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The importance of parental ability for cognitive ability and student achievement: Implications for social stratification theory and practice

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ABSTRACT

Socioeconomic status (SES) is considered a powerful influence on children's cognitive development and student achievement. This model has generated an enormous literature on the nature of, explanations for, and policy implications arising from SES inequalities in early childhood cognitive outcomes and student achievement. An alternative model focuses on the associations between SES and parental ability, the parent-child transmission of ability, and the association between children's ability and their test scores. This study analyses two ability and three achievement measures, with composite and multiple SES measures and a commonly used indicator of the home environment (HOME) in children aged from 3 to 15. The associations between SES and children's test scores are only partially accounted for by the home environment, which itself has only small to moderate associations with test scores, independent of SES. Adding mother's cognitive ability substantially reduces the coefficients for the composite SES measure by between 50% and 60%, and for mother's education by between 56% and 87%. The contemporaneous effects of SES and the home environment are small or very small. Sizable percentages of the variance in the five outcome measures are attributable to genetics ranging from 38% for the Peabody Picture Vocabulary Test (PPVT) to 77% for reading recognition. The contributions of the shared environment ranged from 14% for reading recognition to 41% for the PPVT. Therefore, genetics is important, and the non-trivial contributions of the common environment are more likely to reflect school and neighborhood factors rather than parental SES and the home environment.

1. Introduction

It is almost axiomatic that socioeconomic status (SES) is a strong influence on children's cognitive development and performance at school. SES figures prominently in research and theory in both children's cognitive development and student achievement. SES is a major focus for policy initiatives aiming to reduce educational inequalities (Postlethwaite & Kellaghan, 2008; Scott-Jones, 1984; Tong, Baghurst, Vimpani, & McMichael, 2007; OECD, 2010; Hopfenbeck et al., 2018). Theory and policy generally consider the associations between SES and children's test scores to be sizable, causal and contemporaneous.

1.1. Measurement of SES and parenting

SES is typically measured by father's and mother's educational attainment and occupational status, family income and less frequently by family wealth, either singly or in some combination (Bradley & Corwyn, 2002; Hauser, 1994; Mueller & Parcel, 1981; Buchmann, 2002; Oakes & Rossi, 2003). Composite measures combine SES components into a single variable, whereas multiple measures include two or more SES measures in the same analysis. Estimates from composite variables are easy to interpret and facilitate comparisons between models and contexts. However, the cost of composite SES measures is conceptual clarity. Composite SES measures do not allow identifying possible causal pathways for the associations of family SES with children's cognitive development and achievement (O'Connell, 2019; Rindermann & Baumeister, 2015).

Parental education is typically measured by years of formal education, highest qualification, or highest level attained. The measurement of parental occupation varies, categorically by occupational group and

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social class, and continuously by occupational prestige, socioeconomic status (i.e., some combination of narrowly defined occupational groups' education and income) and social interaction patterns (Meraviglia, Ganzeboom, & De Luca, 2016). In child development studies, income data is usually collected from parents. For student achievement, it is difficult to obtain direct measures of income, so alternative measures are often used, such as household possessions or subjective affluence. Even in surveys of adults, income and wealth questions are problematic in terms of refusal, recall, reliability, and stability (Hauser & Warren, 1997, p. 179).

The most commonly used measure of the home environment and parenting is Caldwell and Bradley's (1984, 2016) Home Observation for Measurement of the Environment (HOME) inventory. HOME measures the quality of the cognitive stimulation and emotional support provided by children's parents (Totsika & Sylva, 2004). According to Crane (1996) the home environment mediates the relationship between SES and cognitive outcomes, but also has effects independent of SES.

1.2. Explanatory theory

According to Bradley and Corwyn (2002) the association between SES and children's cognitive ability involves differential 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-achievement relationship—financial capital, cultural status, and social connections—corresponding to the theoretical concepts of economic capital, cultural capital and social capital. However, the bulk of the explanations focus on parents' education and occupation, economic resources (e.g., family income and wealth) and cultural practices, such as cultural capital and parenting.

The association of parental education with achievement has been attributed to parental beliefs and attitudes concerning the value and utility of education, stimulating home behaviors and the transmission of cognitive competencies (Brown & Iyengar, 2008). Other explanations for the relationship with parental education are home literacy environments (Park, 2008), scholarly culture (Evans, Kelley, & Sikora, 2014) and the frequency of reading to children during early childhood (Kalb & van Ours, 2014).

The link between parental occupation or social class with student performance has been attributed to parental attitudes to the value of education (Hyman, 1966; Chen & Uttal, 1988); codes of speech (Bernstein, 1971); cultural capital which creates barriers to social mobility for children from lower SES backgrounds (Bourdieu, 1977); class cultures where middle-class parents foster their children's talents through organized leisure activities and extensive reasoning (Lareau, 2002) and the richness and complexity of the language used by parents to their children (Hart & Risley, 1995).

Explanations for income-achievement relationship focus on the ability of families to utilize resources to improve their children's outcomes (Chmielewski & Reardon, 2016). High income families can enroll their children at high-fee private schools or at high performing public schools serving wealthy neighborhoods (Heckman, 2000, p. 10; Orr, 2003, p. 283). Duncan, Kalil, and Ziol-Guest (2017) surmise that income governs access to high-quality childcare and schools, and performance-enhancing goods and services (e.g., tutors). In addition, low-income parents, under severe financial pressure, experience greater psychological stress, undermining their capacity for enriched parenting (Mayer, 1997, p. 45). Analyzing data from German students, Dräger and Pforr (2022) concluded that 'parental investments' is the most important mediator of the relationship between parental income and test scores. 'Parental investments' was operationalized by the number of books in the home, frequency of parent-led learning related activities, and the frequency of participation in high cultural activities, the same factors often postulated as meditators for the effects of parental education.

Good parenting is considered important for children's cognitive development and academic performance. Baumrind (1966) distinguished between permissive, authoritative, and authoritarian parenting, with authoritative parenting most beneficial. Parenting practices are related to social class and SES: low SES parents are more likely to adopt detrimental authoritarian and permissive parenting styles (Hoff, Laursen, & Tardif, 2002). SES is also related to marital stress and the quality of romantic relationships which may impact on children's development (Conger, Conger, & Martin, 2010). McLoyd (1998) concluded that the relationship between socioeconomic disadvantage and children's socioemotional functioning is mediated by harsh, inconsistent parenting, less cognitive stimulation, and elevated exposure to acute and chronic stressors.

1.3. The Magnitudes of SES associations with ability and achievement

Despite the immense literature and expectations around SES, the magnitudes of the relationships between SES and children's ability and achievement are only modest.

For cognitive ability, White's (1982) meta-analysis of over 100 studies found an average correlation of 0.33 (at the individual level) between SES and IQ. Letourneau et al.'s (2011) meta-analysis on the relationship between SES and cognitive and language development of children aged 3–12 estimated a *Hedges g* of 0.35 equivalent to a Pearson correlation of about 0.17. They (2011, p. 218) concluded that the link between SES and literacy and language development is "very small to small". More recently, Harwell et al.'s (2017, p. 208) meta-analysis of 86 studies estimated an average correlation of 0.27 between SES and IQ.

For student achievement, White (1982) meta-analysis of over 200 studies calculated a mean correlation between SES (measured in various ways) and academic achievement (at the student level) of 0.22. Correlations between SES and achievement generally increase with the number of SES components, ranging from below 0.20 for single variable measures to around 0.40 for composite measures (White, 1982, pp. 468, 470). Sirin (2005) calculated average SES-achievement correlations around 0.30. Harwell, Maeda, Bishop, and Xie (2017) estimated an average SES-achievement correlation of 0.22, which the authors describe as "surprisingly modest" (Harwell et al., 2017, p. 197). The SES composite measure in the OECD's Programme for International Student Assessment (PISA) study which comprises many variables[3] correlated at 0.37 with 15-year-olds' mathematics scores (Lee, Zhang, & Stankov, 2019, p. 316).

No single SES component stands out as having the strongest associations with student achievement. White (1982) found that family income ($r = 0.32$) had clearly stronger correlations with student achievement than parental education ($r = 0.19$) or parental occupation ($r = 0.20$). Sirin's (2005) meta-analysis estimated average correlations with achievement of 0.29 for family income, 0.30 for parents' education and 0.28 for father's occupational status. Harwell et al. (2017) reported average correlations with student achievement of 0.26 for income, 0.23 for mother's education and father's occupation, 0.20 for father's education and 0.14 for mother's occupation. In PISA, the correlations with math achievement were highest (0.33) for parental occupational status (the International Socioeconomic Index, see Ganzeboom, 2010), followed by parents' education (0.26) and wealth (0.17) unreliably measured by household possessions (Lee et al., 2019, p. 316).

HOME scores have moderate to strong correlations with children's test scores. Bradley, Caldwell, and Rock (1988) reported that HOME scores at age 10 correlate at around 0.4 with achievement in language arts, math and a composite achievement measure. The correlations of

[3] The PISA composite measure comprises many variables: highest parental International Socio-Economic Index of Occupational Status (ISEI); the highest level of education of the student's parents converted into years of schooling; the PISA index of family wealth (household possessions only); the PISA index of home educational resources including books in the home; and the PISA index of possessions relating to 'classical culture'.

HOME with SES vary widely, ranging from 0.30 to 0.65 (Bradley & Caldwell, 1979).

1.4. Appraisal and Issues

For SES inequalities in ability and achievement, there are a plethora of explanations, but no single theoretical explanation enjoys overwhelming empirical support. The relationships are weaker than the theoretical explanations imply, and the postulated mediating factors only partially account for the observed relationships. Furthermore, there are many credible explanations, each with some empirical support. It is not obvious why so many factors have plausible theoretical relationships with children's cognitive ability and student achievement.

Recent studies support the multiple dimensions or measures approach. Each of the distinct SES components—parental education, parental class, family income and wealth—have statistically significant relationships with schooling outcomes (Blossfeld, 2019; Hällsten & Thaning, 2018; van de Werfhorst, 2010, p. 1352). Furthermore, both fathers' and mothers' socioeconomic characteristics seem to matter for educational, occupational and economic outcomes (Ballarino, Meraviglia, & Panichella, 2021; Erola, Jalonen, & Lehti, 2016; Korupp, Ganzeboom, & van der Lippe, 2002; Thaning & Hällsten, 2020).

Again, it is not clear why separate components of SES—father's and mother's education and occupation, family income, wealth—make independent contributions to social stratification. Multidimensional explanations are plausible with each dimension tapping independent social processes, but such explanations tend to be *post facto*. It is difficult to explain why father's *and* mother's education, and, father's *and* mother's occupation, have independent effects since they purportedly index the same underlying concept, for example class culture, cultural capital and scholarly culture.

There are also unexplained findings regarding parental occupation. Despite emanating from very different research traditions, continuous occupational measures are highly correlated, leading Meraviglia et al. (2016) to ask "of what exactly all continuous measures measure?". They hypothesize that a unidimensional latent occupation factor underlies the variety of continuous occupational measures. Unexpectedly, occupational measures with very different theoretical pedigrees (e.g. Marxist, Weberian, none) are sometimes strongly correlated (Lambert & Bihagen, 2014, p. 6). Furthermore, greater explanatory power of occupational classifications has nothing to do with the sophistication of the theory, but much more prosaically with a greater number of occupational categories (Lambert & Bihagen, 2014, pp. 6,7–10).

1.5. An alternative explanation - SES as an epiphenomenon

An alternative explanation for SES effects on children's cognitive development and academic achievement involves the relationships between SES, parental and children's cognitive abilities and children's performance in tests of cognitive development and school achievement. According to the cognitive ability/genetic transmission model, the observed effects of parents' occupation, education, family income, wealth or composite SES measures on their children's test scores are due to:

1. The moderate to large correlations of parents' socioeconomic characteristics (e.g., father's and mother's education and occupation, family SES) with parents' abilities.
2. The sizable correlations between parents' and their biological children's cognitive abilities.
3. The strong correlations between children's abilities and their test scores.

In addition, there are sizable genetic components to both cognitive ability and student achievement, and much smaller contributions from the shared environment which theoretically encompass SES and the home environment.

The cognitive ability/genetic transmission model is not new. Crawford, Goodman, and Joyce (2011) noted that role of parents' socioeconomic position, in 'explaining' children's cognitive outcomes is likely to be overstated since the correlation between the two may be due to high-ability parents raising high-ability children. Lemos, Almeida, and Colom (2011) attributed the association between parents' education with adolescents' ability, not to better family environments but simply because they and "their parents are brighter". Swagerman et al. (2017) in reference to reading ability concluded that "parents and offspring tend to resemble each other for genetic reasons, and not due to cultural transmission". Murray (2020), p. 237) pointed out that any measure of parental SES is not only a measure of the child's environment, but is also a measure of parents' abilities and talents, all of which have genetic components. Similarly, Isunget et al. (2021) noted that children not only inherit their parents' cultural resources, but also their genes, potentially confounding social explanations. Erola, Lehti, Baier, and Karhula (2021) suggested that the correlations between parents' socioeconomic resources and their children's socioeconomic outcomes may simply be because parents' genes impact on how well they succeeded in life, and have the same effect on their children.

Parents' ability is correlated with commonly used SES measures. Analyzing data from the 1979 National Longitudinal Study of Youth (NLSY79), Hauser et al. (2002, p. 207) reported correlations between Armed Forces Qualification Test (AFQT) score, a commonly used measure of ability (see Torres, 2013, p. 162) and educational attainment of 0.66 and 0.62 among nonblack men and women, and correlations of 0.55 and 0.43, respectively, between AFQT score and occupational status in 1993, 13 years after the AFQT data were collected. Strenze's (2007) meta-analysis found that ability measured between ages 3 and 23 correlates, on average, at 0.56 with educational attainment, 0.45 with occupational status and 0.23 with income among adults. Torres (2013) also analyzing the NLSY79, reported a correlation of 0.53 between mother's AFQT score measured in 1980 and a composite measure of (her) family SES measured twenty years later.

It is well-established that cognitive ability is strongly associated with students' test scores. Walberg (1984) computed an average correlation of 0.71 between various IQ measures and academic achievement. Kriegbaum, Becker, and Spinath's (2018) meta-analysis estimated a mean correlation of 0.47 between intelligence and achievement in standardized tests. According to Zaboski, Kranzler and Gage's (2018) meta-analysis, the correlations of *g*, the underlying latent general ability factor, with basic reading, reading comprehension and basic mathematics are above 0.70.

In regression analyses of child's test scores with parent's ability and measures of students' SES, parent's ability has substantially stronger effects. Typically, the standardized SES coefficient, net of parent's cognitive ability, is small. Analyzing data from children of NLSY79 mothers (NLSY79-C), Cooksey (1997) reported significant and robust effects of mother's AFQT scores on reading and math scores although their relative size compared to other factors was not discussed. Cooksey (1997) considered AFQT score not as a measure of mother's ability but as an aspect of human capital. Guo (1998) in a study on the effects of poverty, reported that mother's ability was a powerful influence on children's test scores. The size of the coefficient of AFQT on the Peabody Picture Vocabulary Test (PPVT) was about twice as large as those for the reading and math achievement tests (1998, p. 280). Currie and Thomas (1999) found that mother's AFQT scores "had a powerful negative effect on the probability that her child is in the bottom decile of the PPVT" whereas their SES measure had no effect. Across the distribution of PPVT scores, Currie and Thomas (1999) report large, standardized coefficients for mother's AFQT score of between 0.6 and 0.7 and much smaller coefficients ($0.15 < \beta < 0.28$) for a composite SES measure. Similarly, Carlson and Corcoran (2001) concluded that mothers' AFQT is a strong predictor of their children's reading and math scores, but mothers' education showed no or much weaker effects. Torres (2013) found SES did not explain the association between mother's ability and children's tests scores; adding SES reduced the impact of mother's ability by only 9–16%.

1.6. Role of Genetics

Behavioral genetic studies typically disaggregate the variance of a phenotypical trait into additive genetic (A), common environmental (C) and unshared or unique environmental (E) components (Eaves, Last, Young, & Martin, 1978). The unshared environmental component includes measurement error. It is the common environment (C) that siblings and twins share that encompasses SES and the home environment, school and neighborhood factors and the influence twins and siblings have on each other. Such studies typically compare monozygotic (MZ) twins and dizygotic (DZ) twins. Genetic and environmental components can also be estimated from kinship data, where there are differences in genetic relatedness, for example full siblings, half siblings, cousins, and unrelated siblings.

Twin and kinship studies demonstrate that much more of the variance in children's cognitive ability and achievement is attributable to genes rather than to the shared family environment. For cognitive ability in children, Plomin, DeFries, Knopik, and Neiderhiser (2013) posit an average heritability estimate of 0.5, which means the percentage of variance in cognitive ability attributable to genetics is 50%. Haworth et al. (2010) found that the heritability of cognitive ability increases from 0.41 at age 9, to 0.55 at age and 0.66 at age 17. Bouchard (2013) examined data from a variety of related pairs (twins, twins and siblings, parents and offspring) and also concluded that heritability of IQ increases steadily with age approaching 0.80 at 18–20 years old.

The heritability of student achievement is comparable to, or greater than, that for cognitive ability (Kovas et al., 2013). For student achievement, the heritabilities were generally between 0.5 and 0.8, averaging about 0.7, with much lower estimates for the shared environment (see Plomin et al., 2013, pp. 222–228; Pokropek & Sikora, 2015). A meta-analysis of 61 twin studies from 11 cohorts of primary school children reported heritabilites ranging from 0.4 to 0.7, whereas the contributions of the shared environment were mostly around 0.10 (de Zeeuw, de Geus, & Boomsma, 2015). Asbury and Plomin (2014) cited heritability estimates of around 0.6 for reading, and between 0.6 and 0.7 for math.

The five cognitive and achievement domains that are the focus of this study also comprise substantial genetic components (Dalliard, 2014; Hart, Petrill, & Kamp Dush, 2010; Rodgers, Rowe, & May, 1994; van den Oord & Rowe, 1998). However, there is little consistency in the estimates across studies, which may be due to differences in the sample size, age profiles and methods.

The AFQT measure also has a substantial genetic component. Rowe, Vesterdal, and Rodgers (1999) estimated a heritability of 0.64 for the AFQT based on sibling pairs in the NLSY79. The proportion of the variance in AFQT scores in the NLSY79 attributable to the shared environment was much lower at 0.23. Lyons et al. (2017) analyzing twin data estimated the heritability of the AFQT at 0.59 at age 20.

The genetic components to nurturing were identified in the early 1990s when Plomin and Bergeman (1991) demonstrated that several parenting measures generally considered to be purely environmental—HOME, family environment scales, and a social readjustment rating measure of life events—had substantial genetic components. Klahr and Burt (2014) concluded that "children's genetically influenced characteristics appear to shape, at least to some extent, the parenting they receive".

1.7. Causal Effects

The causal effects of SES on children's test scores are much weaker than the observed correlations. Utilizing longitudinal data that measured family income before and after test scores were measured, Mayer (1997) estimated the 'true effects' for family income on children's Peabody Picture Vocabulary Test, reading and math scores of 0.13, −0.01 , 0.07 (standardized), none of which were significantly different from zero.

Most of the research on the causal effects of SES have focused on parents' education using Instrumental Variables (IV), and twin and adoption studies. For the US, Carneiro, Meghir, and Parey's (2013) IV estimates were standardized effects of 0.05 for reading and 0.09 for math for a year of maternal education at ages 7 and 8. At age 14, the IV estimates were also small (0.05, 0.06). For the UK, Silles's (2011) IV estimates for both mother's and father's education on children's cognitive development were not statistically significant. Analyzing the same data, Sabates and Duckworth (2010) found that the additional year of schooling received by mothers was significantly associated with improvements in their child's relative position in mathematics test scores over time. However, the effects were very small and there was no significant effect for reading scores. Dickson, Gregg, and Robinson (2016) concluded that parental education has a positive causal effect on children's test scores, especially for lowly educated mothers. The estimates were again small, at around 0.10 standard deviations for a one-year increase in parental education (2016, p. F211). The general conclusion from these studies is the causal effect of parental education on children's test scores is small or very small.

Children-of-twin designs disaggregate the contribution of the common environment separating the contribution of parents sometimes referred to as cultural transmission. They tend to find no effects for cultural transmission but with significant contributions for the shared environment of siblings and twins (Baier, Eilertsen, Ystrøm, Zambrana, & Lyngstad, 2022; Eifler & Riemann, 2022; Haegeland, Kirkebøen, Raaum, & Salvanes, 2010; Swagerman et al., 2017; van Leeuwen, van den Berg, & Boomsma, 2008). This suggests that the contributions of the shared environment are largely independent of parents implicating other environmental factors.

1.8. The Present Investigation

The literature review suggests that there are two distinct approaches to understanding children's cognitive outcomes. The SES model assumes that inequalities in SES are the driver for inequalities in cognitive ability and student achievement. Many theoretical explanations have been proposed to explain these relationships canvassing a wide range of factors.

The alternative cognitive ability/genetic transmission model emphasizes the relationships between parents' and their children's cognitive abilities, and the relationship of the former with SES and the latter with children's test scores. Here, the SES relationships with children's ability and achievement scores are considered not causal, but to some extent spurious, confounded by parents' and their children's cognitive abilities. According to the cognitive ability/genetic transmission model SES has statistical relationships with children's ability and achievement scores mainly because it mediates the relationship between parental and child abilities.

There are only a handful of studies that have included mother's AFQT scores on children's cognitive outcomes. However, these studies are now quite old analyzing a much younger and smaller group of children and did not include comprehensive measures of SES used in the present study. In some studies, mother's AFQT was not considered a measure of mother's ability, which implies a genetic component, but something else, such as human capital or family background.

Fig. 1 is a Directed Acyclic Graph (DAG) of the underlying model. The central relationship is between SES and children's test scores. In the DAG approach, SES would be considered the treatment and test scores, the outcome. However, to establish a causal relationship backdoor paths need to be blocked (Breen, 2022). There are backdoor paths for the association between SES and test scores that involve parents' abilities: from SES to mother's ability to child's ability and test score, and through

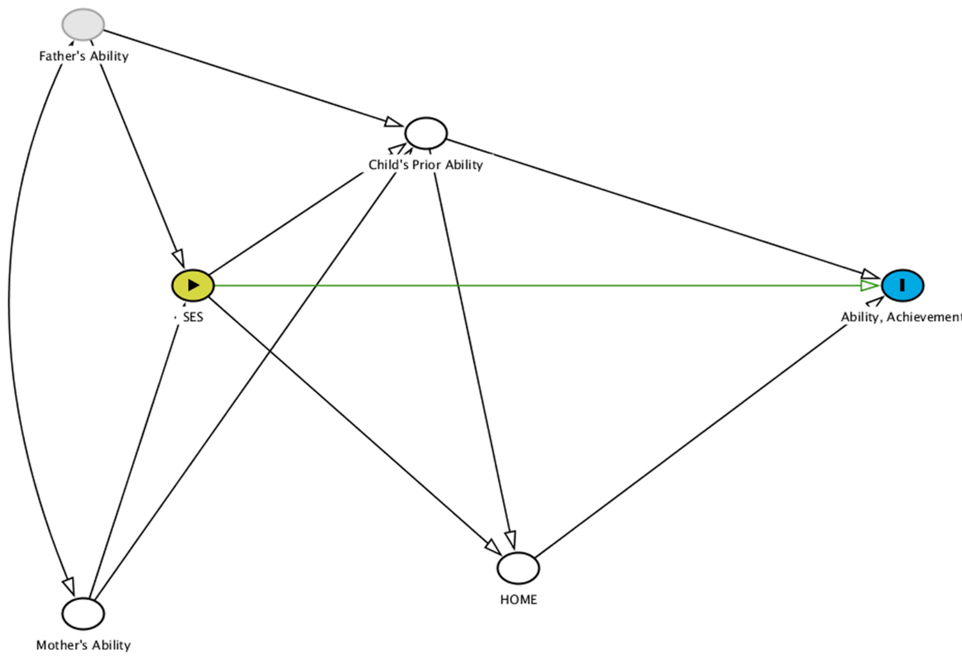

Fig. 1. Directed Acyclic Graph for the Causal relationship between SES and Children's test Score. Note that "Father's Ability" is not Observed in these Data.

HOME. Once these backdoor paths are blocked then the causal effects of SES on test scores can be ascertained. Since there is no measure available of father's ability, only the backdoor paths through mother's ability can be blocked.

This study comprises three sets of analyses. The first set analyses NLSY-C data to estimate the effects of a composite SES measure on children's test scores, controlling for the HOME environment measure, mother's ability, and child's ability measured two years prior. Controlling for HOME informs on the extent that the home environment accounts for SES effects. Controlling for mother's ability indicates the extent that associations of SES and the home environment with test scores can be attributed to mother's ability. According to the SES model, mother's ability has little impact vis-à-vis SES and its addition will not substantially reduce the estimates for SES. In contrast, the cognitive ability/genetic transmission contends that mother's ability has substantially stronger effects vis-à-vis family SES, and its addition to the analysis will substantially reduce the SES coefficients. Adding prior ability completes the model, providing estimates of the contemporaneous effects of SES and the home environment on ability and achievement.

The second set of analyses substitutes the composite measure of family SES with its five constituent variables—father's and mother's education and occupational status, and family income—to show which SES components are more and less important. According to the cognitive ability/genetic transmission model, the addition of mother's ability will substantially reduce the coefficients for mother's education and occupational status, and to some extent family income, but has little impact on the coefficients for father's education and occupation. The final model adds prior ability to estimate the magnitudes of the contemporaneous effects of SES components on child ability and achievement.

The third set of analyses estimates the contributions of additive genetics, the common environment and the unshared environment to the variance of the cognitive and achievement outcomes. These analyses test the hypothesis that genetics is involved and estimates the overall contribution of the common environment that siblings share.

2. Materials and methods

2.1. Data

The NLSY79 initially interviewed 12,686 individuals in 1979 born between 1957 and 1964 (aged 14–22 in 1979). Respondents were interviewed annually from 1979 to 1994 and since 1994 biennially (Cooksey, 2018; BLS, 2022e). The most recent survey round of data analyzed for the present study is 2018.

The NLSY79-Children's study (NLSY79-C) comprises biological children born to female NLSY79 respondents. The NLSY79-C began in 1986, and the expanded mother-child data collection occurred biennially since then. By 2014, a total of 11,521 children had been identified as born to 6283 female NLSY79 respondents. Between 1986 and 2014, test data were collected from NLSY79-C children aged 15 and under. In 1986, there were 6107 NLSY-C children aged 15 or younger decreasing to 276 in 2014 (see BLS 2022f).

2.2. Measures

2.2.1. Cognitive and achievement outcomes

The five cognitive outcomes analyzed are the Peabody Picture Vocabulary Test (PPVT) scores; the Wechsler digit memory span, and the Peabody Individual Achievement Tests (PIAT) for reading comprehension, reading recognition and math. The PPVT is a measure of verbal intelligence (Dunn & Dunn, 1997) and the digit span memory test a measure of working memory and thus fluid intelligence (Shelton, Elliott, Matthews, Hill, & Gouvier, 2010). In contrast, the reading and math tests assess the skills and knowledge children have acquired, principally through schooling. Guo (1998) classifies the three PIAT reading and math assessments as measures of academic achievement and the PPVT and digit memory assessments as measures of academic ability.

All measures are normed on a single year of age basis. For the digit memory test, the normal scores have a mean of 10 and a standard deviation of 3. The other four cognitive measures are normalized to a mean of 100 and a standard deviation of 15 (see BLS, 2022b). Separate cognitive measures were constructed for each age. The means, standard deviations and the numbers of non-missing cases for the five measures by children's age are presented in table 1 in Supplementary Material.

The means and standard deviations are slightly different because the data were transformed from year of testing scores to age of testing scores. Sizable numbers of children were tested more than once for each cognitive outcome (table 2 in the Supplementary Material).

2.2.2. Parents Socioeconomic Attainments and Family Income

At each interview, the NLSY79 collected data on mother's educational attainments and that of her spouse or partner which were used to construct measures of mother's and father's years of education based on the age children were tested.

Fathers and mothers' occupational status are measured by socioeconomic index (SEI) scores. SEI scores were originally developed by Duncan (1961) from census occupational codes; they essentially score census occupational groups by the incomes and educations of their incumbents.

Mother's occupation was coded according to the 1980 census occupational classification for NLSY79 survey waves conducted between 1984 and 2000. Father's (or partner's) occupation was coded according to the 1970 occupational classification for survey waves up until 2000. In 2002 and subsequent waves, both father's and mother's occupations were coded according to the 2000 census occupational classification.

The 1970 and 1980 occupational codes were recoded to SEI scores using correspondence tables (Featherman, Sobel, & Dickens, 1975; Nakao & Treas, 1994). For occupations classified according to the 2000 schema, the codes are first converted to the 2010 occupational schema (there were only minor changes) and converted to SEI scores according to the correspondences detailed by Hout, Smith, and Marsden (2014). The parental occupational status measures are for the same year that children took their tests.

The measures of family income are based on the total net family income for the calendar year prior to interview. It comprises the net incomes of all family members of the household. Family incomes for each year are adjusted to 2020 dollars using the consumer price index (BLS, 2022c). To overcome the strong positive skew of income distributions, the family income measures at each child's age (from 3 to 15) were converted to near normal distributions using the Inverse Hyperbolic Sine (IHS) transformation.[4] The advantage of the IHS transformation compared to the commonly employed logarithmic transformation is that it retains zero values (Friedline, Masa, & Chowa, 2015). For each survey year, approximately 3% of net family incomes were recorded as zero.

Table 3 in the Supplementary Material presents the means and standard deviations for the measures of father's and mother's education and occupational status, family income and family wealth.

2.2.3. Composite SES

For each age 3–15, the composite family SES measures were constructed by first standardizing the five SES component variables— father's and mother's educational and occupational attainment, logged family income—and then averaging non-missing values.

2.2.4. Home Observation Measurement of the Environment (HOME)

The HOME measures are based on reports by either the mother or the interviewer. There are four separate HOME measures: for ages less than 3, from 3 to 5, from 6 to 9 and from 10 to 14. The HOME measure comprises two subscales: cognitive stimulation and emotional. Each HOME measure comprises many items. The HOME measure includes measures of several of the factors canvassed as explaining SES effects: parenting including parental disciplinary behavior; frequency young children are read to; books in the home; frequency of parent-led learning related activities; the frequency of museum visits; parental attitudes to education and the frequency the child participates in extra-curricular activities (BLS, 2022d; 2022a). For these analyses, the standard HOME scores were used; and standardized to a mean of zero and a standard deviation of one. Table 3 in Supplementary Material includes the means and standard deviations of the unstandardized HOME measures by children's age.

2.2.5. Mother's Ability

Mother's cognitive ability is measured by AFQT score from parts of the *Armed Services Vocational Aptitude Battery*, a special survey administered in 1980 to NLSY79 respondents. The raw AFQT score in the NLSY79 data is the sum of scores in the arithmetic reasoning, word knowledge, subtests and paragraph comprehension tests and half the score in the numeric operations subtest (BLS, 2022). In 1989 the scores were modified and modified again in 2006 - 'renormed' controlling for respondents' age. The Gaussified measure of AFQT used for these analyses has been adjusted for age (Beasley, 2013). It has a mean of zero and a standard deviation of one.

2.2.6. Prior Ability

Prior cognitive ability was constructed from factor analysis of the individual items using two-parameter (difficulty and discrimination) Item Response Theory (IRT) models. Separate measures were obtained for each age from 3 to 12. Items from all five domains were included.

In the first stage, IRT models were fitted for each domain with age-appropriate items.[5] Items that were too difficult or too easy or were poor at distinguishing between low and high performing students were discarded. After finalizing the item pools for each domain, IRT was used to isolate the latent factors from all age-appropriate items which involved further pruning of items if they produced missing correlations in the polychoric correlation matrix. The process was repeated until all items had acceptable statistical properties. From the first factor isolated from the multiple-domain models, factor scores were obtained, standardized, and designated as *g*, the latent general ability factor. Prior ability was measured by *g* isolated from the items in the tests conducted 2 years earlier.

2.2.7. Summary Correlations

To assess the approximate magnitudes of the relationships between variables, Table 4 in the Supplementary Material presents the correlations for the five cognitive measures averaged across all ages, with pairwise deletion of missing data. The inter-domain correlations are highest for the two reading domains (0.73), between 0.5 and 0.6 for the PPVT, reading and math, and between 0.38 and 0.48 for digit memory with the four other domains. The composite SES measure correlates around 0.80 with father's and mother's education, at 0.75 with father's and mother's occupation and at 0.68 with IHS-transformed family income. Family SES correlates at around 0.4 with the HOME measure, towards the lower end of Bradley and Caldwell's (1979) range.

The correlations of the composite family SES measure with children's test scores range between 0.24 for digit memory span close to 0.40 for the PPVT and math. The overall correlations of the composite family SES measure with children's test scores are between 0.24 and 0.39. Family SES correlates at 0.62 with mother's ability which is higher than Torres's (2013) estimate of 0.53. The correlation of SES with children's ability is just below 0.4.

Mother's ability correlates at only 0.26 with digit memory and between 0.4 and 0.5 with scores in the other four domains. The correlation of the children's prior ability with mother's ability is 0.46, consistent with studies cited earlier that report intergenerational correlations for ability between 0.4 and 0.5. Prior ability correlates at between 0.5 and 0.6 with the PPVT, PIAT reading and math and at 0.4 with digit memory.

[4] The Inverse Hyperbolic Sine transformation is calculated as follows: IHS $(x)=\log(x + \mathrm{sqrt}(x^2 + 1))$.

[5] The IRT analyses were conducted using Proc IRT in SAS.

2.3. Statistical methods

2.3.1. General linear models for clustered data

Generalized Estimating Equations (GEEs) were introduced by Liang and Zeger (1986) to analyze clustered data. Since the data analyzed are children's test scores assessed at multiple time points, the within-subject residuals cannot be assumed to be statistically independent. In contrast to random effects models, GEEs allow specification of the within-subject correlations. Ghisletta and Spini (2004) provide a useful introduction to the approach.

The correlational structure was specified as compound symmetry. Compound symmetry approximates the pattern of correlations across students' ages for each of the five dependent variables. Since GEE is not a likelihood-based method, statistics like AIC and BIC are not appropriate. The QIC statistic is appropriate for quasi-likelihood estimation which includes GEE (Cui & Qian, 2007; Pan, 2001). For each model analyzed in this study, the compound symmetry specification invariably produced the lowest QIC statistics among those available (independence, autoregressive, m-dependent) for the residual correlation matrix.[6]

The estimates from these GEE analyses can be interpreted in the same manner as coefficients obtained from ordinary least squares regression: the impact on the dependent variable for a one-unit change in the predictor variable. SES, HOME, mother's ability, and child's prior ability are standardized, so the coefficients can be interpreted as the average increase in test score for a one-standard deviation increase in the respective predictor variable. The magnitudes of their effects can be compared between models within each domain.

The metric coefficients for fathers' and mother's education are the predicted increase in test scores for one-year increase in education. For parents' occupational status, the estimated coefficients represent the average increase in test scores for a 10-unit increase in occupational status. The coefficients for the IHS transformed variables are interpreted in the same way as log transformed independent variables as percentage effects (Friedline et al., 2015).[7] The text refers to the estimated difference in test scores comparing children from families where family incomes differ by a factor of 2 (i.e., a 100% increase).

The standard errors are Huber–White standard error estimates, also known as "robust standard error" or "sandwich variance" estimates, adjusted for multiple imputation (detailed below).

2.3.2. Missing Data

Since the analyses are of children's test score at each age for which test data is available, list-wise deletion of missing data would limit analyses to observations with valid data on all the predictor variables. For example, at age 10, the analysis would be limited to the 1753 valid observations for father's occupational status whereas there is valid test score data for over 3000 children for four of the five test domains (see tables 1 and 3 in Supplementary Material). Such a strategy would discard large amounts of carefully collected and analyzable data.

Missing data were imputed using multiple imputation which is one of the best options for accurate estimation and statistical inference (Newman, 2014; van Ginkel, Linting, Rippe, & van der Voort, 2020; Von Hippel, 2007). It is usually recommended that the dependent variable be included in the imputations. However, in this context including the dependent variables would not be appropriate since most child-age observations on the dependent variable are missing simply because the child did not take the test on that occasion. So, the data are structurally missing, that is, missing due to the organization of the study. Separate sets of imputed data sets were generated for each of the 5 domains.

First, 25 data sets are generated where missing values are replaced by plausible values randomly drawn from the distribution of predicted values from regression analysis of the observed variables (Allison, 2012; Baraldi & Enders, 2010). The 25 imputed data sets are then analyzed by using generalized estimating equations and the results combined with appropriate adjustments for statistical inference (Yuan, ND). SAS was used for the multiple imputations (SAS, 2011, p. 4683; Dong & Peng, 2013).

2.3.3. Genetic and Environmental Variance Components

The genetic and environmental variance components were estimated from the associations among sibling and cousin pairs that differ by their genetic relatedness. Following Rodgers et al. (2016), genetic relatedness scores were assigned to each sibling and cousin pair:

- MZ twins have identical genomes so have a genetic relatedness score of 1.0.
- Dizygotic twins (DZ) and full biological siblings share, on average, 50% of their genes so their relatedness score is 0.50.
- Half-siblings have only one common parent, so their relatedness score is 0.25.
- Cousin pairs share one pair of grandparents, so their relatedness score is 0.125.
- Unrelated sibling pairs score 0.

Following, Rodgers et al. (2016), same-sex twin pairs with unknown zygosities were assigned a relatedness score of 0.75, since about half will be MZ twins and half will be DZ twins.

Table 5 in the supplementary material presents the Pearson correlations for all sibling/cousin pairs and by genetic relatedness for height, HOME and the five cognitive and achievement measures, and prior ability. Monozygotic (MZ) exhibit very high correlations. The magnitudes of the correlations roughly correspond with the degree of genetic relatedness for most outcomes. Height is included as a control variable since the variance in height is almost entirely genetic.

The estimates for the genetic and environmental components were obtained using the OpenMX software package (Boker et al., 2011, Neale et al., 2016, OpenMx Development Team 2014b). The models include adjustments for age and gender using regression equations since there are age and gender effects on these outcomes; without these adjustments the MZ and DZ twin associations are over-estimated (McGue and Bouchard Jr 1984). This method has been used previously in genetic and environmental analyses of 'sibling' data (see Nielsen, 2006; Hart et al., 2010; Nielsen & Roos, 2015).

OpenMX estimates the unstandardized path coefficients and the standardized ACE variance components (which sum to one). The A, C and E estimates generate variances and covariances that best approximate that of the observed data.

The coefficients are estimated using Full Information Maximum Likelihood (FIML) which compares the observed data and predicted means and covariances for each row of sibling-pair data rather than the sample and predicted variance-covariance matrices. OpenMx allows the estimation of likelihood-based confidence intervals for each parameter estimated (Neale and Miller 1997, Neale et al., 2016). The intervals are lowest and highest values at which the likelihood ratio deteriorates significantly ($P > 0.05$).

2.3.3.1. Missing Data. FIML handles missing data by filtering out missing values when they are present and using only the data that are not missing in a row of data (Boker et al., 2011, 166–167). Missing data comprises twin pairs with: no data on zygosity; no age data for both twins; DZ twin pairs with missing data on gender for either twin; or twin pairs missing on all six analysis variables. Baraldi and Enders (2010) provide an accessible introduction to maximum likelihood estimation

[6] It was not possible to test the fit of the "unstructured" residual correlation matrix. There are too many parameters to fit.

[7] Percentage effect= $b_1 * \log(1.y)$ for a y percent change in x. For a doubling of income, $b_1 * \log(2)$.

and how FIML handles missing data. More detail on filtering missing data is available from the OpenMX website (OpenMx Development Team 2014a).

3. Results and Discussion

Tables 1 and 2 present the effects of the predictor variables on the five cognitive outcomes obtained from the GEE analyses. Although the cognitive outcomes have been normed by age, age is included in these analyses because age (in months) impacts on test scores. Model 1 is the base SES model comprising just SES and age. Model 2 adds mother's ability. Model 3 removes mother's ability and adds the HOME measure. Model 4 includes SES, HOME and mother's ability. Model 5 adds children's prior ability isolated from IRT modelling. The tables include standardized coefficients to enable comparisons of the magnitudes of the coefficients across domains, as well as within domains.[8]

3.1. Composite SES Measure

Model 1 in Table 1 shows the effects of the composite SES measure without considering the effects of the home environment, mother's ability or prior ability. The largest SES coefficient was for the PPVT: a one standard deviation in SES translates to a change in PPVT score of 6.7 units, equivalent to a standardized effect of 0.33. The weakest SES effect is for digit memory span ($\beta = 0.18$) and math (0.28). These standardized effects, net of children's age, are substantially smaller than the bivariate correlations (presented in table 4 in the Supplementary Material) because of the correlated residuals.

SES coefficients decline by at least a half with the addition of mother's ability (model 2). The declines were largest for reading comprehension (63%) followed by the PPVT (57%), reading recognition and math (54%) and digit memory (53%). Controlling for mother's ability, the standardized SES coefficients are small: 0.14 for the PPVT and around 0.10 for the other four domains.

Except for digit memory, the coefficients for mother's ability are sizable. On average, a one-standard deviation difference in mother's ability increased PPVT scores by 7.7 score points, and by between 4 and 5 score points for the three PIAT reading and math measures. The coefficients for mother's ability are about 2–3 times greater than that for SES. These coefficients for mother's ability translate to standardized effects between 0.2 for digit memory and nearly 0.4 for the PPVT.

The HOME measure has moderate effects on children's test scores, net of SES (model 3). The largest standardized coefficients for the home environment are for the PPVT (0.20) followed by reading comprehension (0.13). Its coefficient is smallest for digit memory and reading recognition (0.08). Only for the PPVT is the standardized coefficient for HOME larger than that for SES.

The SES coefficients declined moderately with the addition of the HOME measure (model 3). The largest decline is for the PPVT where the SES coefficient declined by about 20% indicating that some of the SES-PPVT relationship can be accounted for by the home environment. For the other domains, the addition of the HOME measure produced smaller declines. Although the HOME measure includes measures of many of the factors proposed to explain SES effects, the HOME measure does not substantially reduce SES effects, nor are SES effects largely mediated by the HOME measure.

The readdition of mother's ability in model 4 produces sizable reductions in the SES coefficients compared to that in model 3: by about two-thirds for reading comprehension, nearly 60% for the PPVT and above 50% for the three other domains. SES effects are likely to be further reduced if father's ability were also included. The standardized coefficients of mother's ability are clearly and substantially stronger than the SES coefficients: over 4 times larger for reading comprehension, over 3 times larger for the PPVT, math and reading recognition and over twice as large for digit memory. The standardized coefficients for mother's ability are highest for the PPVT (0.38) and between 0.31 and 0.34 for the three achievement domains. The standardized coefficient for mother's AFQT scores on digit memory was substantially smaller (0.19).

The coefficients for the HOME environment decline much less than the SES coefficients with the addition of mother's ability; about 20% for the PPVT and digit memory, and between 25% and 30% for the other domains. Thus, mother's ability only partially accounts for the moderate effects of the home environment.

Net of mother's ability and HOME, the standardized coefficients for SES are small: around 0.10 for the PPVT and math and less than 0.10 for the other three domains. Again, these coefficients are likely to be even smaller if father's ability was included. So, even without considering child's ability, the direct effects of SES are small or very small.

The addition of prior ability (models 5) further reduces the SES and HOME coefficients. The standardized SES effects decline further. The coefficients for the home environment are small ($0.04 < \beta < 0.15$). The larger coefficient for the home environment on the PPVT ($\beta = 0.15$) indicates the importance of parenting practices on the PPVT. Early childhood parenting often involves teaching children vocabulary with pictures, a skill that the PPVT measures.

Except for digit memory, these coefficients for mother's ability in model 5 are non-trivial, with standardized coefficients around 0.30 for the PPVT and math, and around 0.25 for reading comprehension and reading recognition.

The effects of mother's ability are independent of both SES and HOME. Therefore, the effects of mother's ability cannot be attributed to either SES or factors indexed by the HOME measure. The explanation for the effects of mother's ability in model 5 involves factors correlated with both mother's ability and children's test scores, but independent of SES and HOME. One possible explanation is that mother's ability partially indexes the effects of father's ability which is correlated with mother's ability.[9] Another explanation is that they reflect sibling effects. Siblings' abilities are also correlated with mother's ability. Higher (lower) ability siblings could positively (negatively) influence the test scores of younger siblings. A third explanation is that the mother's ability coefficients index unmeasured non-cognitive traits common to both mother and child, for example conscientiousness or neuroticism.

3.2. Multiple SES Measures

These analyses replace the single composite SES measure with multiple SES measures: father's and mother's education and occupation, and family income. The five models estimated correspond to those estimated in Table 1. It is noteworthy that the Table 2 estimates for the variables common to both sets of analyses - HOME, mother's ability and prior ability - are similar to the corresponding estimates in Table 1, despite substantially more predictors.

Of the four SES measures, mother's education shows the largest standardized coefficients followed by father's education (Table 2). Father's and especially mother's occupational status have only small, or very small, standardized effects. Family income has only weak effects on test scores: a doubling of family income is associated with increases of only 0.6 score points for the PPVT and no significant association with digit memory scores. The predicted change in achievement in reading comprehension and recognition, and math for a doubling of family income is less than half a score point. For the PPVT, a doubling of income is associated with an average increase of only 0.85 score points.

[8] Standardized effects (β) are calculated from the metric coefficients (b) and standard deviations of respective predictor and dependent variables, $\beta = b^*\frac{\sigma(x)}{\sigma(y)}$.

[9] The most recent meta-analysis estimated an average spousal correlation for IQ at around 0.4 {Horwitz & Keller, 2022, pg. 26].

Table 1
Estimates from GEE Analyses of SES, HOME, Mother's and Child's Prior Ability on Child's Ability and Achievement.

	Model 1		Model 2		Model 3		Model 4		Model 5	
	b	*β*	b	*β*	b	*β*	b	*β*	b	*β*
Peabody Picture Vocabulary Test										
Intercept	90.94***	.	90.9***	.	90.83***		90.81***	.	90.76***	.
Age	-0.01	*0.00*	-0.01	*0.00*	-0.00	*0.00*	-0.00	*0.00*	-0.01***	*0.00*
SES	6.68***	*0.33*	2.88***	*0.14*	5.53***	*0.27*	2.28***	*0.11*	1.93***	*0.09*
HOME	.	.			4.05***	*0.20*	3.19***	*0.16*	3.00***	*0.15*
Mother's Ability	.	.	7.72***	*0.38*	.	.	6.87***	*0.34*	6.10***	*0.30*
Prior Ability	.	.	.	.	.	.	.	.	2.38***	*0.12*
Digit Memory										
Intercept	9.76***		9.77***		9.76***		9.76***		9.74***	
Age	0.04***	*0.04*	0.04***	*0.04*	0.04***	*0.04*	0.04***	*0.04*	0.04*	*0.04*
SES	0.58***	*0.18*	0.27***	*0.09*	0.50***	*0.16*	0.24***	*0.08*	0.19***	*0.06*
HOME					0.26***	*0.08*	0.19***	*0.06*	0.15***	*0.05*
Mother's Ability			0.60***	*0.19*			0.56***	*0.18*	0.42***	*0.13*
Prior Ability									0.41***	*0.13*
Reading Comprehension										
Intercept	100.64***		100.69***		100.61***		100.66***		100.55***	
Age	-0.19***	*-0.05*	-0.18***	*-0.04*	-0.18***	*-0.04*	-0.18***	*-0.04*	-0.18***	*-0.04*
SES	3.37***	*0.24*	1.25***	*0.09*	2.90***	*0.21*	1.02***	*0.07*	0.80***	*0.06*
HOME					1.82***	*0.13*	1.35***	*0.10*	1.25***	*0.09*
Mother's Ability			4.66***	*0.33*			4.32***	*0.31*	3.52***	*0.25*
Prior Ability									2.20***	*0.16*
Reading Recognition										
Intercept	103.93***		104.00***		103.92***		103.99***		103.91***	
Age	-0.05*	*-0.01*	-0.04*	*-0.01*	-0.04*	*-0.01*	-0.04*	*-0.01*	-0.05**	*-0.01*
SES	2.87***	*0.19*	1.31***	*0.09*	2.65***	*0.18*	1.2***	*0.08*	1.07***	*0.07*
HOME					1.17***	*0.08*	0.82***	*0.05*	0.73***	*0.05*
Mother's Ability			4.67***	*0.31*			4.45***	*0.30*	3.80***	*0.25*
Prior Ability									1.81***	*0.12*
Math										
Intercept	100.45***	.	100.52***	.	100.44***	.	100.51***	.	100.44***	.
Age	0.00	*0.00*	0.01	*0.00*	0.01	*0.00*	0.01	*0.00*	0.00	*0.00*
SES	3.40***	*0.23*	1.56***	*0.11*	3.10***	*0.21*	1.41***	*0.10*	1.27***	*0.09*
HOME	.	.			1.43***	*0.10*	1.03***	*0.07*	0.93***	*0.06*
Mother's Ability	.	.	4.92***	*0.34*	.	.	4.65***	*0.33*	4.11***	*0.29*
Prior Ability	.	.	.	.	.	.		.	1.55***	*0.11*

Note: The PPVT and Digit memory are the ability measures. All predictor variables centered about their means. Correlated Residuals (Compound Symmetry). Multiple Imputation from 25 datasets. Standardized Coefficients (β) italicized. * 0.01<P<0.05; ** 0.01 >P > 0.001, *** P<0.001, two-tailed tests.

A one-year increase in mother's education is associated with an increase of nearly 2 score points in the PPVT and between 1 and 1.3 score points for the three PIAT domains (Table 2). These are small effects considering the standard deviations which are between 15 and 20. The coefficients for father's education are smaller than that for mother's education. This may be because the mothers are biological mothers but the fathers, sometimes designated as mother's partners, were not always biologically related to the child. In addition, some mothers repartnered.

The coefficients for father's occupational status are small, for example a 10-point increase in father's socioeconomic status is associated with an increase of only 0.46 PPVT score points. The coefficients for mother's occupation are smaller again.

With the addition of mother's ability in model 2, the effects of most of the SES components decline, most dramatically for mother's education. The reductions in the coefficients for mother's education are large: 75% for the PPVT, 56% for digit memory, 87% for reading comprehension, 60% for reading recognition and 56% for math. Except for digit memory, the coefficient for mother's occupational status also declines substantially with the addition of mother's ability. Therefore, mother's ability largely accounts for the associations between mother's socioeconomic characteristics and children's test scores. The coefficients for father's education and occupation decline much less precipitously with the addition of mother's ability. This is because mother's ability is only moderately correlated with father's socioeconomic characteristics through assortative mating. It is likely that if father's ability had been added then the coefficients for father's education and occupation would decline similarly.

With the addition of mother's ability, the coefficients for family income decline by about half for the PPVT, reading comprehension and recognition, and by about two-thirds for math. Thus, family income is only very weakly associated with children's test scores, when considering mother's ability.

Comparison of models 1 and 3 show that the addition of the HOME measure reduces the magnitudes of some of the coefficients: more strongly for family income but only marginally for father's and mother's education and occupation. The coefficient for father's occupation hardly changed at all. So, the small reduction in the SES coefficients between models 1 and 3 in the previous set of analyses (presented in Table 1) can be partially attributed to the relationship between the home environment and family income.

As was the case for model 2, the addition of mother's ability in model 4 substantially reduces the coefficient for mother's education. Compared to the coefficients in model 3, the reductions in the effects of mother's education are large: 75% for the PPVT, 59% for digit memory, 88% for reading comprehension, 60% for reading recognition and 67% for math. The smaller coefficients for mother's occupation and family income were also reduced. The coefficients for father's education and occupation were largely unchanged with the addition of mother's ability.

Without considering children's prior abilities, but net of HOME and mother's ability (model 4) the standardized coefficients for the SES components are small or very small. Mother's and father's education tend to show the largest standardized coefficients although all ten are below 0.10.

Model 5 shows that the addition of prior ability makes little difference to the estimates. This is again because of the correlated residuals. The coefficients for SES and HOME coefficients decline slightly with larger declines in the coefficients for mother's ability. These residual

Table 2
Estimates from GEE Analyses of SES Components, HOME, Mother's and Child's Prior Ability on Child's Ability and Achievement.

	Model 1		Model 2		Model 3		Model 4		Model 5	
	b	β	b	β	b	β	b	β	b	β
Peabody Picture Vocabulary Test										
Intercept	91.48***	.	91.21***	.	91.29***		91.07***	.	90.99***	.
Age	-0.02	0.00	-0.01	0.00	-0.01	0.00	0.00*	0.00	-0.01*=	0.00
Father's ED	0.72***	0.12	0.57***	0.09	0.61***	0.08	0.49***	0.07	0.43***	0.06
Mother's ED	1.97***	0.20	0.5*	0.03	1.66***	0.20	0.42	0.05	0.33	0.04
Father's SEI	0.46***	0.07	0.29***	0.04	0.46***	0.05	0.30***	0.03	0.24***	0.03
Mother's SEI	0.30**	0.04	0.09	0.01	0.23*	0.02	0.04	0.00	0.06	0.01
Family Income	0.31**	0.05	0.15***	0.03	0.11*	0.01	-0.02	0.00	-0.03	0.00
HOME	.	.			3.90***	0.19	3.20***	0.16	3.01***	0.15
Mother's Ability	.	.	7.47***	0.38	.	.	6.63***	0.33	5.93***	0.29
Prior Ability	.	.	.	.	.	.	.	.	2.33***	0.11
Digit Memory										
Intercept	9.80***	.	9.79***	.	9.80***		9.79***	.	9.76***	.
Age	0.04***	0.04	0.04***	0.04	0.04***	0.04	0.04***	0.04	0.04**	0.04
Father's ED	0.08***	0.07	0.07***	0.06	0.07***	0.06	0.06***	0.05	0.05***	0.04
Mother's ED	0.18***	0.14	0.08**	0.06	0.17***	0.13	0.07***	0.05	0.06***	0.04
Father's SEI	0.03***	0.02	0.02***	0.01	0.03***	0.02	0.02*	0.01	0.01	0.01
Mother's SEI	0.02*	0.01	0.01	0.01	0.02*	0.01	0.00	0.00	0.01	0.01
Family Income	0.00	0.00	-0.01	-0.01	-0.01	-0.01	-0.02	-0.01	-0.02	-0.01
HOME	.	.			0.24***	0.08	0.19***	0.06	0.15***	0.05
Mother's Ability	.	.	0.54***	0.17			0.50***	0.16	0.37***	0.12
Prior Ability	.	.	.	.				.	0.40***	0.13
Reading Comprehension										
Intercept	100.86***	.	100.82***	.	100.80***		100.77***	.	100.65***	.
Age	-0.19***	-0.05	-0.18***	-0.04	-0.18***	-0.04	-0.18***	-0.04	-0.18**	-0.04
Father's ED	0.39***	0.08	0.28***	0.05	0.33***	0.06	0.23***	0.05	0.18*	0.03
Mother's ED	1.01***	0.18	0.13*	0.02	0.89***	0.16	0.11	0.02	0.04	0.01
Father's SEI	0.27***	0.04	0.17***	0.03	0.27***	0.04	0.17***	0.03	0.15	0.02
Mother's SEI	0.13*	0.02	0.01	0.00	0.11**	0.02	0.00	0.00	0.02	0.00
Family Income	0.18**	0.02	0.09***	0.01	0.11**	0.01	0.04	0.00	0.03*	0.00
HOME	.	.			1.74***	0.12	1.35***	0.10	1.25***	0.09
Mother's Ability	.	.	4.59***	0.33			4.25***	0.31	3.52***	0.25
Prior Ability	.	.	.	.				.	2.18***	0.16
Reading Recognition										
Intercept	104.15***	.	104.13***	.	104.13***		104.1***	.	104.01***	
Age	-0.05*	-0.01	-0.04**	-0.01	-0.05*	-0.01	-0.04**	-0.01	-0.05**	-0.01
Father's ED	0.32***	0.06	0.23***	0.04	0.28***	0.05	0.21***	0.04	0.18***	0.03
Mother's ED	1.34***	0.22	0.53***	0.09	1.26***	0.21	0.51**	0.08	0.44***	0.07
Father's SEI	0.20***	0.03	0.15***	0.02	0.21***	0.03	0.15***	0.02	0.13***	0.02
Mother's SEI	0.05	0.01	-0.02***	0.00	0.04**	0.01	-0.02	0.00	0.00	0.00
Family Income	0.10*	0.01	0.05	0.01	0.06*	0.01	0.02	0.00	0.01	0.00
HOME	.	.			1.07***	0.07	0.81***	0.05	0.72***	0.05
Mother's Ability	.	.	4.22***	0.28	.	.	4.02***	0.27	3.45***	0.23
Prior Ability	.	.	.	.	.	.	.	.	1.78***	0.12
Math										
Intercept	100.69***	.	100.66***	.	100.66***		100.70***	.	100.55***	.
Age	0.00	0.00	0.01	0.00	0.01***	0.00	0.01*	0.00	0.00	0.00
Father's ED	0.38***	0.07	0.29***	0.06	0.34***	0.06	0.25***	0.05	0.24***	0.05
Mother's ED	1.40***	0.24	0.51***	0.09	1.30***	0.22	0.43***	0.07	0.41***	0.07
Father's SEI	0.24***	0.04	0.17***	0.03	0.24***	0.04	0.14***	0.02	0.15**	0.02
Mother's SEI	0.05	0.01	-0.03	0.00	0.04*	0.01	-0.04	-0.01	-0.02	0.00
Family Income	0.16**	0.02	0.09	0.01	0.11*	0.01	0.05	0.01	0.05	0.01
HOME	.	.			1.31***	0.09	0.92***	0.06	0.92***	0.06
Mother's Ability	.	.	4.53***	0.32	.	.	3.78***	0.26	3.81***	0.27
Prior Ability	.	.	.	.	.	.	.	.	1.52***	0.11

Note: The PPVT and Digit memory are the ability measures. All predictor variables centered about their means. Correlated Residuals (Compound Symmetry). Multiple Imputation from 25 datasets. Standardized Coefficients (β) italicized. * 0.01<P<0.05; ** 0.01>P>0.001, *** P<0.001, two-tailed tests.

effects of mother's ability are sometimes non-trivial, with standardized effects of 0.29 for the PPVT and 0.24 for reading comprehension.

3.3. Genetic and environmental variance components

Table 3 presents the variance components estimates. As expected, height has a very large genetic component: 93% of its variance is attributed to genetics. In contrast to height, variation in the HOME measure is largely (67%) attributable to the common environment. There is a not insubstantial genetic component to the HOME environment measure indicating that parents adjust their parenting in response to children's temperament and personality.

Children's test scores in the five domains exhibit sizable genetic components: 38% for the PPVT, 57% for reading comprehension, 67% for math, 76% for digit memory and 77% for reading recognition. Two-thirds of the variation in cognitive ability, which was generated from the individual test items, is attributable to genetics. These estimates for the genetic component of between 40% and 80% of the variance are consistent with the estimates from meta-studies cited in the introduction.

The contributions of the shared environment are non-trivial: 14% for reading recognition, 18% for math, 24% for reading comprehension. Since the previous sections show that the effects of SES and the home environment are quite small, these estimates for the common

Table 3
ACE Variance Components for Children's Height, Home Environment, Test Scores and Cognitive Ability (NLSY79-C).

Measure	Additive Genetic		Common Environment		Unique Environment.		Age	Male
	A	95% CI	C	95% CI	E	95% CI		
Height	0.93	[0.89,0.96]	ns		0.07	[0.04,0.11]	0.00	5.7 ***
HOME Environment	0.31	[0.29,0.32]	0.67	[0.66,0.68]	0.02	[0.01,0.03]	3.3 ***	-15.4 ***
PPVT	0.38	[0.35,0.39]	0.41	[0.38,0.43]	0.21	[0.21,0.21]	-0.11 ***	-0.09
Digit Memory	0.76	[0.73,0.77]	ns		0.24	[0.21,0.28]	-0.02 ***	-0.44 ***
Reading Comprehension	0.57	[0.55,0.61]	0.24	[0.21,0.28]	0.19	[0.17,0.21]	-0.15 ***	-1.7 ***
Reading Recognition	0.77	[0.64,0.82]	0.14	[0.14,0.19]	0.10	[0.06,0.17]	-0.31 ***	-2.56 ***
Math	0.67	[0.57,0.77]	0.18	[0.16,0.19]	0.15	[0.12,0.21]	-0.34 ***	0.33 ***
Cognitive Ability (Individual Items)	0.66	[0.59,0.72]	0.25	[0.21,0.29]	0.09	[0.06,0.13]	0.03 ***	-0.05 ***

Note: ns= not Significant

environment more likely reflect school, neighborhood and inter-sibling factors rather than parental influences.

Over 40% of the variation in the PPVT is attributable to the common environment. The large contribution for the shared environment for the PPVT probably reflects parents teaching their young children how to read. Digit memory shows no shared environment component since this is not a skill taught by parents, kindergartens or schools.

4. Conclusions

These analyses suggest that in the context of children's cognitive development and student achievement in reading and math, the emphasis placed on SES or aspects of SES in research and policy is undeserved. There is little point in developing theoretical explanations for the associations of SES with children's test scores when they are so small. Similarly, policies aiming to reduce the SES-student performance relationship are likely to fail since the contemporaneous impact of SES is too weak. The small effect of SES, once mother's ability is considered, is a compelling explanation for the lack of success in substantially reducing socioeconomic inequalities in education over the last few decades.

The general conclusion of this study - the effects of SES and parenting for children's cognitive development and school achievement observed in many studies do not have sizeable contemporaneous effects - runs counter to the dominant understanding among researchers and policymakers. SES and its components mostly mediate the effects of parents' abilities. Furthermore, variations in children's test scores have large genetic components and smaller, but non-trivial, common environmental components.

Theoretical explanations for the relationship between parental education and children's performance—parental beliefs and attitudes, stimulation at home, the home literacy environments, reading to children and familiarity with elite culture—ignore the most parsimonious explanation that parental educational attainment is associated with parental ability which is genetically transmitted from parents to their children. It may be that some of these hypothesized factors do independently affect children's cognitive development and student achievement, but that can only be established after considering parents' abilities.

These analyses suggest that the stronger effects of parents' education on children's test scores compared to parents' occupation and family income found in these data, and in other data, is because parent's education is more strongly associated with parents' abilities than other SES indicators. This is the most complelling explanation rather than cultural capital, parental aspirations, early childhood reading, the number of books in the home or other factors postulated to explain the effects of parents' education.

We speculate that the reason why there are so many proposed explanations for SES effects is because many factors are correlated with both parental abilities and children's test scores, and so ostensibly provide credible theoretical explanations. However, they cannot satisfactorily explain the observed associations of SES with early childhood ability and student achievement because the dominant causal pathway involves parents' abilities and their genetic transmission.

Parents' abilities provide an answer to Meraviglia et al.'s (2016) question "of what exactly all (occupation) continuous measures measure?". The underlying dimension is parents' ability, not occupation. Additional SEM analyses indicate that among adults' aged 18–61, education, several different occupation measures and personal income load on an underlying latent general cognitive ability dimension.[10]

The cognitive ability/genetic transmission model explains why the causal effects of parental education and income on children's test scores are either small or not statistically significant. The bulk of the SES-test score correlation involves the association between parental ability and parents' socioeconomic attainments and parent to child genetic transmission. Net of these relationships, SES effects are small.

Parents' abilities could also explain why some occupational measures with very different theoretical foundations are nevertheless strongly correlated (Lambert & Bihagen, 2014, p. 6). The stronger that two occupation measures are correlated with ability, the stronger their observed correlation.

Parental abilities may also account for why occupational measures with larger numbers of categories exhibit stronger explanatory power (Lambert & Bihagen, 2014, pp. 6,7–10). With skill based occupational measures, the finer the distinctions between occupations, the greater the correlation between occupational status and ability. The correlations between occupational prestige and mean occupational IQ scores across several studies average around 0.7 (Huang, 2013, p. 118).

The contribution of the shared environment to children's test scores are non-trivial: 14% for reading recognition, 18% for math, 24% for reading comprehension and 41% for the PPVT. These percentages are typically larger than the variance accounted for in these outcomes in regression type analyses involving several predictor variables. Therefore, the shared environment is important, but probably reflects social processes involving kindergartens, schools and neighborhoods, rather than families considering the small effects for SES and the home environment. This argument is consistent with children-of-twin studies which often find twin and sibling effects but no effects for cultural transmission.

Like all studies this study has limitations. As indicated earlier, the study does not include father's ability. If father's ability were included, the SES coefficients would be even smaller. Furthermore, father's ability may partially account for the surprisingly sizable effects of mother's ability in the final models. The study has not taken into account measurement error. If measurement error for SES is greater than that for the

[10] The analysis was based on data from both male and female NLSY79 respondents. The error terms for the three occupation measures were specified as correlated. The loadings on the latent ability dimension were 0.94 for ability, 0.62 for education, between 0.52 and 0.57 for the three occupation measures and 0.39 for logged personal income. The model closely reproduced the observed variance-covariance matrix.

ability measures, SES effects will be larger but probably not substantially so.[11] A third limitation is that parents' non-cognitive traits are not included which may also influence children's test scores although the HOME measure does include parental behaviors.

This study's conclusions are about children's scores in two cognitive domains and achievement in reading and math in the United States and may not be applicable in other contexts and for other outcomes. However, researchers and policymakers need to be aware that genetics is most likely involved in any relationship involving genetically related persons, such as children and their parents, grandparents and siblings.

Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.rssm.2023.100762.

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