standardised effect (β) around 0.2 for SES and between 0.6 and 0.7 for mother's Armed Forces Qualification Test (AFQT) score, a commonly used measure of ability,[5] on Peabody Picture Vocabulary Test score among children aged 6 and older. Similarly, Carlson and Corcoran (2001) found that mother's AFQT score had strong effects on their 7- to 10-year-old children's reading and mathematics scores, with much smaller effects for family income and no effects for mother's education. Mother's AFQT score accounts for about half of racial test score gaps in reading and mathematics whereas 'home inputs' account for 10–20% (Todd & Wolpin, 2007). Mayer (1997, pp. 90–91) reported a standardised, but not statistically significant, effect of 0.10 for family income on children's test score, net of parents' education, mother's AFQT score and other factors.

SES effects are weak, net of prior achievement

In the presence of prior achievement, the effects of students' SES are small. Armor et al. (2018, p. 624) analysing state-wide data from North Carolina comprising over 2 million observations found that the standardised coefficients for SES (the measure included parents' education) and prior achievement were 0.06 and 0.72 for mathematics, and 0.07 and 0.69 for reading. From an analysis of the UK Avon Longitudinal study, Nunes et al. (2017, p. 89) found that prior achievement in reading (administered around 8 years of age) accounted for 37% of the variance in science scores at age 11 and SES only 2%. For science achievement at age 14, prior achievement in reading comprehension accounted for 31% of the variance, while SES accounted for 1% of the variance. Analysing combined literacy and numeracy scores in the Australian national assessment programme for New South Wales students, Lu and Rickard (2014, p. 32) reported small effects of student and school SES ($\beta < 0.10$), and very large effects for prior achievement ($\beta > 0.80$). For Germany, Baumert et al. (2010, pp. 159–160) reported no significant effects for the parents' occupation (ISEI score) on mathematics score and only one significant (but trivial) effect for parental education, net of prior achievement (from PISA) in mathematics ($\beta \approx 0.5$) and reading ($\beta \approx 0.2$), and cognitive ability ($\beta \approx 0.2$). Kriegbaum and Spinath (2016) found only small effects of SES ($\beta < 0.10$) including the ESCS measure, on math achievement, net of prior achievement (from PISA 2003), IQ and interest in math. Since SES effects were mediated, to some extent, by children's prior achievement, intelligence and motivation, the authors comment that the SES–achievement correlation should not be understood as an indicator of educational inequity *per se* (Kriegbaum & Spinath, 2016, p. 61).

Ignoring prior achievement is likely to upwardly bias the effects of policy relevant factors. Carnoy et al. (2016) controlled for students' mathematics score from the Trends in International Mathematics and Science Study (TIMSS) administered one year earlier in the analyses of teacher effects in the Russian PISA 2012 study. They conclude that the positive effects of teacher 'quality' and 'opportunity to learn' are much more modest than claimed in PISA reports. Analysing PIRLS data, Caro et al. (2018) argue that without controls for prior achievement, estimates of teacher strategies are spurious. More generally, 'spurious' aptly describes the effects of sociodemographic, schools and other factors in cross-sectional achievement studies that cannot control for prior achievement (e.g., PISA, TIMSS, PIRLS).

Prior achievement poses fundamental challenges to the SES model. The strong to very strong effects of prior achievement place severe limits on the magnitude of SES effects and other contemporaneous influences, like schools, teachers and programmes. These effects will necessarily, at best, be small. The small SES effects found when controlling for prior achievement severely undermines theoretical explanations for SES effects that emphasise contemporaneous factors, such as school tracks and streams, adolescent oppositional cultures, working- and middle-class cultures, teacher quality and school resources. Furthermore, if it is maintained that SES is important to student achievement, then the bulk of its effects must occur at a younger age, before the age of first testing, which would reorientate SES-focused theory to early childhood or even peri-natal environments.

The most common response to the strong efforts of prior achievement is simply to ignore it. But ignoring such a powerful predictor cannot be justified either on theoretical or empirical grounds. Another common response is that prior achievement is simply a function of SES, so can be safely ignored. However, SES cannot account for the effects of prior achievement because it is not possible to explain the effects of a stronger influence ($0.5 < r < 0.9$) by a weaker influence ($0.2 < r < 0.5$). SES is too weakly correlated with cognitive ability for SES to be considered the dominant influence on cognitive ability (see section 'Cognitive ability has stronger correlations with achievement than SES'). The effects of prior achievement do not decline substantially when controlling for SES. They would do so if SES explained the effects of prior achievement. The cognitive ability/genetic transmission model would argue the opposite - and what is found empirically -that the effects of SES decline substantially with the addition of prior achievement.

Fixed effects analyses

Fixed-effects models are used to estimate the effects of a predictor on an outcome, net of the effects of all unmeasured but stable influences (Allison, 2005; Angrist & Pischke, 2009, pp. 221–246). In the educational context, stable influences include student's innate ability, and possibly non-cognitive attributes, such as the Big 5 personality traits. Fixed-effects models examine if changes in a predictor variable (e.g., family structure, family income, father’s or mother's occupational status, type of school attended) are associated with changes in students’ test scores. In essence, individual students are their own controls. Fixed-effects analyses find very small or no effects of SES measures on achievement (Armor et al., 2018; Lauen & Gaddis, 2013; Marks, 2016).

SES theory cannot explain domain differences in SES effects

Dronkers and Róbert (2008, p. 295) contended that reading performance is less dependent on schools and more dependent on parental cultural capital. Logically then, the associations with SES would be lower for mathematics and science than for reading literacy since the former have less cultural content than the latter. A literary home environment where parents value and encourage literary and other cultural pursuits would have less impact on performance in mathematics compared to reading literacy. However, a pattern of stronger SES effects for reading is not supported empirically. Van de Werfhorst et al. (2003, pp. 49–52) report similar reading and mathematics test score means across occupational class groups in the UK. If anything, occupational class differences in mathematics achievement were larger. Similarly, Sirin’s (2005, p. 433) meta-analysis of SES effects reported a slightly larger SES–achievement correlation for mathematics (0.35) than for reading literacy (0.32).

School SES effects are most likely statistical artefacts

The OECD (2018) highlights the effects of schools' socioeconomic status on student performance. On average in OECD countries, a one standard deviation increase in school ESCS is associated with an increase in student performance by 60 score points, net of students' ESCS. In some countries (the Czech Republic, France, Japan, Malta, the Netherlands, Slovenia and Chinese Taipei) the effects are very large - over 100 score points (2018, p. 127). Also, PISA reports often attribute between-school differences in achievement to ESCS. For example, the report on the 2015 assessments concluded that 'On average across OECD countries, 62.6% of the performance differences observed across students in different schools can be accounted for by the socio-economic status of students and schools' (OECD, 2016a, p. 227). These extraordinarily high estimates are good examples of how the SES model is misleading because the estimates would be very much smaller—and credible—if student ability or prior achievement were included in the analyses.

The literature reports small ($\beta < 0.10$) or very small ($\beta < 0.05$) school SES effects controlling for prior achievement. Rumberger and Palardy (2005) estimated standardised school SES effects of 0.05 for mathematics and 0.06 for reading (but 0.20 for science) on achievement growth, net of prior achievement, student SES, ethnicity and other factors. The North Carolina study mentioned earlier estimated standardised school SES effects around 0.05 for both mathematics and reading, net of SES and prior achievement (Armor et al., 2018, p. 624). For English primary schools, Lauder et al. (2010, p. 56) found a small effect for school-level social class for reading and none for arithmetic. For Australia, Lu and Rickard (2014, pp. 31–32) reported standardised school SES effects ranging from 0.03 and 0.13 and Marks (2015) reported estimates around 0.05 or less. For Flanders, Boonen et al. (2014) found no significant effects for school SES (or school prior achievement) on mathematics achievement at the end of second grade, net of prior achievement, student SES and other covariates. From their meta-analysis of school SES, van Ewijk and Sleegers's (2010, p. 147) strongly advise researchers to control for prior attainment to avoid severe upward bias in their school SES estimates. A fixed-effects analysis found no effects for poverty, aggregated by classrooms, on student achievement (Lauen & Gaddis, 2013).

School SES effects, like other aggregated school-level predictors, are likely to be statistical artefacts (Armor et al., 2016; Gorard, 2006; Harker & Tymms, 2004; Hutchison, 2007; Ludtke et al., 2002; Nash, 2003). Recent research has characterised school-contextual effects as 'phantom effects' because the poorer the measure of SES, the stronger the effects of the corresponding school SES measure (Perry, 2019; Pokropek, 2015; Televantou et al., 2015). Marks (2015) added random error to a composite measure of SES that increased, not decreased, the magnitude of school SES effects on student achievement. Analysing PISA data, Zhou and Ma (2021) found the stronger the correlation between prior achievement and present achievement, the greater the chance of phantom effects for school SES.

THE ALTERNATIVE COGNITIVE ABILITY/GENETIC TRANSMISSION MODEL

The alternative cognitive ability/genetic transmission model assumes that student performance in PISA and other achievement tests is mainly a function of general cognitive ability, together with small effects of specific abilities, for example language literacy and mathematics. Cognitive ability has a sizeable genetic component that increases with children's age. Cognitive ability is important to parents' educational and socioeconomic attainments and each parent transmits half their genome to their children.

Conceptually, cognitive ability is very similar to achievement. Its measurement does not rely on students' proxy reports on their parents, and its constituent items are moderately to highly correlated. Furthermore, cognitive ability has much greater explanatory power than SES; it can account for the SES–achievement relationship and a range of empirical phenomena relating to student achievement, which the SES model cannot.

Conceptualisation

In PISA, literacy is defined generally as 'concerned with the capacity of students to apply knowledge and skills in key subject areas and to analyse, reason and communicate effectively as they pose, solve and interpret problems in a variety of situations' (OECD, 2007, p. 16). This definition closely resembles the dictionary definition of intelligence—'the ability to acquire and apply knowledge and skills'[6]—and prominent psychological definitions—'the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience' (Gottfredson, 1997, p. 13) and the 'ability to understand complex ideas, to adapt effectively to the environment, to learn from experience, to engage in various forms of reasoning, to overcome obstacles by taking thought' (Neisser et al., 1996, p. 77). Rindermann (2008, p. 128) maintains that there is no important theoretical difference between student achievement and ability tests, since they both assess 'thinking and knowledge'. Baumert et al. (2009) point out that like intelligence tests, reading and mathematical assessments involve reasoning and making logical inferences. Since PISA is independent of school curriculums, it is more a test of general ability than curriculum-based tests like TIMSS or PIRLS. Armor (2003, p. 19) noted similarities between achievement tests and intelligence tests; both include subset items for different types of mental skills: vocabulary, reading comprehension, mathematical concepts, numerical skills and so on. He suggested that the substantial overlap between IQ and achievement scores indicates they are measuring something in common: general reasoning skills. At the country level, PISA test scores have been used to compare cognitive ability between countries (Burhan et al., 2017; Meisenberg & Woodley, 2013; Weiss, 2009).

Measurement

The measurement of cognitive ability began over a hundred years ago as a way of identifying children who were not likely to be academically successful. Nowadays, intelligence is measured by specifically designed tests usually comprising multiple choice items testing verbal and mathematical reasoning, pattern recognition, spatial and other abilities. Different IQ measures are highly intercorrelated, suggesting they are measuring the same underlying concept. The median correlation of IQ tests with other IQ tests range from 0.64 to 0.81, averaging about 0.77 (Jensen, 1980, pp. 314–315; Jensen, 1998, p. 91).

According to Sternberg (1996, p. 11), the most widely accepted view is that intelligence is hierarchal in structure with general ability '*g*' at the top of the hierarchy and specific abilities at lower levels. *g* is isolated from factor analysis. Different IQ tests and test batteries produce highly correlated estimates of *g* (Bouchard & McGue, 2003; Johnson et al., 2004; Jensen, 1998, pp. 81–83; Johnson et al., 2008).

Cognitive ability is very stable over the school career and its stability increases with age. For New Zealand, the temporal correlations for IQ for children aged 7, 9, 11 and 13 ranged from 0.74 to 0.84 with higher correlations at older ages (Moffitt et al., 1993, p. 463). They (1993, p. 499) conclude that there is very little measurable naturalistic change in IQ across middle childhood and early adolescence, and the changes are idiosyncratic, not associated with environmental changes. For the USA, McCall (1977) documents increasing correlations of childhood IQ and IQ at age 40 with children's age. The correlations between IQ measured at ages 9 and 40 were around 0.70. Jensen (1998, p. 316) concludes that IQ is unstable during very early childhood but from age 2 to 10 it becomes increasingly stable. After age 10, IQ measured at successive ages gradually approaches a correlation of 0.90 with IQ at age 18. According to the 1921 and 1936 Scottish birth cohort studies, the correlation in general intelligence measured at age 11 and old age (about age 80) was 0.7 (Deary et al., 2004; Johnson et al., 2010, p. 60).

Cognitive ability has substantially stronger correlations with achievement than SES

Cognitive ability is more strongly associated with student achievement than SES. Walberg's (1984) meta-analyses calculated correlations of 0.71 and 0.48 for IQ with general and science learning, compared to 0.25 for SES. Kreigman et al.'s (2018, p. 135) meta-analysis estimated a correlation of 0.44 between intelligence and student achievement, rising to 0.60 when correcting for attenuation and range restriction. The correlations were higher for *g* measures of intelligence (0.49) compared to non-verbal measures (0.38), and higher for achievement in mathematics (0.50) than reading (0.43) or English (0.44). According to Zaboski et al.'s (2018) meta-analysis, the correlations of *g* with basic reading, reading comprehension and basic mathematics were all above 0.7. Rindermann (2018, p. 53) cites a German study that concludes the average correlation between cognitive ability and the PISA scales is 0.65.

The sizeable correlations between cognitive ability and achievement imply that the effects of ESCS, schools and other factors on PISA test scores are likely to be substantially upwardly biased without controls for cognitive ability.

SES is too weakly correlated with cognitive ability for SES to be considered the dominant influence on cognitive ability. White's (1982, p. 469) meta-analysis of over 100 studies estimated an average correlation of 0.4 between SES and IQ equivalent to only 16% of the variation. Harwell et al.'s (2017, p. 208) meta-analysis of 86 studies estimated a smaller correlation of 0.27 between SES and IQ. The relationships are likely to be much weaker when considering parents' abilities. Of course, extreme economic and social deprivation or adversity during early childhood undermines cognitive development (Duncan et al., 1994; Plomin & Deary, 2015; Richards & Wadsworth, 2004). However, extreme deprivation and adversity are not synonymous with SES.

Cognitive ability has stronger effects on achievement than SES

Cognitive ability has stronger effects on achievement vis-à-vis SES. In the US 1988 National Education Longitudinal Study, the standardised effects for ability and a composite SES measure on grades at school (GPA) were 0.38 and 0.12, respectively, among eighth grade boys, and 0.42 and 0.07 among eighth grade girls (Dumais, 2002, p. 56). Teachman (1996, p. 36) concludes that intellectual ability 'is by far the most important predictor of grades'. Analysing teacher assessments of 7-year-olds in reading, writing and maths from the UK millennium cohort, Layte (2017) concluded that about two-thirds of the effect of social class is mediated by cognitive ability. The effects of cognitive ability were the largest of many predictors, with insignificant effects for social class, maternal education, mother–child interaction and school in a deprived area, and only small effects for income (2017, p. 498). For Australia, Marks (2016) reported that a one standard deviation increase in early childhood ability increased Year 3 numeracy achievement by 44 score points compared to 10 score points for a comparable one-standard deviation increase in a composite SES measure. For New Zealand, IQ measured at age 8 had a large effect on grades in the tenth grade, net of family income, parents' education and other background factors (Maani & Kalb, 2007). For Ireland, O'Connell (2018) estimated standardised effects for ability at around 0.6 for reading and 0.5 for mathematics among 13-year-olds compared to standardised effects around 0.05 or less for parental education and income. For Germany, Weber et al. (2013) concluded that ability and motivation accounted for 70% of the variation in children's mathematics grades. For Brazil, the standardised effect for intelligence on scholastic achievement among 7- to 11-year-olds was 0.69 whereas the standardised effects for income (0.04) and parents' education (−0.04) were not statistically significant (Colom & Flores-Mendoza, 2007, p. 248). For Israel, the standardised effects of ability on reading and science among eighth and ninth graders were 0.55 and 0.38 respectively, compared to around 0.01 for a composite SES measure (Resh, 1998, p. 426).[7] For Iceland, Thorlindsson (1987) reports standardised effects of 0.54 and 0.26 for verbal ability and social class on grade point average. For Slovenia, the correlation between intelligence and grades in the last four years of the 9 years of primary school was 0.48 and the standardised beta for intelligence was 0.39, net of a cultural capital measure comprising parents' education, participation in cultural activities and economic capital (Flere et al., 2010).

Cognitive ability is strongly associated with adult socioeconomic attainments

SES effects incorporate the effects of parents' abilities. Parents' ability is correlated with commonly used SES measures. Jensen (1998, p. 279) reported correlations of between 0.6 and 0.7 between IQ and years of formal education. Analysing data from the 1979 National Longitudinal Study of Youth (NLSY79), Hauser et al. (2002, p. 207) reported correlations of 0.66 and 0.62 between AFQT score and educational attainment among non-black men and women, and correlations of 0.55 and 0.43, respectively, between AFQT test score and occupational status in 1993, 13 years after the AFQT test data were collected. Strenze's (2007, p. 411) meta-analysis found that ability measured between ages 3 and 23 correlates at 0.56 for educational attainment, 0.45 for occupational status and 0.23 for income during adulthood. Torres (2013, p. 166), also analysing the NLSY79, reported a correlation of 0.53 between mother's AFQT score measured in 1980 and a composite measure of family SES measured 20 or more years later.

Cognitive ability is transmitted from parents to their biological children

The average correlation between parent's (mostly mother's) cognitive ability and their biological child, based on 8000 pairs is 0.42 (Plomin et al., 2013, p. 195). The father–child ability correlation is between 0.4 and 0.5 (Anger, 2012; Black et al., 2009; Grönqvist et al., 2017; Scarr & Weinberg, 1978). The observed parent-child correlations are a little lower than the theoretical correlation of 0.5, which assumes that cognitive ability is a continuous polygenic trait, and each parent and biological child dyad share 50% of their genomes. If both parents are considered, the average correlation between average parental ability and the average ability of their children is around 0.72, close to the theoretical expectation of 0.707 (Bouchard & McGue, 1981).[8]

Cognitive ability has a strong genetic component

Many studies have estimated heritabilities for cognitive ability—that is, the proportion of variation in a trait due to genetic differences—of between 0.5 to 0.8 with much smaller proportions, typically less than 0.2, attributed to the common environment which includes family SES (Deary et al., 2009; van Leeuwen et al., 2008; Nielsen, 2006; Plomin et al., 1997; Plug & Vijverberg, 2003; Rowe et al., 1999). To reiterate, these figures mean that 50% to 80% of the variance in cognitive ability can be attributed to genetic differences between individuals. The heritability of cognitive ability increases during childhood from around 0.4 at age 7 to around 0.8 during late adolescence, at which time the contribution of common environment becomes negligible (Bouchard, 2009, 2013).

Genetic nurture refers to the effects of parents' non-transmitted genes on their offspring's outcomes mediated by the environment that parents create for their children (Bates et al., 2018; Belsky et al., 2018; Kong et al., 2018). Bates et al. (2019) concluded that non-transmitted genetic effects are fully accounted for by parental SES. So, not only are genes transmitted directly from parent to child relevant to student achievement, but non-transmitted genes also have effects that may be mediated by SES or parenting.

Student achievement has a strong genetic component

A meta-analysis of 61 twin studies from 11 cohorts of primary school children reported average heritability estimates of around 0.7 for reading, 0.5 for reading comprehension, 0.6 for mathematics, 0.6 for language, 0.4 for spelling and 0.7 for general educational achievement. The contributions of the common environment (which includes SES and the community) were substantially smaller, with estimates mostly around 0.10 (de Zeeuw et al., 2015). Other studies also show strong heritabilities for student achievement (Grasby et al., 2016; Pokropek & Sikora, 2015; Rimfeld et al., 2019). The heritability of student achievement in primary school is greater than that for cognitive ability (Kovas et al., 2013). Its high heritability reflects several genetic traits, not just cognitive ability (Krapohl et al., 2014).

Twin and kinship studies have identified sizeable genetic correlations between student achievement domains and with cognitive ability indicating common sets of genes (Hart et al., 2009; Petrill, 2016; Wainwright et al., 2005). The average genetic correlation between student achievement and cognitive ability is about 0.6 (Plomin et al., 2013, p. 228).

Polygenic scores, which are weighted sums of genetic (DNA) differences associated with a particular trait—in this instance, educational attainment—accounted for 7% of the variance in achievement test scores at age 12, and 15% at age 16 in an independent sample (Allegrini et al., 2019). Although polygenic scores are only a recent innovation, and larger samples and technical advances have dramatically increased their explanatory power over a short time, polygenic scores are already accounting for as much variation in student achievement as typical SES measures.

ACCOUNTING FOR EMPIRICAL PHENOMENA

This section uses evidence from the literature cited in previous subsections to explain empirical phenomena relating to achievement and its relationships with SES. Relevant empirical observations and findings are far more congruent with the cognitive ability/genetic transmission model than the SES model.

Explaining observed relationships

The SES achievement relationships can be explained, to a substantial extent, by parents' ability and parent-child transmission. Parental cognitive abilities influence their educational attainment, occupational status, and to a lesser degree family income and wealth. Therefore, parental ability is correlated with family SES. Children randomly receive half of each parent's genome so inherit genes relating to general cognitive ability and specific abilities. In turn, these general and specific abilities influence their performance in achievement tests.

Assuming that the correlation between parents' abilities and family SES is 0.6 (see section 'Cognitive ability is strongly associated with adult socioeconomic attainments'), the correlation between parents' genomes (taken together) and their biological children is 0.7 (see section 'Cognitive ability is transmitted from parents to their biological children') and the correlation between children's cognitive ability and achievement is 0.6 (see section 'Cognitive ability has stronger correlations with achievement than SES'). Therefore, the expected correlation between SES and student achievement is 0.25 (0.6 × 0.7 × 0.6) based only on cognitive ability's relationships with parental SES and student achievement, and its genetic transmission. Alternatively, assuming that the correlation between students' abilities and achievement is 0.7, a realistic figure for PISA, then the expected SES–achievement correlation is 0.29 (0.7 × 0.7 × 0.6).

Of course, these correlations are only putative. Lower assumed correlations would produce lower estimated SES–achievement correlations according to the cognitive ability/genetic transmission model. However, it is not tenable, as the SES model assumes, that any, or much less all, of the three correlations equal zero.

The finding of little or no SES effects on achievement in fixed-effects models is consistent with the cognitive ability/genetic transmission model where achievement is considered as a relatively stable attribute closely related to cognitive ability with a sizeable genetic component.

High intradomain correlations

The correlations between achievement and prior achievement range from strong to very strong, increasing with students' progression through schooling. Armor (2003, p. 33) estimated correlations for combined reading and math achievement for New York City students from Grades 3 to 8. For adjacent grades, the correlations ranged from 0.8 at the lowest grades to nearly 0.9 at higher grades. The correlation of scores in Grades 3 and 8 was 0.73, a surprisingly high correlation for measures taken 5 years apart. Duckworth et al. (2012, p. 444) reported a correlation of 0.78 for combined achievement scores at Grades 5 and 9.

In the UK's National Child Development Study, the intradomain correlations of achievement scores at ages 7 and 11 were 0.56 for mathematics and 0.60 for reading. The intradomain correlations at ages 11 and 16 were stronger: 0.76 for mathematics and 0.78 for reading (McNiece et al., 2004, p. 134). For England, Strand (2006, p. 215) reported intradomain correlations of 0.77 and 0.67 for mathematics and reading Key Stages (KS) 2 and 3 achievement scores taken at ages 11 and 14.[9] Using twin data, Rimfeld et al. (2018, pp. S10–11) reported intradomain correlations of 0.83 and 0.85 for English and mathematics between KS1 (taken at age 8) and KS2 scores. The intradomain correlations for KS2 and KS3 scores were 0.91 mathematics and 0.84 for reading. The intradomain correlations are stronger for tests taken closer together and at older ages (Rimfeld et al., 2018, pp. S10–11). Nunes et al. (2017, p. 89) reported an intradomain correlation of 0.73 for science at ages 11 and 14.

For Australia, intradomain correlations in the National Assessments—Literacy and Numeracy (NAPLAN) range from 0.6 to 0.9 and are higher for numeracy and spelling than for other domains, and higher in secondary school than in primary school (Marks, 2021). For Germany, the correlation in mathematics test scores (one based on PISA) taken one year apart in 2003 and 2004 was 0.73 (Kriegbaum et al., 2015). For the Netherlands, Timmermans and van der Werf (2017, p. 229) reported intradomain correlations of around 0.6 and 0.7 for reading, spelling and mathematics for Grades 4 to 6.

What explains the increasingly high stability of student achievement? The SES model cannot explain high and increasing intradomain correlations. The stability of student achievement over the school career is higher than the stability of parents' occupational status, income and wealth (but not parents' education) as parents move in and out of the workforce, change jobs, gain promotions and in some instances, split up and re-partner.[10]

The explanation is genetic. The increasing stability of achievement with age corresponds with the increasing stability of cognitive ability, which can be explained by the increase in heritability with age. Rimfeld et al. (2018) concluded that genetic factors account for 70% of the stability of student achievement across grade levels. Analysing US and international twin data, Soden et al. (2015) attributed the longitudinal stability in reading comprehension to the influence of genetic factors. For the Australian national assessments, Grasby and Coventry (2016) also attributed the stability of students' achievement scores in the five test domains primarily to genes.

Prior achievement has stronger effects on student achievement than cognitive ability because it incorporates both general cognitive ability and domain-specific abilities, such as language or mathematical ability.

High interdomain correlations

Although articles and reports based on data from achievement tests almost invariably treat each achievement domain as independent of the other domains, achievement domains are at least moderately correlated. In a meta-analysis of studies conducted in the USA, Aiken (1971, p. 306) concluded that the correlation between reading and mathematics achievement in primary school was between 0.45 and 0.55, again tending to be larger in higher grades.

In the UK's 1958 birth cohort NCDS, the correlations between reading and mathematics test scores were 0.50 at age 7, 0.74 at age 11 and 0.65 at age 16 (McNiece et al., 2004, p. 134). In the 1970 British Cohort Study, the intercorrelations for spelling, reading and mathematics at age 10 ranged from 0.60 to 0.75. At age 16, the intercorrelations for spelling, reading and arithmetic were between 0.45 and 0.70 (Parsons, 2014, pp. 27, 35). For Australia, Marks (2021) reported interdomain correlations for numeracy and four literacy domains between 0.50 and 0.75.

In a French-Canadian study of school readiness, the correlation between Grade 2 reading and math was 0.75 (Pagani et al., 2010, p. 989). In 2011, over 4000 Grade 4 Italian students were tested in reading in PIRLS and math and science in TIMSS. Reading scores were highly correlated with math (0.76) and science (0.85) comparable with the correlation (0.81) between science and math in TIMSS (Grilli et al., 2016, p. 10).

The best explanation for the strong interdomain correlations is also genetic. The 'generalist genes' hypothesis is that the same genes affect cognitive ability and student achievement in diverse learning domains. In addition, there are common genes that affect cognitive ability and the different achievement domains, which largely explains their correlations.

Kovas et al. (2005) found substantial genetic overlap between mathematics and reading (genetic correlation = 0.74), and between mathematics and *g* (0.67). Similarly, Davis et al. (2008) found sizeable genetic correlations between reading and mathematics (r = 0.57), between reading and *g* (r = 0.61) and between *g* and mathematics (r = 0.75). Haworth et al. (2008) concluded that science shares genetic influences with English, mathematics and *g*. Nonetheless, science is more than just *g*, as there were specific genetic and environmental influences on science. Similarly, Harlaar et al. (2012) found shared and independent genetic influences on reading, word decoding and mathematics.

Very high interdomain correlations in PISA

In PISA, the inter-correlations of student performance across the domains of reading, mathematics and science among individual students are extraordinarily high, over 0.8, and in rare instances over 0.9 (Bond & Fox, 2001, p. 259; Cromley, 2009). These correlations are based on plausible values obtained from multidimensional IRT models, which assume three (or four) correlated latent dimensions.

The very high correlations of students' test scores belie the assumption that PISA collects information on students' competencies in largely independent learning domains. The obvious explanation for the very high interdomain correlations is that the estimates of students' scores in each domain incorporate sizeable components of general cognitive ability. The bifactor IRT model is more appropriate for national and international achievement tests as it can specify a general ability factor and independent (i.e., uncorrelated) domain-specific factors. Brunner (2008, p. 161) compared a two-dimensional standard model and a bifactor model with data from students that sat the German PISA 2000 study and a cognitive ability test. He found that the general ability factor explained 40% of the variance in PISA mathematics items and 49% of the variance in the reading items. In contrast, domain specific factors for mathematics and reading accounted for 8% and 17% of the variance. Baumert et al. (2009, p. 169) found that a bifactor model provided a better fit to PISA data than a *g* only model, although the loadings of PISA subtests on *g* were much larger than their loadings on the specific mathematical and verbal factors. Baumert et al. (2009) concluded that general ability is a key determinant in the acquisition of knowledge and skills at school, and domain specific abilities make an additional contribution to student performance. Bifactor analyses of Polish 2009 PISA data found that student responses to test items are largely accounted for by general cognitive ability, with little variance accounted for by independent reading, mathematics and science factors. The correlations of ESCS were highest with *g* (r = 0.37) and much lower with the mathematics (r = 0.07), reading (r = 0.03) and science (r = 0.02) factors (Pokropek et al., forthcoming). The small correlations between ESCS and the achievement domains are inconsistent with the SES model which emphasises the importance of the family and school for domain specific skills. The larger correlation between *g* and ESCS is consistent with the cognitive ability/genetic transmission model.

Explaining differences between SES indicators and achievement

As noted above, Strenze's (2007, p. 411) meta-analysis estimated correlations between ability measured during childhood and adolescence of 0.56 with educational attainment, 0.45 with occupational status and 0.23 with income during adulthood. These correlations are consistent with the correlations reported by Lee et al. (2019, p. 316) between parents' socioeconomic characteristics and mathematics scores in PISA 2015: 0.31 for highest parents' occupational status (ISEI), 0.26 for parents' education, 0.24 for educational resources, 0.22 for cultural possessions, and 0.17 for wealth. Highest occupational status has the strongest correlation because it incorporates both parental education and occupation status, which are both highly correlated with parental ability.

The enduring effects of PISA test scores

According to the cognitive ability/genetic transmission model, the effects of PISA test scores at age 15 on subsequent educational and labour market outcomes is because performance in PISA is a proxy for cognitive ability. The importance of cognitive ability for school completion, university and college entry, successful labour market status and earnings is well established (Belley & Lochner, 2007; Bratti, 2007; Dronkers, 1998; Fergusson et al., 2005; Frey & Detterman, 2004; Halsey et al., 1980; Hanushek, 2006; Hegelund et al., 2018; Koenig et al., 2008). Fischbach et al. (2013) and one OECD (2010a) paper equate PISA test scores with cognitive ability (or abilities) but other publications avoid this connection by referring to PISA test scores as 'PISA competencies' or just reading ability (Knighton & Bussière, 2006; OECD, 2010b).

Educational differentiation

If between- and within-school differences in PISA achievement tests are largely a function of SES, then controlling for SES should substantially reduce these differences. However, apart from countries with sizeable proportions of private schools, controlling for SES only marginally reduces between-school and within-school programme differences in student achievement (Marks, 2006). This indicates that between- and within-school differences in achievement are only weakly associated with SES.

Ability is the dominant influence on educational differentiation. Analysing students in two German states—Bavaria, in which school track was strictly based on ability tests, and Hesse where track placement was less strict—Esser and Relikowski (2015, p. 27) conclude 'the crucial condition for both educational achievement and institutional sorting is children's cognitive abilities which they have by birth and further develop within families and during prior elementary school attendance'. For the Netherlands, Dronkers and Korthals (2016, p. 160) conclude that 'early ability is the most important variable with which to explain success at each stage of the educational career from the elementary school track recommendation…'. Analysing PISA data, they concluded that the effects of social background are minimised when track selection is based purely on prior performance (Korthals & Dronkers, 2016).

Resilient students

Rather than products of best-practice institutional arrangements and well-tailored educational policies, as the OECD claims, resilient students are more likely to be simply high ability students from low SES backgrounds. To assume that resilience can be attributed to institutional arrangements is misleading. Chinese students perform just as well in Australia and New Zealand as they do in Shanghai, so their performance has little to do with the supposedly superior institutional arrangements and teaching practices of Shanghai schools (Feniger & Lefstein, 2014; Jerrim, 2015). To examine the importance of institutions and policies on the high performance of low SES students, it is necessary to consider student ability or prior achievement.

Cultural capital

In a review of cultural capital theory, Kingston (2001) notes that because cultural capital is only weakly associated with family's socioeconomic background, it cannot explain the relationship between SES and student performance. He argues that controls for ability are necessary before permitting conclusions on cultural capital effects. Barone's (2006) analysis of PISA data from 25 countries found that in no country do cultural capital measures account for more than 30% of the effects of SES. He (2006, p. 1051) concludes that the PISA indicators of family cultural capital have only modest explanatory power and the ‘effects associated with these variables may be better interpreted as an indirect sign of the importance of cognitive resources’.

Roscigno and Ainsworth-Darnell (1999) found that net of prior achievement, there were no significant effects of measures of cultural capital measures on GPA and achievement in reading and mathematics. Dumais (2002, p. 55) found the impact of ability on grades was *ten times* that of cultural capital among boys and *thirteen times* greater among girls. Jæger (2011), using fixed-effects models, found the effects for number of books and the extent to which children read for enjoyment on academic achievement were small ($\beta < 0.10$). Other indicators of cultural capital had negligible effects.

According to cultural capital theory, the mechanism for cultural capital effects on student performance is through teacher perceptions; teachers unconsciously perceive cultural signals from students from high SES families and consequently reward them. However, there is little evidence that teacher perceptions of students are influenced by SES or cultural factors. Teachers do not discriminate by socioeconomic origin (Hauser, 1969). Similarly, cultural capital does not bias teachers’ perceptions of children's academic ability for the awarding of grades. Teachers’ judgements of students are not based on students’ participation in elite culture, but mainly, and obviously, on their test scores (Dumais, 2006, p. 96). Similarly, Jæger and Møllegaard (2017, p. 138) conclude that their results contradict their ‘hypothesis that prolonged exposure to cultural capital affects teachers’ perceptions of children's academic ability’. Contrary to a fundamental proposition of cultural capital theory, teachers do not mediate the relationship between cultural capital and student achievement (Wildhagen, 2009).

CONCLUSION

The paper critiques the dominant SES model used in the analysis of student achievement. The SES model is failing for several reasons. Its conceptualisation is muddled and contradictory. SES data collected from students are often unreliable, and both parental education and 'books in the home' are, to some extent, endogenous to student achievement. There is also a lack of consistency between the measured components cross-nationally and, in some countries, over time, so it is difficult to sustain the idea that the same concept is being compared. Despite its high profile among researchers and policymakers, SES has only moderate effects on achievement. Even the expansive ESCS measure in PISA explains only modest amounts of variance in PISA test scores. SES effects are likely to be, to a considerable extent, proxies for the effects of parental ability. It is no accident that policies that focus on such an ambiguous and poor explanatory concept as SES are not successful.

We are not arguing that the home environment is completely irrelevant to student performance. Very wealthy and high-income families can send their children to private schools, which increases the chances of university entry (Jerrim et al., 2016). Undesirable changes in home circumstances (e.g., job loss, divorce) can adversely impact student performance (Lehti et al., 2019; Nilsen et al., 2020). Parents influence their children in myriads of ways and most parents monitor their children's education. However, the overall impact of the home environment, SES and parenting are much weaker than commonly assumed. The problem is that the SES model has become an *idée fixe* among researchers and policymakers, and they insist that it explains much of the variance in student achievement, is theoretically credible, and is sensitive to policies that aim to reduce educational inequalities.

The cognitive ability/genetic transmission model provides more compelling explanations than the SES model. It accounts for the SES–achievement relationship, the small or negligible SES effects when controlling for cognitive ability or prior achievement, or in fixed-effects analyses, the increasing intradomain correlations, the sizeable interdomain correlations, educational differentiation, the enduring effects of PISA test scores on subsequent educational and socioeconomic attainments, and the existence of 'resilient' students. Teachers' judgements of students' aptitudes are based largely on their test performance, not SES or cultural signals. The cognitive ability/genetic transmission model does not require *ad hoc* additions to maintain basic plausibility. It can be part of a vibrant growing understanding of student performance.

Although there is a great reluctance among research and policy communities to admit that cognitive ability plays a substantial role in student performance, nonetheless teachers, schools and educational authorities implicitly acknowledge its importance. Teachers routinely allocate students to different learning groups and set work based largely on their prior performance. Most primary schools provide remedial teaching, and at higher grades advanced or extension classes. In middle secondary school, streaming in mathematics and science is not uncommon. In upper secondary school, students are allocated, or allocate themselves, to more and less academically demanding subjects. Some school systems formally track students either on entry to secondary school, or a few years later based largely on their prior performance. So, acknowledging the importance of general and specific abilities would not change the organisation and practices of educational institutions. However, it would change the rhetoric surrounding, and the implementation of, and most likely the success of, educational policies.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available from the OECD Data repository at https://www.oecd.org/pisa/data/.

CONFLICT OF INTEREST

None.

ETHICAL APPROVAL

Ethics approval does not apply.

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ENDNOTES

[1] New Zealand and Finland are still high performing countries but their average scores have declined (OECD, 2019a, p. 17).

[2] The kappa statistic is a measure of agreement for categorical outcomes for two raters. It ranges from zero (no agreement) to one (perfect agreement). It is superior to simple percentages because it takes into account the possibility of agreement occurring by chance (Cohen, 1968).

[3] Progress in International Reading Literacy Study which assesses reading in Grade 4 students.

[4] Rational choice arguments are mostly about continuing with schooling or dropping out. In the context of student

achievement, it could apply to the importance that parents and student place on learning and schoolwork.

[5] AFQT score is a commonly used measure of ability (see Torres, 2013, p. 162). It has a median correlation of 0.81 with standard measures of cognitive ability (Herrnstein & Murray, 1994, pp. 608–609).

[6] Oxford English Dictionaries (https://www.lexico.com/en/definition/intelligence).

[7] These standardised effects are calculated from the published coefficients and standard deviations.

[8] Calculated from $\sqrt{0.5^2 + 0.5^2}$.

[9] For the English Key Stages see: https://www.gov.uk/government/publications/national-curriculum-in-england-framework-for-key-stages-1-to-4

[10] Authors' analyses of the Children of NLSY79 mother's data shows two-year apart correlations of around 0.8 for father's occupation, 0.7 for mother's occupation, 0.5 for income and 0.7 for wealth. These correlations successively decline with longer periods between observations.

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