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No evidence for cumulating socioeconomic advantage. Ability explains increasing SES effects with age on children's domain test scores

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ABSTRACT

Studies that investigate the effects of socioeconomic background (SES) on student achievement tend to find stronger SES effects with age, although there is much inconsistency between studies. There is also a large academic literature on cumulative advantage arguing that SES inequalities increase as children age, a type of Matthew Effect. This study analysing data from the children of NLSY79 mothers (N ≈ 9000, Obs ≈ 27,000) investigates the relationship of SES by children's age for two cognitive domains (Peabody Picture Vocabulary test and digit span memory) and three achievement domains (reading comprehension, reading recognition and math). There are small increases in the SES-test score correlations for several domains, but there are more substantial increases in the test score correlations with mother's ability and prior ability. Regression analyses found linear increases in SES effects for all domains except digit memory. However, when considering mother's ability, the substantially reduced SES effects did not increase with children's age. Much of the effects of SES on children's domain scores are accounted for by mother's ability. The effects of prior ability also increase with age and SES effects are small. Therefore, there is no evidence for cumulative socioeconomic advantage for these domains. Generally, increases in SES effects on children's cognitive development and student achievement are likely to be spurious because of the importance of parents' abilities and their transmission from parents to children.

1. Introduction

Does the impact of socioeconomic (SES) on children's test scores increase as children grow older? Coleman et al. (1966, p. 300) presented two scenarios for inequalities in student achievement: (1) socioeconomic inequalities are greatest in the earliest years and then decline, and (2) socioeconomic differences increase with age. Both scenarios are plausible, the first because of the theoretical importance of the home environment, especially parenting, during early childhood (Bradley & Corwyn, 2002; Byford, Kuh, & Richards, 2012; Hart & Risley, 1999); and second because of SES differences in parents' interactions with their children's learning and schooling, and the growing importance of peers (DiPrete & Eirich, 2006; Lareau, 1989; van Ewijk & Sleegers, 2010). There are two other possibilities: no change in SES effects with age; and SES has such little impact, that the question of changes with age is moot.

Theories of cumulative advantage argue that SES inequalities accumulate over the educational career (DiPrete & Eirich, 2006), a socioeconomic "Matthew Effect". Skopek & Passaretta, 2020, p. 90 noted that Matthew Effects could cause small initial SES differences to evolve into sizeable SES-achievement gaps as children mature and progress through school. Erikson (2020, p. S49) citing Hoff (2003) and Heckman (2008), argued that children of highly educated mothers are exposed to more elaborate vocabularies at a very early age, and this leads to enhanced verbal ability as "skill begets skill". Much of the literature on cumulative advantage in education focuses on between-school tracking and within-school streaming, and school quality (DiPrete & Eirich, 2006, p. 286). The general contention is that SES differences in achievement in the lower grades are amplified by tracks, streams, and high-quality schools as higher SES students increasingly benefit from more effective and challenging academic environments. Skopek & Passaretta, 2020, p. 90 proposed an additional mechanism; independent of prior achievement, higher SES students enjoy more favourable and prestigious academic curricula than equally well-performing children from lower SES families. This literature tends to discuss cumulative advantage (or disadvantage) as if it is well-established empirically across a range of educational contexts and achievement domains.

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More than five decades after publication of the Coleman report, there is no conclusion to the simple question: do SES effects on cognitive development and student achievement increase as children grow older? Table 1 summarises relevant studies. Most found increases in SES effects with age, some found declines, one found increases during the summer vacation, but not during school terms, and others found changes depending on the domain or how achievement is measured. The tentative conclusion from these studies is that SES effects increase as children grow older, more so for math than for reading.

These studies, and the great majority of studies on the relationships between SES and educational outcomes, do not consider parents' and their children's cognitive abilities. Observed increases in the effects of SES on student achievement with age could be accounted for by the following empirically supported contentions:

1. Parents' abilities are associated with their educational and occupational attainments, and incomes, the most common indicators of SES.
2. Cognitive ability and student achievement have sizable genetic components which increase with age.
3. Parents' and their children's cognitive abilities are correlated, consistent with the genetic transmission model for a polygenic trait.
4. Cognitive ability is strongly associated with children's performance in cognitive and achievement tests. These relationships tend to become stronger with age.

1.1. Parents' abilities are associated with their educational and occupational attainments, and incomes, the most common indicators of SES

According to Strenze's (2007, p. 411) meta-analysis, 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. For the data analysed in the present study, the National Longitudinal Survey of Youth (NLSY), Zagorsky (2007, p. 493) reported a correlation of 0.62 between scores in the Armed Forces Qualification Test (AFQT), a commonly used ability measure, and ultimate years of education. Torres (2013, p. 166) reported a correlation of 0.53 between mother's AFQT score and a composite measure of family SES.

1.2. Cognitive ability and student achievement have sizable genetic components which increase with age

Meta-analyses indicate that about half the variance in cognitive ability can be attributed to genetics, that is the heritability. The Bouchard Jr. and McGue (1981) meta-analysis of 111 studies estimated a heritability of 0.51 for IQ. Polderman et al.'s (2015, MaTCH) meta-analysis of 1507 studies comprising 448,775 twin pairs estimated a heritability of 0.47.[1] The heritability of cognitive ability increases from less than 0.25 at age 5 to over 0.6 at age 15 (Bouchard Jr., 2013). Haworth et al. (2010) estimated heritabilities of 0.41 at age 9, 0.55 at age 12 years and 0.66 at age 17.

Assortative mating is the tendency for parents to be more similar than would be expected if mate selection were random. Meta-studies indicate that the cognitive abilities of parents are correlated between 0.3 and 0.5 (Bouchard Jr. & McGue, 1981; Jensen, 1998, p. 176). Assortative mating increases the heritability of a trait (Loehlin, Harden, & Turkheimer, 2009).

A meta-analysis of 61 twin studies from 11 cohorts of primary school children showed the 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 encompasses SES,

Table 1
Summary of previous studies of changes in SES-achievement relationship with age.

Study	Country	Achievement measure	SES measure	Finding
Coleman from White (1982, p. 469)	US	Verbal	Composite	Decreasing correlations: 0.21 grades 1 & 6, 0.18 grades 9 & 12.
	US	Math	Composite	Decreasing correlations: 0.22 (grade 1), 0.21 (Gr. 6), 0.16 (Gr. 9), 0.13 (Gr. 12).
White's (1982)	Meta-Study	Various	Various	Decline in SES-achievement correlation.
Pungello, Kupersmidt, Burchinal, and Patterson (1996)	US	Math	Income Groups	Increasing differences between low income and not low income from grades 2 to 7.
	US	Reading	Income Groups	No Change.
Sirin's (2005, p. 436)	Meta-Study	Various	Various	Correlations between SES and academic achievement increased then declined: 0.19 for kindergarten, 0.27 for elementary school, 0.31 for middle school and 0.26 for high school.
McCoach, O'Connell, Reis, and Levitt (2006)	US	Reading	SES Composite	No increase in SES gaps during school term but increasing SES gaps during summer vacations which accumulated.
Aikens and Barbarin (2008)	US	Reading	SES Composite	Higher SES associated more rapid reading growth thereafter.
Caro, McDonald, and Douglas Willms (2009)	Canada	Composite	SES Composite	SES-achievement gap stable between ages 7 and 11 years, widened at an increasing rate from age 11 to 15.
Ermisch and del Bono (2012)	England	Composite	Parental Education	Increasing Gaps with Key Stage Level.
Baumert, Nagy, and Lehmann (2012)	Germany	Composite	Reading	No evidence for Matthew Effect.
	Germany	Composite	Math	increase from 0.16 in grade 4 to 0.21 in grades 5 and 6.
Magnuson, Waldfogel, and Washbrook (2012)	UK	Reading, Math	Parental education	Increasing achievement gaps widen esp. in secondary school.
	US			Depends on how achievement measured.
Marks (2016)	Australia	Numeracy	SES Composite	Increase in bivariate SES relationship.

(*continued on next page*)

[1] Go to https://match.ctglab.nl/#/home, Analysis- > Domain- > Cognitive.

Table 1 (*continued*)

Study	Country	Achievement measure	SES measure	Finding
	Australia	Reading	SES Composite	Slight Increase
Harwell, Maeda, Bishop, and Xie (2017)	Meta-Study	Various, includes IQ	Various	Increasing with level: effect sizes 0.33 for kindergarten, 0.23 for elementary school, 0.16 for middle school and high school.
Hsin and Xie (2017)	US	Composite	Mother's Education	From kindergarten to grade 5 no change in the total effects of SES, but increases in direct effects through cognitive and non-cognitive skills.
	US	Composite	Family Income	
Dämmrich and Triventi (2018)	17 OECD Countries	Books in the Home	Reading	No clear trend.
			Math	Increased between primary and secondary school.
von Hippel, Workman and Downey (2018)	US	Reading , Math	Composite SES	Little change after kindergarten. Gaps tend to shrink during school Year and grow during summer vacation.
Peng, Wang, Wang, and Lin (2019)	China, meta-analysis	Various	Various	SES achievement correlation increases from kindergarten (0.23) to middle school (0.27), but is lower in high school (0.21).
Skopek and Passaretta (2020)	Germany	Cognition/ Achievement	Parental Education	SES gaps emerge and expand well before school and then remain stable.

were substantially smaller with estimates mostly around 0.10 (de Zeeuw, de Geus, & Boomsma, 2015). Like cognitive ability, the heritability of achievement tends to increase with age, although some studies find a dip in heritability estimates at older ages (Kovas et al., 2013; Soden et al., 2015, p. 4; Morris, Davies, Dorling, Richmond, & Davey Smith, 2018).

1.3. *Parents and their children's cognitive abilities are correlated, consistent with the genetic transmission model for a polygenic trait*

Parents and their biological children's cognitive abilities are correlated between 0.4 and 0.6 (Jencks et al., 1972, p. 274; Scarr & Weinberg, 1978; Black, Devereux, & Salvanes, 2009; Anger, 2012; Plomin, DeFries, Knopik, & Neiderhiser, 2013, p. 195; Grönqvist, Öckert, & Vlachos, 2017). These correlations are consistent with the expected parent-offspring correlation of 0.5 for the transmission of a polygenic trait. If both parents are considered, the mid-parent mid-child correlation is around 0.72, close to the theoretical expectation of 0.707 (Bouchard Jr. & McGue, 1981).[2]

Not only are genes transmitted directly from parent to child for cognitive ability and other educationally relevant traits, but non-transmitted genes also have effects mediated by SES or by other factors. Genetic nurture refers to the effects of parents' non-transmitted genetic alleles on their offspring's outcomes (most often educational) 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, p. 1) concluded that the "non-transmitted genetic effect was fully accounted for by parental SES".

1.4. *Cognitive ability is strongly associated with children's performance in cognitive and achievement tests. These relationships tend to become stronger with age*

For the US, Walberg (1984, p. 23) computed an average correlation of 0.71 between various IQ measures and academic achievement. Roth et al.'s (2015) cross-national meta-analysis of over 100,000 students calculated a correlation of 0.54 between intelligence and students' grades. The correlations increased with level of schooling, 0.45, 0.54 and 0.58 for elementary, middle and high school students, respectively (Roth et al., 2015, p. 123). Kriegbaum, Becker, & Spinath, 2018, p. 135 meta-analysis estimated a correlation of 0.44 between intelligence and student performance rising to 0.60 when correcting for attenuation and range restriction. Correlations were higher in grades 5 to 9 (0.46) than in grades 1 to 4 (0.42) and higher for mathematics (0.50) than for reading (0.43) or English (0.44). According to Zaboski, Kranzler, and Gage (2018) meta-analysis, the correlations of *g*, the underlying measure of general ability isolated from factor analysis, with basic reading, reading comprehension and basic mathematics, are above 0.7.

1.4.1. *The current study*

We question theories of cumulative socioeconomic inequalities in children's cognitive development and school achievement. We argue that increases in SES effects on children's test scores with age are likely to be spurious, due to the relationships between parental abilities and family SES, genetic transmission of cognitive ability and other education relevant traits from parents to their children, and the relationship between children's ability and their scores in standardized tests. Therefore, the purpose of this study is to examine these arguments with measures of children's cognitive development and student achievement. The topic is important because researchers often assume that SES is the primary influence and its effects increase with age. Such assumptions may lead to wasteful and ineffective policies.

These investigations analyse normed test scores in five domains with comprehensive and accurate age-specific measures of family SES, a measure of mothers' ability measured during adolescence or early adulthood, and their children's age-specific latent (*g*) cognitive abilities.

2. Materials and methods

2.1. *Data*

The data analysed is the US Children of 1979 National Longitudinal Study of Youth mothers (NLSY79-C). The initial NLSY79 study interviewed 12,686 respondents in 1979 born between 1957 and 1964 (aged 14 to 22 in 1979). They were reinterviewed annually from 1979 to 1994 and since 1994 biennially (U.S. Bureau of Labor Statistics, 2018c).

The NLSY79-C comprises biological children born to female NLSY79 subjects. The NLSY79-C began in 1986, and mother-child data collection occurred biennially since then. By 2014, a total of 11,521 children had

[2] The theoretical correlation for a polygenic trait between both parents and their offspring is $\sqrt{(0.5^2 + 0.5^2)}$.

been identified as born to 6283 NLSY79 female participants. Test data were collected from children aged from 3 to 15. In 1986, there were 6107 NLSY-C children aged 15 or younger decreasing to only 276 in 2014 (see U.S. Bureau of Labor Statistics, 2018d).

The NLSY-C data over-represents ethnic minorities because of the focus on disadvantaged families in the NLSY79 (U.S. Bureau of Labor Statistics, 2018d). In addition, there is sample attrition of both mothers and children. The regressions analyses reported in the results section included weights for representativeness and sample attrition (see U.S. Bureau of Labor Statistics, 2018e). The Pearson correlations presented to illustrate the strength of the associations and trends are unweighted.

2.2. Measures

2.2.1. Cognitive outcomes

Five childhood outcomes are investigated. Two are cognitive: the Peabody Picture Vocabulary Test (PPVT) and the Wechsler digit memory span scores; and three are achievement measures: the Peabody Individual Achievement Tests (PIAT) for reading comprehension, reading recognition, and math. At ages 3 and 4, children were tested only by the PPVT, at age 5 only by the PPVT and PIAT math, and at age 6 in all domains but digit memory. From ages 7 to 12, children were tested in all domains, and from age 13 to 15 only in the two PIAT reading domains and PIAT math.

All test items were dichotomous scored one for correct and zero for incorrect. For each domain, the first test item was determined by the child's age and their responses to practice questions. Testing ceased when the participant incorrectly answered a predefined number of consecutive items, for example 5 of 7 items for math. In the same domain and at the same age, there were no common first and last items and the number of items assessed varied between participants.

This study analysed the NLSY79-C constructed summary measures which were normed on a single year of age basis. For the digit memory test, the normed scores have a mean of 10 and a standard deviation of 3. The four other cognitive measures were normalized to a mean of 100 and a standard deviation of 15 (see U.S. Bureau of Labor Statistics, 2018a). The means, standard deviations and the numbers of non-missing cases for each cognitive measure by age are presented in the appendix (Table A1). Sizable numbers of children were tested more than once for each cognitive outcome. Not all students were tested in each domain (Table A2).

2.2.2. Socioeconomic variables

The NLSY79 collected data on mother's educational attainments and that of her spouse or partner. These data were utilized to construct measures of mother's and father's years of schooling and post-school education based on data for the year that the child took the test. The measures range from zero to twenty.

Mothers and fathers' occupational status are measured by socioeconomic index (SEI) scores. SEI scores were originally developed by Duncan (1961) which essentially score minor (census coded) occupational groups by the income and education levels 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 mother's and father'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 were first converted to the 2010 occupational schema (there were only minor changes) and then recoded to SEI scores according to the correspondences detailed by Hout, Smith, and Marsden (2014). The parental occupational SEI measures are for the same years that their children were tested.

The measures of family income were based on the total net family income for the previous calendar year to the interview. It comprised the net incomes of all related members of the household including the mother's partner. Family incomes for each year were adjusted to 2016 dollars using the consumer price index (U.S. Bureau of Labor Statistics, 2018b). The family income measures are for the financial year before the children were tested. To reduce the effects of outliers, the income measures were logged.

The composite measures of family SES are based on five SES indicators: father's and mother's education and occupational status, and family income. Family wealth could not be included since wealth data were not collected at every survey round. For each age level, the SES measures were constructed by averaging the five variables. Missing data was handled by multiple imputation from standardised indicators. For each age level, the composite SES measures were standardised to a mean of zero and a standard deviation of one. These age-specific SES measures were used for both the correlational and regression analyses. The correlations between the composite SES measures with students' domain scores (pooled across ages) ranged between 0.25 for digit memory to 0.39 for the PPVT and math (Table A3). The correlations of the composite SES measures two years apart are close to 0.9 and decline with increasing time intervals between measures (Table A5).

2.2.3. 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 and paragraph comprehension subtests and one-half of the score in the numeric operations subtest.

The AFQT measure has been criticized because it is correlated with age, arising from the age range of NLSY79 participants (Fischer et al., 1996, pp. 55–65). In 1989, the scores were modified, and in 2006 renormed to adjust for participants' age. The measure used for this paper is based on the 2006 scores 'Gaussified' into a normally distributed variable (Beasley, 2013). The Gaussified measure of mother's ability has a mean of zero and a standard deviation of one.

Fischer et al. (1996, pp. 55–65) also argued that AFQT was not a measure of cognitive ability but of academic aptitude. However, AFQT is highly correlated ($r \approx 0.8$) with standard measures of cognitive ability (Herrnstein & Murray, 1994, p. 609). It has been frequently used as a measure of cognitive ability (Deary, Der, & Shenkin, 2005; Herrnstein & Murray, 1994; Korenman & Winship, 2000; Rindermann & Ceci, 2018; Zagorsky, 2007).

2.2.4. Ability and prior ability

Measures of cognitive ability for ages 3 to 14 were constructed from factor analysis of the individual items. Two-parameter (difficulty and discrimination) Item Response Theory (IRT) models were fitted. A distinct advantage of IRT modelling is that missing data for an item or even many items does not remove the respondent's data from analysis. This is important because there was much variation in which test questions were administered to children in the same domain and at the same age.

In the first stage, IRT models were fitted for each domain with age-appropriate items.[3] Items that were too difficult or too easy, or were poor at distinguishing between low and high ability 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.

Table A4 lists the items and the percentages of variance explained by

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

the first or principal unrotated factor for both single-domain and the multiple-domain models. The first factors were clearly the strongest factors indicated by eigenvalues. There was no indication of multifactor solutions. From the first factor isolated from the final models, factor scores were obtained, standardized, and designated as *g*. Prior ability was measured by *g* isolated from the tests conducted 2 years earlier.

At ages 3 and 4 there were only PPVT items, so the multiple-domain factor was the same as the single-domain factor. Between ages 7 and 12 when students were tested in all 5 domains, the variation accounted for by *g* increased from 25% to 37% consistent with the increasing heritability of cognitive ability with age. If the PPVT and digit memory items are excluded, the percentage of variance explained by the principal factor increases by about 10 percentage points.

Pooling all the data, mother's ability correlates at 0.26 with digit memory and between 0.4 and 0.5 with the other four domains. Cognitive ability, *g*, correlates most strongly with PPVT scores (r = 0.78), most weakly with digit memory (r = 0.47) and between 0.66 and 0.73 with the other domains. Mother's ability and *g* correlate at 0.46 consistent with studies cited earlier that have reported intergenerational correlations for ability. Family SES correlates at 0.62 with mother's ability which is higher than Torres's estimate (Torres, 2013, p. 166). SES and *g* correlate at 0.41. The average correlation between ability and prior ability is 0.6 (Table A4). The correlations of ability and prior ability were generally higher at older ages (Table A5) again consistent with the increasing heritability of cognitive ability.

2.3. Statistical methods

2.3.1. Correlations

The relationships of students' test scores with SES, mother's ability and prior ability, and trends by age, are summarised graphically by Pearson correlations. Small samples tended to produce estimates inconsistent with the estimates from larger samples, so correlations based on samples smaller than 500 were not included in the figures. This limitation was not implemented for the regression analyses described below. Smoothed LOESS (LOcally Estimated Scatterplot Smoothing) curves are fitted to the correlation-age data points, weighted by the numbers of cases.[4] Correlations one year apart are based on alternate cohorts and correlations two years apart are based on the same cohorts.

2.3.2. General linear models for clustered data

Generalized Estimating Equations (GEEs) were introduced by Liang & Zeger, 1986 to analyse clustered data that otherwise could be modelled as a generalized linear model. The main advantage of GEE is that it accommodates within-subject correlations. Since the data analysed are of children's test scores assessed at multiple time points, the within-subject residuals cannot be assumed to be statistically independent. GEE estimates the within-subject residual correlations, which reduces the effects of the predictor variables and increases the standard errors. For these analyses, the within-subject residual correlations were specified as compound symmetry. Autoregressive or unstructured residual correlation specifications were not feasible because the models would be under-identified because of the large number of time points and sparse data within subjects.[5]

The GEE approach maximizes the amount of data analysed. For each respondent, there are between zero and four observations of their test scores (Table A2). The GEE approach estimates the working correlation matrix from data containing missing values using the all available pairs method, in which all non-missing pairs are used in the moment estimators of the working correlation parameters (Diggle, Heagerty, Liang, & Zeger, 2013 Chapter 13). That means, if a subject has missing test score data at one time point, the non-missing data at other time points are still utilized. Obviously, respondents not tested in a domain are not included in the analyses for that domain. In contrast to the dependent variables, missing values for the predictor variables are handled list-wise which is reflected by the decline in the numbers of participants and observations with the addition of predictor variables (see Tables 2 to 6). As noted earlier, missing data for SES was minimized through multiple imputation and for prior ability through IRT modelling.

The estimates from these GEE analyses are 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. The robust standard errors take into account the clustering of observations within subjects.

For each set of the analysis, two models are estimated: a main-effects model and an interaction model that includes age interaction terms, in addition to the main effects. All predictor variables are centred about their means, so that the estimates of the main effects are meaningful. If the predictor variables are not centred in the interaction model, the estimates for the main effects are for when age equals zero which is often misleading (see Jaccard, Wan, & Turrisi, 1990; Jaccard & Turrisi, 2003, pp. 23–26).

For each pair of main-effects and interaction models, the main effects are quite stable because of centring. In the interaction effect analyses, the main effects are interpreted as the effects of the predictor variables at the average age that participants took the tests for the respective domain. The estimate for the interaction terms is the change in the coefficient for a unit change in the associated predictor variable for one additional year of age.

There are four sets of models. The first set specifies SES as the only substantive predictor variable. The second set adds mother's cognitive ability to examine if increases in SES effects can be accounted for by mother's cognitive ability. The third set replaces mother's cognitive ability with children's prior ability, to ascertain if the effects of prior ability increase with age and account for increasing SES effects. The final set of models include SES, mother's ability and prior ability to establish the relative importance of SES, mother's ability and prior ability, and their interactions with age.

3. Results

Fig. 1 presents the raw correlations between SES and test scores by children's age for the five domains. The PPVT (blue diamond, solid line) and math (purple triangle, long-dash short-dash line) show the highest correlations and digit memory (red squares, dashed line), the lowest correlations. For reading comprehension (green star, dotted line) there is dramatic increase in the SES–achievement correlation with age. There are shallower increases in the correlations with age for the PPVT and math. For reading recognition (brown circle, short-dash dot short-dash line) there is an anomalous correlation (0.44) at age 5 but for older ages the correlations are stable at around 0.35. The correlations between SES and digit memory decline from ages 7 to 9 and then increase. So even without considering mother's or child's ability, the evidence for cumulating socioeconomic inequalities is not unequivocable.

Fig. 2 presents the correlations between mother's ability (AFQT) score and test scores. There is a substantial increase in the correlation between mother's ability and reading comprehension with children's age. The AFQT correlations with the PPVT, math and reading recognition show clear but smaller increases. For digit memory, the correlations increase between ages 8 and 12. The LOESS curves show largely linear or curvilinear relationships.

The correlations between prior ability and children's test scores show clear increases with age for all five domains (Fig. 3). For the PPVT, there is an anomalous very large correlation at age 6 (≈0.7) and very low

[4] LOESS regression is a nonparametric technique that uses local weighted regression to fit a smooth curve through points in a scatter plot. For more information go to: https://blogs.sas.com/content/iml/2016/10/17/what-is-loess-regression.html.

[5] Few children were tested on 4 or more occasions in a single domain (Table A 2).

Table 2
Metric and standardized effects of SES, mother's ability and prior ability on Picture Vocabulary Test Scores.

	Model 1		Model 1A	Model 2		Model 2A	Model 3		Model 3A	Model 4		Model 4A
	Metric	Std.	Metric	Metric	Std.	Metric	Metric	Std.	Metric	Metric	Std.	Metric
Intercept	94.81 ***	.	94.82 ***	93.16 ***	.	93.17 ***	94.89 ***	.	94.94 ***	93.59 ***	.	93.63 ***
Age	0.69 ***	.	0.68 ***	0.76 ***	.	0.73 ***	0.62 ***	.	0.61 ***	0.67 ***	.	0.67 ***
SES	5.68 ***	*0.27*	5.70 ***	1.97 ***	*0.09*	1.99 ***	4.58 ***	*0.22*	4.78 ***	1.63 ***	*0.08*	1.78 ***
Mother's Ability	.	.	.	7.89 ***	*0.39*	7.90 ***	.	.	.	5.69 ***	*0.28*	5.68 ***
Prior Ability	.	.	.	.	.	.	7.47 ***	*0.37*	6.37 ***	6.36 ***	*0.31*	5.43 ***
SES by Age	.	.	0.09 **	.	.	0.02	.	.	−0.11	.	.	−0.08
Mother Ability by Age	.	.	.	.	.	0.09 *	.	.	.	.	.	−0.01
Child Prior Ability by Age	.	.	.	.	.	.	.	.	0.52 ***	.	.	0.44 ***
N of Participants	9452			8963			6816			6546		
N of Observations	19,964			19,065			10,383			9993		

Note: All predictor variables centred about their means. Weighted analyses. Missing values for SES components imputed. Standardised coefficients in first model in italics. *0.01<P<0.05; **0.01>P>0.001; ***P<0.001.

Table 3
Metric and standardized effects of SES, mother's ability and prior ability on digit memory test scores.

	Model 1		Model 1A	Model 2		Model 2A	Model 3		Model 3A	Model 4		Model 4A
	Metric	Std.	Metric	Metric	Std.	Metric	Metric	Std.	Metric	Metric	Std.	Metric
Intercept	9.91 ***	.	9.91 ***	9.77 ***	.	9.77 ***	9.83 ***	.	9.83 ***	9.74 ***	.	9.74 ***
Age	0.04 ***	.	0.04 ***	0.04 ***	.	0.03 **	0.05 ***	.	0.04 ***	0.05 ***	.	0.03 **
SES	0.57 ***	*0.18*	0.57 ***	0.26 ***	*0.08*	0.26 ***	0.41 ***	*0.13*	0.41 ***	0.22 ***	*0.07*	0.23 ***
Mother's Ability	.	.	.	0.64 ***	*0.20*	0.64 ***	.	.	.	0.41 ***	*0.13*	0.41 ***
Prior Ability	.	.	.	.	.	.	0.72 ***	*0.23*	0.73 ***	0.64 ***	*0.20*	0.65 ***
SES by Age	.	.	0.02 *	.	.	−0.01	.	.	0.00	.	.	−0.02
Mother Ability by Age	.	.	.	.	.	0.05 ***	.	.	.	.	.	0.04 *
Child Prior Ability by Age	.	.	.	.	.	.	.	.	0.05 ***	.	.	0.03 *
N of Participants	8621			8212			7507			7185		
N of Observations	18,139			17,351			15,684			15,069		

Note: All predictor variables centred about their means. Weighted analyses. Missing values for SES components imputed. Standardised coefficients in first model in italics. *0.01<P<0.05; **0.01>P>0.001; ***P<0.001.

Table 4
Metric and standardized effects of SES, mother's ability and prior ability on reading comprehension test scores.

	Model 1			Model 1A		Model 2			Model 2A		Model 3			Model 3A		Model 4			Model 4A	
	Metric		Std.	Metric		Metric		Std.	Metric		Metric		Std.	Metric		Metric		Std.	Metric	
Intercept	102.13	***	.	102.14	***	101.15	***	.	101.18	***	101.45	***	.	101.48	***	100.81	***	.	100.88	***
Age	−1.29	***	.	−1.33	***	−1.25	***	.	−1.36	***	−1.17	***	.	−1.29	***	−1.13	***	.	−1.26	***
SES	3.16	***	*0.22*	3.16	***	1.24	***	*0.09*	1.26	***	2.48	***	*0.18*	2.42	***	1.08	***	*0.08*	1.09	***
Mother's Ability	.		.	.		4.48	***	*0.32*	4.47	***	.			.		3.07	***	*0.22*	2.93	***
Prior Ability	.		.	.		.		.	.		4.52	***	*0.32*	4.71	***	3.86	***	*0.27*	4.02	***
SES by Age	.		.	0.19	***	.		.	0.02		.		.	−0.08	**	.		.	−0.08	*
Mother Ability by Age	.		.	.		.		.	0.29	***	.		.	.		.		.	0.05	
Child Prior Ability by Age	.		.	.		.		.	.		.		.	0.50	***	.		.	0.44	***
N of Participants	8860					8430					8288					7921				
N of Observations	28,963					27,752					25,082					24,119				

Note: All predictor variables centred about their means. Weighted analyses. Missing values for SES components imputed. Standardised coefficients in italics. * 0.01<P<0.05; ** 0.01>P>0.001, *** P<0.001.

Table 5
Metric and standardized effects of SES, mother's ability and prior ability on reading recognition test scores.

	Model 1			Model 1A		Model 2			Model 2A		Model 3			Model 3A		Model 4			Model 4A	
	Metric		Std.	Metric		Metric		Std.	Metric		Metric		Std.	Metric		Metric		Std.	Metric	
Intercept	105.48	***	.	105.47	***	104.29	***	.	104.29	***	104.64	***	.	104.65	***	103.81	***	.	103.86	***
Age	−0.20	***	.	−0.24	***	−0.18	***	.	−0.27	***	−0.03		.	−0.16	***	−0.01		.	−0.14	***
SES	2.77	***	*0.18*	2.78	***	1.12	***	*0.07*	1.13	***	2.58	***	*0.17*	2.58	***	1.13	***	*0.08*	1.18	***
Mother's Ability	.		.	.		5.12	***	*0.34*	5.14	***	.		.	.		3.72	***	*0.25*	3.54	***
Prior Ability	.		.	.		.		.	.		4.00	***	*0.27*	4.13	***	3.38	***	*0.23*	3.50	***
SES by Age	.		.	0.17	***	.		.	0.02		.		.	−0.05	*	.		.	−0.05	
Mother Ability by Age	.		.	.		.		.	0.24	***	.		.	.		.		.	0.02	
Child Prior Ability by Age	.		.	.		.		.	.		.		.	0.58	***	.		.	0.54	***
N of Participants	9200					8748					8543					8169				
N of Observations	33,949					32,528					27,910					26,860				

Note: All predictor variables centred about their means. Weighted analyses. Missing values for SES components imputed. Standardised coefficients in italics. * 0.01<P<0.05; ** 0.01>P>0.001, *** P<0.001.

Table 6
Metric and standardized effects of SES, mother's ability and prior ability on PIAT math test scores.

	Model 1		Model 1A	Model 2		Model 2A	Model 3		Model 3A	Model 4		Model 4A
	Metric	Std.	Metric	Metric	Std.	Metric	Metric	Std.	Metric	Metric	Std.	Metric
Intercept	102.51 ***	.	102.50 ***	101.34 ***	.	101.35 ***	102.02 ***	.	102.04 ***	101.21 ***	.	101.26 ***
Age	0.18 ***	.	0.14 ***	0.21 ***	.	0.12 ***	0.18 ***	.	0.09 ***	0.20 ***	.	0.10 ***
SES	3.31 ***	*0.23*	3.32 ***	1.33 ***	*0.09*	1.35 ***	3.17 ***	*0.22*	3.17 ***	1.44 ***	*0.10*	1.48 ***
Mother's Ability	.	.	.	5.43 ***	*0.38*	5.44 ***	.	.	.	4.11 ***	*0.29*	3.99 ***
Prior Ability	.	.	.	.	.	.	4.01 ***	*0.28*	4.06 ***	3.30 ***	*0.23*	3.33 ***
SES by Age	.	.	0.17 ***	.	.	0.01	.	.	−0.01	.	.	−0.05
Mother Ability by Age	.	.	.	.	.	0.25 ***	.	.	.	.	.	0.12 ***
Child Prior Ability by Age	.	.	.	.	.	.	.	.	0.35 ***	.	.	0.27 ***
N of Participants	9210			8757			8546			8173		
N of Observations	34,080			32,653			27,992			26,943		

Note: All predictor variables centred about their means. Weighted analyses Within Subject Correlated Residuals (autoregressive). Missing values for SES components imputed. Standardised coefficients in italics. * 0.01<P<0.05; ** 0.01>P>0.001, *** P<0.001.

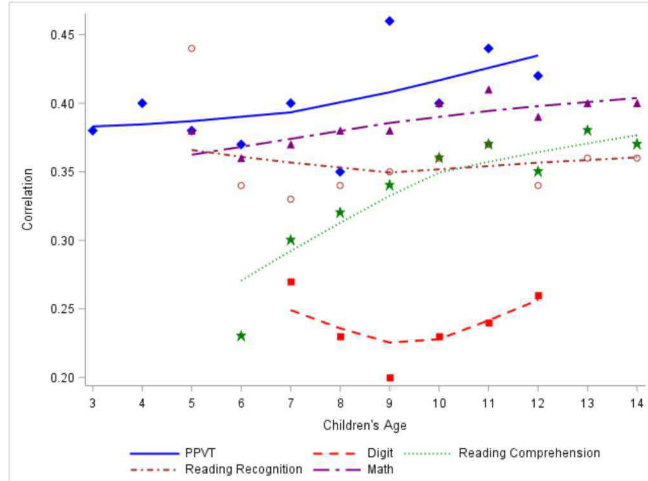

Fig. 1. SES–test score correlations by age with LOESS curves.

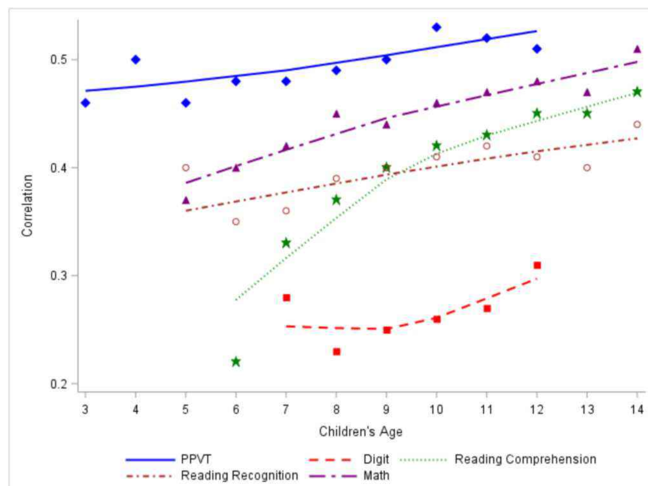

Fig. 2. Mother's ability–test score correlations by age with LOESS curves.

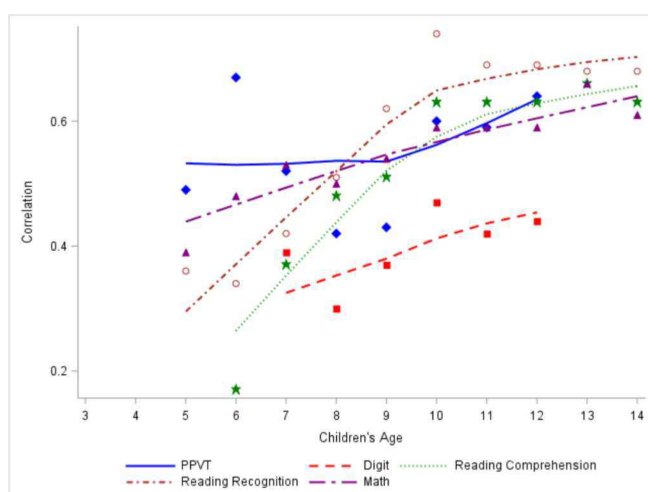

Fig. 3. Prior *g*– test score correlations by age with LOESS curves.

correlations at ages 8 and 9. The correlations then increase between ages 9 and 12. The LOESS curves for reading comprehension and math are generally linear. For reading recognition, the correlation increases rapidly until age 10 and then stabilizes. The correlations between prior ability and digit memory are weaker but also show an increase with age.

Model 1 in Tables 2 to 6 shows the effects of SES and age without considering mother's ability or prior ability. Model 1 shows moderate increases in test scores for a one standard deviation increase in SES. These effects translate into standardized effects of 0.27 for the PPVT, 0.18 for digit memory, 0.22 for reading comprehension, 0.18 for reading recognition and 0.23 for math. These standardized effects are smaller than the correlations (Table A3) because part of the effects of SES have been absorbed by the correlated residuals.

Model 1A shows that the effects of SES increase with age. The increases are small. For the PPVT, the SES effect increases by 1.6% for each one-year increase in children's age, 3.5% for digit memory, 6% for reading comprehension and reading recognition, and 5% for math. Contrary to some of the studies cited in Table 1, the increase in SES effects with age is no smaller for reading than for math.

Model 2 included mother's ability. The addition of mother's ability substantially reduces SES effects: by 65% for the PPVT, 54% for digit memory, and around 60% for reading comprehension, reading recognition, and math. The standardized effects for mother's ability are moderate: 0.39 for the PPVT, 0.20 for digit memory, 0.32 for reading comprehension, 0.34 for reading recognition and 0.38 for math. SES effects, net of mother's ability, are small: 0.09 for the PPVT, 0.08 for digit memory, 0.09 for reading comprehension 0.07 for reading recognition, and 0.09 for math. Thus, the effects of mother's ability are 3 to 4 times that of SES, except for digit memory where the effect for mother's ability is about twice as large as that for SES.

Model 2A shows that the effects of mother's ability increase with children's age for all domains. For each one-year increase in children's age, the effects of mother's ability increase by 1% for the PPVT, 8% for digit memory span, and about 5% for reading comprehension, reading recognition and math. Model 2A also shows that when controlling for changes in the effects of mother's ability with age, there are no statistically significant SES-age interaction effects. So, apparent increases in SES effects with age are accounted for by increases in the effects of mother's ability.

Model 3 presents the estimates substituting children's prior ability for mother's ability. Comparing models 2 and 3, the effect of prior ability tends to be weaker than that for mother's ability. This is because the correlated residuals have absorbed part of the effect of prior ability. The addition of prior ability has not substantially reduced SES effects in contrast to the addition of mother's ability in model 2. This is because SES and mother's ability are more highly correlated than SES and child's ability (Table A3).

According to model 3A, there is no increase in the effects of SES with age, net of prior ability. The SES-age interactions tend to be small and negative, but only statistically significant for reading comprehension. The effects of prior ability increase with age more strongly than for mother's ability: 8% for the PPVT, 7% for digit memory, 11% for reading comprehension, 14% for reading recognition and 9% for math. These increases are consistent with the genetic model of increasing heritability of both cognitive ability and achievement with age.

Model 4 includes all 3 substantive predictors. Controlling for both mother's ability and child's prior ability, SES effects are small ($\beta \leq 0.10$). Both mother's ability and prior ability have moderate effects for all five domains. There are three explanations for the moderate effects of mother's ability, net of child's ability: proxy effects of father's ability due to assortative mating, genetic nurture and maternal socialization. Since father's and mother's abilities are correlated, the residual effects of mother's ability are, to some extent, proxies for father's abilities. In contrast, to previous studies (e.g., Bates et al., 2018), the effects of genetic nurture are not subsumed by SES. Our interpretation of the effects of mother's ability in model 4 is that they index parenting and other maternal behaviours associated with children's cognitive development and achievement that are independent of SES. These behaviours include genetic nurture as well as purely environmental effects. We speculate that the weaker effect of mother's ability on digit memory is because mothers do not encourage their child to memorise digits forwards and backwards, whereas they often promote literacy and numeracy skills.

Model 4A shows that net of SES and mother's ability, the effects of prior ability increase with children's age: 8% for the PPVT, 5% for digit memory, 11% for reading comprehension, 15% for reading recognition and 8% for math. These percentage increases are comparable with that found in model 3A, indicating that the increase in the effects of prior ability with age are robust to the inclusion of mother's ability and mother ability-age interactions. The effects of mother's ability did not increase significantly with age except for digit memory. There were no statistically significant positive SES-age interactions.

4. Conclusions and discussion

The main conclusion from this study is that the increase in the SES effects on cognitive development and student achievement as children grow older observed in these data is spurious, confounded by parental and child's abilities. Increases in SES effects with age for some domains disappear with the inclusion of mother's ability and mother's ability age interaction terms, or with analogous measures of prior ability. Net of mother's and child's abilities, SES effects on children's test scores are small, so changes in its effects with age are unimportant.

This study is more than just a textbook example of spuriousness and confounding variables. It has important practical implications. The small SES effects found net of mother's ability or prior ability should alert researchers that SES is not the main influence of cognitive development or student achievement, so developing theories and policies that focus largely on SES is unproductive. For policymakers, the focus should be directly on children's cognitive development and school performance not on SES, a moderately associated correlate. Policies should identify and assist children lagging behind and aim to improve the skills of all children regardless of background.

Student achievement is strongly associated with high stakes examinations, students' grades, dropping out, university entrance and overall educational attainment (Knighton & Bussière, 2006; Marks, 2007, 2010, p. 31; OECD, 2010; Fischbach, Keller, Preckel, & Brunner, 2013; Wiberg, 2019). This study suggests that at least some of the impact of SES on consequential educational outcomes can be attributed to parental abilities and their genetic and environmental transmission to students.

The main limitation of this study is the absence of father's ability. Its inclusion is likely to show that the SES effects are even smaller but would not change the study's main conclusions. Another limitation is that *g* was isolated from tests conducted two years earlier. It would have been preferrable to analyse age-appropriate measures of cognitive ability administered at the same age when the specific domain tests were administered. A third limitation is that it does not directly incorporate genetics. It is possible to perform genetic analyses utilizing data from the NLSY79 kinship links (Hart, Petrill, & Kamp Dush, 2010; Rodgers et al., 2016). Such a study may clarify the role of genetics in the interrelationships of SES, mother's ability, prior ability, children's test scores and age in these data.

The findings from this study are likely to apply to contexts other than the cohort of US children with mothers born between 1957 and 1964. Replication of these analyses in other contexts would establish if the finding that ability accounts for increases in SES effects on children's cognitive and achievement outcomes applies more generally. SES and income differentials are apparently stronger in the US than in comparable countries (Bradbury, Waldfogel, & Washbrook, 2018; Chmielewski & Reardon, 2016). In the absence of analyses in other contexts, it would seem reasonable to assume that since SES effects on cognitive and achievement outcomes are small in this US sample, the expectation in other contexts would be comparable or smaller SES effects, and no real increase with children's age.

Underlying this discussion is the broad SES-attainment paradigm: the popular belief, pervasive in the social sciences, that parental SES is the main causal influence on children's outcomes. The SES paradigm cannot explain the small SES effects when controlling for mother's ability, or the increasing effects of mother's or child's ability with age. As pervasive paradigms begin to fail, there are often attempts to revise and revive them with alternative and more sophisticated versions. The cumulative advantage argument attempts to resurrect the SES concept as a powerful causal influence.

The overarching purpose of this paper is to critique this more subtle version of the SES paradigm - that the relationship between SES and attainment may be small at a single time point but is cumulative so SES becomes increasingly important as children age. This study suggests that the cumulative advantage thesis is not tenable. SES effects do not increase for all domains and where there are increases, they are small. In contrast, the effects of mother's ability and prior ability increase more substantially and arguably for all domains. The apparent growth in the association of parental SES and children's test scores is, in fact, explained by the increasing impact of cognitive ability.

The important policy lesson implied from this study is that the increasing amounts of resources and energy devoted to redress supposedly cumulative socioeconomic inequalities in education could be much better utilized.

Appendix A. Appendix

Table A1
Means and standard deviations of the cognitive and achievement variables by children's age.

Age	PPVT			Digit memory span			Reading comprehension			Reading recognition			Math			Prior ability		
	N	$\overline{X}$	Std.	N	$\overline{X}$	Std.	N	$\overline{X}$	Std.	N	$\overline{X}$	Std.	N	$\overline{X}$	Std.	N	$\overline{X}$	Std.
3	990	89.3	16.9															
4	2575	87.0	21.0															
5	2613	87.0	22.5				219	121.4	18.9	1967	108.2	17.1	2014	98.9	15.7			
6	1536	91.5	19.5				1428	111.5	9.1	3470	105.5	12.3	3532	100.0	13.8			
7	1210	90.8	19.8	2023	9.9	3.1	2959	105.8	10.7	3670	104.0	12.2	3679	100.5	11.9			
8	1108	89.6	19.1	3544	9.8	3.1	3392	104.7	12.9	3582	104.8	13.8	3585	101.0	13.0	1417	0.00	1.00
9	1076	89.8	19.6	3142	9.6	3.0	3603	102.4	14.1	3687	104.3	14.9	3700	101.4	14.9	2932	0.00	1.00
10	2578	92.8	19.8	3264	9.8	3.3	3561	101.0	13.8	3621	104.2	15.4	3620	101.9	15.0	3580	0.00	1.00
11	3577	93.2	20.8	3607	9.9	3.2	3592	99.0	14.4	3642	103.3	15.6	3644	101.4	15.4	4020	0.00	1.00
12	1730	93.9	20.0	1818	10.0	3.2	3420	98.2	13.6	3462	102.8	15.5	3468	101.1	14.4	4108	0.00	1.00
13	375	89.4	17.4	419	9.1	3.2	3378	96.7	13.7	3407	103.0	16.3	3410	100.7	14.6	4351	0.00	1.00
14	485	89.7	18.2	358	9.5	2.9	3228	96.1	13.4	3256	103.4	16.6	3245	99.6	15.1	4303	0.00	1.00
15	157	87.2	19.5	8	12.3	3.1	267	93.6	13.0	272	98.8	16.1	270	94.1	13.8	4463	0.00	1.00
Sum/ Mean	20,010	90.6	20.4	18,185	9.8	3.1	29,047	101.1	14.0	34,036	104.1	15.0	34,168	100.7	14.33	29,174	0.00	1.00

Table A2
Number of measures for the cognitive and achievement variables.

N of measures	PPVT		Digit span memory		Reading comprehension		Reading recognition		Math	
	N	%	N	%	N	%	N	%	N	%
0	2054	17.8	2889	25.1	2646	23.0	2308	20.0	2299	20.0
1	2415	21.0	1840	16.0	905	7.9	857	7.4	852	7.4
2	3706	32.2	4056	35.2	1315	11.4	1099	9.5	1088	9.4
3	3201	27.8	2713	23.5	2079	18.0	1278	11.1	1288	11.2
4	145	1.3	23	0.2	3605	31.3	2748	23.9	2695	23.4
5	.	.	.	.	971	8.4	3231	28.0	3299	28.6

Table A3
Pooled correlations.

	Mother's ability	SES	PPVT	Digit	Reading compreh.	Reading recogn.	Math	Ability
SES	0.62							
PPVT	0.49	0.39						
Digit Span	0.26	0.25	0.38					
Reading Comprehension	0.41	0.34	0.57	0.40				
Reading Recognition	0.40	0.36	0.54	0.48	0.73			
Math	0.45	0.39	0.58	0.45	0.56	0.59		
Ability (*g*)	0.46	0.41	0.78	0.47	0.69	0.73	0.66	
Prior Ability	0.46	0.41	0.58	0.40	0.56	0.61	0.56	0.60

Note: Measures combined over children's ages 3 to 15.

Table A4
Items and percentages of variance accounted for by isolated principal latent factors.

Age	Digit		PPVT		Math		Reading comprehension		Reading recognition		*Multiple domains (g)*
	Items	%	Items	%	Items	%	Items	%	Items	%	
3			1–50	29.5							*29.5*
4			16–55	34.9							*34.9*
5			20–65	30.6	6–35	30.3					*25.1*
6			35–97	27.3	15–40	37.9	19–26	48.0	19–25	75.1	*24.4*
7	3–6[1],8–11	33.6	50–110	29.6	25–55	44.4	19–40	35.1	19–40	45.8	*25.0*
8	3–12	26.9	60–110	24.4	30–60	48.6	23–60	32.7	26–61	43.6	*24.6*
9	3–7,9–12	28.6	70–120	23.3	35–70	47.0	30–66	30.2	30–70	40.8	*24.4*
10	4–7,9–12	27.1	82–152	38.0	40–79	44.1	40–79	38.6	40–79	46.2	*33.3*
11	4–7,9–13	26.9	85–160	42.4	40–81	45.9	40–82	35.5	40–84	43.1	*34.4*
12	4–7,9–14	24.0	90–170	38.0	55–84	56.2	50–84	38.9	50–84	44.5	*37.1*
13					55–84	50.6	50–84	35.1	50–84	39.0	*35.8*
14					55–84	48.2	55–84	36.4	55–84	39.2	*36.3*
15											

Note: 1, Item 5A excluded. Item 14B excluded.

Table A5
Correlations for composite SES measure and ability by children's age.

	3	4	5	6	7	8	9	10	11	12	13	14
Age 3			0.42		0.43		0.31		0.51		0.36	
Age 4				0.46		0.48		0.53		0.54		0.48
Age 5	0.87				0.45		0.50		0.59		0.47	
Age 6		0.88				0.54		0.54		0.51		0.46
Age 7	0.85		0.89				0.61		0.61		0.49	
Age 8		0.86		0.90				0.70		0.64		0.58
Age 9	0.82		0.86		0.90				0.70		0.63	
Age 10		0.84		0.87		0.90				0.69		0.63
Age 11	0.80		0.86		0.87		0.90				0.66	
Age 12		0.82		0.85		0.87		0.90				0.66
Age 13	0.79		0.84		0.86		0.88		0.90			
Age 14		0.82		0.84		0.86		0.88		0.90		
Age 15							0.79		0.70		0.73	

Note: Correlations for SES below diagonal, ability (*g*) above diagonal.

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