Individual differences in executive function partially explain the socioeconomic gradient in
middle-school academic achievement

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Abstract

Children from families with low socioeconomic status (SES) earn lower grades, perform worse on achievement tests, and attain less education on average than their peers from higher-SES families. We evaluated neurocognitive mediators of SES disparities in achievement in a diverse sample of youth whose data were linked to administrative records of performance on school-administered tests of 7th grade reading and math proficiency ($N=203$). We used structural equation modeling to evaluate whether associations between SES (measured at ages 8-9) and achievement (measured at age 13) are mediated by verbal ability and executive function (measured at age 10), a suite of top-down mental processes that facilitate control of thinking and behavior. Children from relatively higher-SES families performed better than their lower-SES peers on all neurocognitive and achievement measures, and SES disparities in both reading and math achievement were partially mediated by variation in executive function, but not verbal ability. SES disparities in executive function explained approximately 37% of the SES gap in math achievement and 17% of the SES gap in reading achievement. Exploratory modeling suggests that SES-related variation in working memory may play a particularly prominent role in mediation. We discuss potential implications of these findings for research, intervention programming, and classroom practice.

Keywords: socioeconomic status, executive function, academic achievement

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Introduction

Children born into families on the lower rungs of the socioeconomic ladder confront poor odds of substantially improving their positions as adults (C. Lee & Solon, 2009). One important mechanism accounting for the persistence of income inequality is the socioeconomic gap in academic achievement (Brooks-Gunn & Duncan, 1997). On average, children from families with relatively low socioeconomic status (SES), typically indexed by parental education and income, earn lower grades, perform worse on standardized achievement tests, and attain less education than their higher-SES peers (Bradley & Corwyn, 2002; Haveman & Wolfe, 1995). Associations between SES and academic achievement persist throughout childhood and adolescence and are evident across the full socioeconomic spectrum (Reardon, In, & York, 2011). Furthermore, at least a portion of the SES-achievement gap is attributable to causal effects of family income: For instance, studies estimating the impact of anti-poverty policy interventions like the Earned Income Tax Credit have identified positive impacts of increased family income on child achievement (Dahl & Lochner, 2012). In the absence of comprehensive policy reforms to reduce income inequality at the societal level, the burden of addressing SES disparities in achievement will fall largely on educators and interventionists. In addition to providing support services addressing the nutritional and mental health challenges frequently faced by students from low-income families, stakeholders might consider changes to curricular or instructional practices to help address the most common cognitive barriers to learning faced by disadvantaged students. To help target these efforts, research is needed to identify specific domains of cognitive functioning that best account for the SES gradient in achievement. The current study contributes to this effort by evaluating the degree to which executive function and verbal ability mediate the association between childhood SES and academic achievement across the

transition to middle school.

Socioeconomic Gradients in Cognitive Development

To date, much of the research on mechanisms underlying the SES-achievement gap has focused on qualities of the child's environment that vary along the SES gradient and are likely to shape cognitive development. Children from lower-SES families are more likely than their peers to be exposed to a variety of stressors, including (but not limited to) family turmoil and instability, violence in the home and neighborhood, and environmental toxins (Evans, 2004). At the same time, they may experience less responsive parenting and social support and may be exposed to fewer cognitively stimulating materials and experiences in both home and school environments (Bradley & Corwyn, 2002). Collectively, this work underscores the degree to which research on SES gradients in developmental outcomes inherently capitalizes on the capacity of SES to serve as a proxy measure of a child's cumulative exposure to a broad array of positive and negative experiences known to powerfully shape physical, socioemotional, and cognitive development.

Although SES is a well-established predictor of performance on broad measures of cognitive ability (e.g., fluid intelligence; Duyme, Dumaret, & Tomkiewicz, 1999; A. Gottfried et al., 2003), more recent research has begun to map SES-cognition associations at a much finer level of analysis by employing modern neuropsychological assessments. Because neuropsychological tests were initially developed to characterize the (often subtle) cognitive and behavioral consequences of localized brain lesions (Heaton & Pendleton, 1981), they are capable of indexing individual differences in well-defined neurocognitive functions associated with the integrity of specific neural systems. A growing body of neuropsychological research points to SES disparities in executive function (EF), a set of capacities related to top-down control of attention and behavior (e.g., Farah et al., 2006; Last, Lawson, Breiner, Steinberg, & Farah, 2018; Mezzacappa, 2004; Noble, McCandliss, & Farah, 2007; Waber et al., 2007).

There is broad consensus that the protracted maturation of the prefrontal cortex (PFC) and its reciprocal connections to other brain regions contributes to the relatively late maturation of EF capacities (Casey, Getz, & Galvan, 2008; Luna, Padmanabhan, & O’Hearn, 2010), which in some cases show efficiency gains into the twenties (Albert & Steinberg, 2011). Farah and colleagues have argued that this protracted maturational timetable may render EF development particularly vulnerable to disruption by the cumulative stresses associated with childhood socioeconomic deprivation (Hackman, Farah, & Meaney, 2010). A meta-analysis of studies reporting correlations between childhood SES and EF in samples ranging in age from 2 to 18 years old identified small but statistically significant correlations between SES and working memory ($r=.18$), attention shifting ($r=.17$), and response inhibition ($r=.14$) (G. Lawson, Hook, & Farah, 2017).

SES is also consistently associated with variation in verbal ability (Hoff, 2003; Hoff & Tian, 2005; Mercy & Steelman, 1982; Nittrouer, 1996; Noble et al., 2007). Noble and colleagues (2007) evaluated SES differences in performance on a broad array of neurocognitive tasks and found the largest effects on measures of verbal ability, alongside smaller but significant effects on measures of EF. SES disparities in verbal ability are also observed longitudinally. For instance, among children born to participants of the National Longitudinal Survey of Youth 1979, a nationally representative cohort study, large differences in vocabulary knowledge between low- and high-SES strata were already apparent by age 3 and persisted through age 13 (Farkas & Beron, 2004). These findings are consistent with observations that children from lower-SES homes may be exposed to a much more limited vocabulary in the home environment relative to their higher-SES peers (Hart & Risley, 2003).

Neurocognitive Foundations of Academic Achievement

The domains of neurocognitive functioning with the strongest associations with SES – namely, executive function and verbal ability – are also important predictors of academic

achievement, independent of SES. Much of the work on EF has focused on its role as a foundation for early childhood school readiness (Blair & Razza, 2007; Bull, Espy, & Wiebe, 2008). Studies have also demonstrated correlations between EF and childhood and adolescent performance on standardized tests of math and reading achievement, measured concurrently (e.g., Best, Miller, & Naglieri, 2011; St Clair-Thompson & Gathercole, 2006) and, in fewer cases, prospectively (Mazzocco & Kover, 2007; Welsh, Nix, Blair, Bierman, & Nelson, 2010). However, the literature on EF and academic achievement is not entirely consistent; some studies have found significant associations between EF and math but not EF and reading (Brock, Rimm-Kaufman, Nathanson, & Grimm, 2009; Schmitt, McClelland, Tominey, & Acock, 2015).

In addition to EF, verbal ability is one of the most consistent predictors of academic achievement (Duncan et al., 2007). Specifically, verbal skills measured around the time of school entry are associated with math and reading achievement across the elementary school years (K. Beron & Farkas, 2004; Kurdek & Sinclair, 2001; Lonigan, Burgess, & Anthony, 2000).

Neurocognitive Mediators of the SES-Achievement Gap

Despite substantial research identifying associations between SES and neurocognitive functioning, and between neurocognitive functioning and academic achievement, few studies have formally evaluated the degree to which individual differences in neurocognitive functioning account for the SES gradient in achievement. Most have been conducted with young children and focused on the role of EF. For instance, research on mechanisms underlying the association between SES and school readiness among preschool children identified mediating roles for attention and inhibitory control (NICHD Early Child Care Research Network, 2003) as well as latent or composite measures of EF (Dilworth-Bart, 2012; Fitzpatrick, McKinnon, Blair, & Willoughby, 2014). Likewise, a study of elementary school

children found that associations between early childhood SES and first grade math and literacy scores are mediated by a latent variable estimate of EF (but not expressive vocabulary) derived from tasks administered in kindergarten (Nesbitt, Baker-Ward, & Willoughby, 2013). Crook and Evans (2014) found that associations between childhood SES and fifth grade math and reading scores are mediated by planning skills, measured in the third grade using the Tower of Hanoi task.

Evidence also exists supporting the mediating role of verbal ability. Fitzpatrick and colleagues (2014) found that, when accounting for effects of both EF and vocabulary knowledge in the same model of preschool readiness, vocabulary is a significant mediator of SES differences in both math and reading, whereas EF is significant only for math. Likewise, Beron and Farkas (2004) found support for the role of verbal ability as a mediator of SES differences in reading achievement among a large sample of elementary school children, although the study did not control for differences in EF.

To our knowledge, only one study to date has investigated neurocognitive mediators of the SES-achievement gap in a post-elementary school sample. Lawson and Farah (2017) used structural equation modeling to evaluate whether EF mediates associations between SES and changes in reading and math achievement over a two-year interval in a sample of 6- to 15-year-olds ($M = 10.13$) drawn from the NIH MRI Study of Normal Brain Development. EF was operationalized as a latent variable using measures of spatial memory span, spatial working memory, shifting, and verbal working memory capacity. An alternative candidate mediator, verbal memory, was operationalized as a latent variable using recall measures from the California Verbal Test of Learning for Children (Woods, Delis, Scott, Kramer, & Holdnack, 2006). Notably, the authors did not control for variation in general verbal ability (e.g., vocabulary knowledge or verbal fluency). Reading and math achievement were assessed with the Woodcock-Johnson III (Woodcock, McGrew, Mather, Woodcock-Johnson, & Itasaca, 2001). Statistical models simultaneously tested mediation of SES-achievement associations

by EF and verbal memory. EF, but not verbal memory, partially mediated the association between SES and math, but not reading achievement. Given that the study did not control for general verbal ability, the specificity of EF mediation should be interpreted with caution.

In summary, mounting evidence implicates neurocognitive functioning as an important mechanism contributing to the SES gradient in academic achievement. However, several critical gaps in the literature need to be addressed to improve our understanding and increase its value for educators. First, very few studies have simultaneously evaluated variation in SES, neurocognitive function, and achievement, a prerequisite for establishing mediation, and the existing literature is based almost entirely on preschool- and elementary-age samples. More work is needed evaluating these processes in older youth in order to establish the generalizability of findings from younger samples. Second, most work to date has evaluated a limited set of hypothesized mediators and has not always accounted for SES-related differences in general verbal ability. To minimize confounding and improve specificity, studies are needed that simultaneously test candidate mediators. Third, because most studies have administered neuropsychological and achievement tests concurrently, correlations may be inflated by transient confounders (e.g., a sleepy child may underperform on both tests); more studies are needed that measure neurocognitive function prior to assessment of academic achievement. Finally, research is needed to bridge the gap between the laboratory and the classroom. In each of the SES-achievement mediation studies reviewed above, academic achievement was assessed in a one-on-one home or laboratory setting with subtests from the Woodcock-Johnson battery. Notwithstanding the excellent psychometric properties of such individually administered tests, they lack the concrete real-world consequences of state-mandated, group-administered assessments of academic proficiency that are often tied to student promotion, permission to enroll in challenging coursework, access to teachers certified in gifted education, and even college admissions.

The current study aims to address each of these gaps in the literature by evaluating

neurocognitive mediators of SES differences in middle-school academic achievement. We investigate these processes in an ethnically and socioeconomically diverse sample of youth currently enrolled in a longitudinal study of family processes and child development (the Parenting Across Cultures study), whose data have been linked to administrative records of performance on state-mandated, school-administered tests of reading and math proficiency. We use structural equation modeling to test the hypothesis that EF (measured as a latent variable) and verbal fluency each partially mediates associations between SES and reading and math achievement, such that children from higher-SES families will, on average, exhibit greater EF and verbal fluency than their peers from lower-SES families, which will in turn be associated with increased academic achievement (see Figure 1). To generate more specific testable hypotheses for future confirmatory research, we then conduct exploratory path analysis using manifest variables to estimate the degree to which each candidate neurocognitive mediator mediates SES differences in achievement (see Figure 2).

Method

Data for this study were collected as part of a prospective longitudinal study of parenting and child adjustment being conducted with a sample of 8-year-old children and their families recruited from a mid-sized city in the Southeastern United States (see <http://parentingacrosscultures.org> for overview). After obtaining university IRB approval and approval from the appropriate elementary school authorities (research review board and school principals), families were recruited from 15 public and two private elementary schools, using recruitment letters written in both English and Spanish. Interviews with 311 families were completed, including 109 European American, 99 Latin American (primarily recent arrivals to the city with more than half from Mexico and with smaller numbers from El Salvador, Guatemala, Honduras, and other Latin American countries), and 103 African American. Following this initial assessment, conducted when the child was (on average) 8

years old, families were interviewed annually; as of this writing, 8 waves of interviews have been completed. For the present study, analyses were limited to the 203 families for whom state-administered end-of-grade (EOG) test scores in reading and math were available for the child's 7th grade year. This subsample did not significantly differ from the subsample of participants missing EOG test scores on family income, parental education or marriage status, or child age, sex, or ethnicity (all subsample comparison p -values > 0.05). Table 1 presents demographic characteristics of the 203 families at the initial assessment. On the basis of the similarities in demographic statistics between our sample and the population of the study site, we conclude that our sample is generally representative of the local population.

Procedures and Measures

The current study uses data collected at four time points, including the initial interview assessment (age 8), annual follow-up assessments at years two (age 9) and three (age 10), and administrative records collected at the end of the child's 7th grade year (age 13). Interview assessments lasted 1.5 to 2 hours and were conducted in participants' homes or at another location (e.g., public library) chosen by the participants. Interviewers traveled to these sites in teams of two or three, and each family member was interviewed by a different interviewer in a place out of hearing of the other family members. We estimated socioeconomic status using questionnaire-based interview data collected from parents at the first two assessments. Neurocognitive performance was assessed with a battery of computerized performance tasks completed by children at the age 10 assessment. Academic achievement scores were derived from administrative records collected at the end of the child's 7th grade year.

Socioeconomic Status. Socioeconomic status was measured as a composite variable based on parents' responses to questions about educational attainment and family income. In the first three years of the project (child ages 8-10), either the mother or father

completed a demographic questionnaire that included questions about the number of “years of formal education” attained by oneself and one’s spouse or partner, if applicable. We computed an index of educational attainment as the mean of all available reports. At the age-9 and -10 assessments, the demographic questionnaire included an item asking the respondent to “indicate the gross annual income of your family” on a 10-point scale with options ranging from “up to \$5000” to “beyond \$81,000”. We computed an index of family income as the mean of these two reports. Finally, we computed a composite index of socioeconomic status as the mean of standardized scores for parental educational attainment and family income (Chronbach’s $\alpha = .83$).

Neurocognitive Performance Measures. As part of the age 10 assessment, children completed a set of widely used neurocognitive performance tasks. The current study uses data from four tasks measuring components of executive function (Verbal Working Memory, Spatial Working Memory, Response Inhibition, and Strategic Planning), and one measure of Verbal Fluency. All performance scores were standardized as z-scores prior to model estimation.

Verbal Working Memory. We assessed Verbal Working Memory using an item recognition memory task (Thompson-Schill et al., 2002). On each trial of this task, participants saw four probe letters on the screen, followed by a brief delay. They were then presented a single target letter and asked whether the target was among the four probes. In half of the trials, the probe item was a member of the target data set (i.e., “positive” trials); in the other half of the trials, the probe item was not a member of the target data set (i.e., “negative” trials). To respond accurately, participants pressed a key corresponding to *yes* for positive and *no* for negative trials.

Each participant completed 4 blocks of experimental trials and 1 block of control trials; each block included 40 trials. For experimental trials, the trial sequence was manipulated to vary the degree to which items from previous trials would interfere with accurate recognition

of target items on current trials. Half of the trials used probe letters that appeared in the previous target set (not the one against which participants are currently comparing). Thus, these “recent” trials introduce interference to the task; if participants fail to effectively update the working memory buffer by clearing items from previous trials and adding items from the current trial, they might inaccurately identify the probe as a member of the target set of letters. We calculated a Verbal Working Memory score as the proportion of accurate responses on this set of 80 high-difficulty trials.

Spatial Working Memory. Spatial working memory was assessed using a computerized task designed to evaluate an individual’s capacity to maintain information in spatial working memory as well as to retrieve it (Chein & Morrison, 2010). Participants were presented with a series of red squares on a grid, one at a time. They were then instructed to recall the order in which the red squares appeared on the grid. Thus, the task required recall of a sequence and the location of the items. The task is “computer adaptive”; when the participant responded correctly, the task became increasingly more difficult, offering an additional square to remember. The number of test items increased until the participant failed to correctly recall two successive trials at a given list length. A participant’s Spatial Working Memory was defined as the maximum list length for which all items were recalled in the correct serial order.

Response Inhibition. A computerized version of the classic Stroop color-word task was administered to assess prepotent response inhibition (Stroop, 1935). On each trial, the participant was presented a color-word (e.g., “blue”, “yellow”) and instructed to identify the color in which the word was printed (while ignoring the semantic meaning of the word) by pressing a corresponding key as quickly as possible. Trials varied on whether the color-word and the printed color of the word were congruent or incongruent. Participants completed two 48-trial experimental blocks. The first block included an equal mix of congruent and incongruent trials, and the second included a greater number of congruent than incongruent

trials. Utilizing all trials, we calculated an interference effect for accuracy as the difference in ratio of accurate responses on incongruent versus congruent trials. To allow interpretation of Stroop results as a capacity, we reverse-scored the variable, such that higher scores represent stronger inhibition of attention to distracting stimuli.

Strategic Planning. A computerized version of the classic Tower of London task was administered to assess strategic planning and impulse control (Berg & Byrd, 2002; Shallice, 1982). On each trial, the participant is presented with pictures of two sets of three colored balls distributed across three rods, the first of which can hold three balls, the second only two balls, and the last only one ball. The first picture shows the starting position of the three balls, and the second depicts the goal position. The participant is asked to move the balls in the starting arrangement to match the other arrangement in as few moves as necessary, using the computer cursor to “drag” and “drop” each ball. Five sets of four problems are presented, beginning with those that can be solved in three moves and progressing to those that require a minimum of seven moves. The trial is considered successfully solved if the solution is correctly submitted within a time limit of 160 s. We computed an index of Strategic Planning as the percentage of trials with perfect solutions (i.e., trials solved in the minimum number of moves), a measure of optimal planning and execution of the task (Albert & Steinberg, 2011).

Verbal Fluency. A measure of verbal fluency asked participants to speak, in 1 min, as many words as possible which either began with a specific letter (3 trials) or were members of a category (e.g., fruits) (3 trials). For each trial, the interviewer recorded the number of unique spoken words. A Verbal Fluency score was computed by averaging the number of words generated for each of the six lists.

Academic Performance. To measure academic performance, we used administrative records of state-mandated, end-of-grade (EOG) test scores in reading and math from the child’s 7th grade year. All 3rd- through 8th-grade students in the study state

are required to take EOG achievement tests in both reading and math. We opted to use grade 7 scores because all children in our sample had completed the age 10 battery of neurocognitive performance measures before the grade 7 EOG testing period, providing the sequential ordering required to evaluate neurocognitive performance as a predictor of EOG scores. EOG tests in reading comprehension measure the ability to demonstrate understanding of a written passage and knowledge of vocabulary. EOG tests in math measure proficiency in five areas: numbers and operations; measurement; geometry; data analysis and probability; and algebra. EOG test score files included raw test scores, student grade level, and year of testing. Because state-level mean scores for the tests varied substantially based on the year of testing, we standardized participants' scores based on the state mean and standard deviation for the corresponding year. Using this method, we transformed each student's raw score to a percentile score, which indicates the percentage of students in the state scoring below that student for the given year.

Data Analysis

All structural equation models were tested using the R package “lavaan” (Y. Rosseel et al., 2017). We used a full information maximum likelihood estimator with robust standard errors to account for data missing at random and non-normality. We define acceptable model fit as a χ^2 -to- df ratio less than 3, CFI greater than or equal to 0.95, RMSEA less than 0.08, and SRMR less than or equal to 0.10 (Schermele-Engel & Moosbrugger, 2003). After establishing acceptable fit for each model, we evaluate the statistical significance of indirect effects using bias-corrected bootstrap confidence intervals (95% CIs) based on 5000 draws with replacement; effects are deemed significant if the CI does not include zero (Preacher & Hayes, 2008). We estimate the magnitude of each significant indirect effect as a mediation ratio (indirect/total effects; Ditlevsen, Christensen, Lynch, Damsgaard, & Keiding, 2005).

Results

Means, standard deviations, and intercorrelations of all continuous variables are reported in Table 2.

Do Executive Function and Verbal Fluency Mediate SES Differences in Reading and Math Achievement?

We first evaluated the fit of Model 1 (Figure 1), in which executive function is estimated as a latent variable, and SES, verbal fluency, and reading and math achievement are manifest variables. The model fit the data well: $\chi^2(14, N = 203) = 14.58, p = 0.408$, $CFI = 1.00$, $RMSEA = 0.01$, $SRMR = 0.03$, $AIC = 5,985.80$, $BIC = 6,078.57$. Factor loadings for the latent EF variable are reported in Table 3. Latent EF accounted for 46.19% of the observed variation in verbal working memory, 18.36% of spatial working memory, 18.60% of planning, and 5.76% of response inhibition.

Altogether, the model explained 52.39% of the variation in reading scores and 57.27% of math scores. All path coefficients are provided in Table 4; full model results, including variance and covariance estimates, are provided in Supplemental Table 1. SES had significant direct effects on verbal fluency ($\beta = 0.51$, 95% *CI* [0.39, 0.64]), EF ($\beta = 0.27$, 95% *CI* [0.13, 0.40]), reading ($\beta = 17.17$, 95% *CI* [12.83, 21.51]), and math ($\beta = 13.66$, 95% *CI* [8.70, 18.63]), all $ps < 0.001$. Latent EF had significant effects on both reading ($\beta = 14.39$, 95% *CI* [4.21, 24.58]) and math ($\beta = 27.01$, 95% *CI* [12.21, 41.81]) scores, such that a one standard deviation increase in EF is associated with scoring 14.39 percentile points higher on the reading test and 27.01 percentile points higher on the math test. In contrast, verbal fluency paths to reading ($\beta = 3.03$, 95% *CI* [-1.50, 7.55]) and math ($\beta = -2.89$, 95% *CI* [-8.73, 2.94]) scores were not significant. Associations between SES, EF, and reading and math scores are illustrated in Figure 3.

Model results provide evidence that in addition to the direct effects of SES on math and reading scores, SES had indirect effects on achievement through its effect on executive function (Table 5). In total (i.e., including direct and indirect effects), a one *SD* increase in SES is associated with a 22.60 percentile point increase in reading score and a 19.44 percentile point increase in math score. Significant indirect effects of SES through EF accounted for 17.12% of the total SES effect on reading scores ($\beta_{\text{SES} \rightarrow \text{EF} \rightarrow \text{Reading}} = 3.87$, 95% *CI* [1.26, 10]) and 37.36% of the total SES effect on math scores ($\beta_{\text{SES} \rightarrow \text{EF} \rightarrow \text{Math}} = 7.26$, 95% *CI* [3.36, 16.72]). Verbal fluency did not mediate SES effects on either reading or math scores.

Which Specific Neurocognitive Skills Mediate SES Differences in Achievement?

To evaluate the degree to which each candidate neurocognitive skill mediates SES differences in achievement, we estimated Model 2, which treats each of the EF indicators from Model 1 as a distinct manifest variable that potentially mediates SES-related differences in achievement (see Figure 2). Because Model 2 estimates all covariances between manifest variables, it is considered saturated, precluding measures of model fit. Altogether, the model explained 49.44% of the variation in reading scores and 46.25% of math scores. All path coefficients are provided in Table 6; full model results are reported in Supplemental Table 2.

Given the lack of an evidence base to motivate specific hypotheses regarding the relative importance of each EF subcomponent to the SES-achievement gap, we consider this an exploratory analysis; as such, although we report the results of significance tests, we encourage the reader to attribute greater informational value to measures of relative effect size (Cumming, 2014), including (1) SES $\rightarrow$ Mediator coefficients (the number of standard deviations (*SD*) each neurocognitive ability is expected to change given a one *SD* increase in SES); (2) Mediator $\rightarrow$ Test Score coefficients (the number of percentile points that a student's test score is expected to change given a one *SD* increase in a given neurocognitive ability); and (3) indirect effect estimates (the number of percentile points that a student's

test score is expected to change given a one *SD* increase in SES, through its effect on a given neurocognitive ability). These effect sizes are illustrated in Figure 4.

Consistent with Model 1 results, parameter estimates from Model 2 indicated that children from higher SES homes scored higher on tests of verbal fluency ($\beta = 0.51$, 95% *CI* [0.39, 0.64]), reading ($\beta = 18.16$, 95% *CI* [13.99, 22.33]), and math ($\beta = 15.40$, 95% *CI* [11.23, 19.57]), all p s < 0.001. In addition, direct paths were significant from SES to verbal working memory ($\beta = 0.28$, 95% *CI* [0.14, 0.42], $p = <0.001$), response inhibition ($\beta = 0.21$, 95% *CI* [0.07, 0.35], $p = 0.003$), and planning ($\beta = 0.21$, 95% *CI* [0.06, 0.36], $p = 0.007$), but not from SES to spatial working memory ($\beta = 0.06$, 95% *CI* [-0.08, 0.20], $p = 0.386$).

Also consistent with Model 1, individual differences in executive function skills explained substantial variability in academic achievement scores. Specifically, paths to math achievement were significant from verbal working memory ($\beta = 7.71$, $p = <0.001$), spatial working memory ($\beta = 4.37$, $p = 0.050$), and planning ($\beta = 4.32$, $p = 0.027$), but not response inhibition ($\beta = -0.64$, $p = 0.705$) or verbal fluency ($\beta = 1.68$, $p = 0.449$). For reading achievement, the only significant EF path was from verbal working memory ($\beta = 5.55$, $p = 0.008$); paths from spatial working memory ($\beta = 1.57$, $p = 0.466$), planning ($\beta = 1.02$, $p = 0.583$), and response inhibition ($\beta = -0.47$, $p = 0.798$) were not significant. In contrast to Model 1 results, reading achievement was also significantly predicted by verbal fluency ($\beta = 5.23$, $p = 0.004$).

Results of the indirect effects analysis provide further evidence highlighting the role of verbal working memory as a mediator of SES differences in both math and reading achievement (see Table 7 and Figure 4). Significant indirect effects of SES through verbal working memory account for 11.01% of the total SES effect on math scores ($\beta_{\text{SES} \rightarrow \text{VWM} \rightarrow \text{Math}} = 2.14$, 95% *CI* = 0.78, 4.32) and 6.81% of the total SES effect on reading scores ($\beta_{\text{SES} \rightarrow \text{VWM} \rightarrow \text{Reading}} = 1.54$, 95% *CI* = 0.37, 3.51). For math scores, a small but statistically significant indirect effect of SES through strategic planning counts for 4.60% of the total SES

effect ($\beta_{\text{SES} \rightarrow \text{TOL} \rightarrow \text{Math}} = 0.89$, 95% $CI = 0.08, 2.37$). For reading scores, a relatively large indirect effect of SES through verbal fluency accounts for 11.91% of the total SES effect ($\beta_{\text{SES} \rightarrow \text{Verbal} \rightarrow \text{Reading}} = 2.69$, 95% $CI = 0.87, 5.19$). No other indirect effects were statistically significant.

Discussion

Socioeconomic status is one of the most consistently identified and powerful predictors of academic achievement in childhood and adolescence (Bradley & Corwyn, 2002), yet the neurocognitive mechanisms underlying SES disparities in achievement remain poorly understood. Motivated by past research, we evaluated executive function and verbal fluency as candidate mediators of the SES-achievement association using longitudinal data from a diverse cohort of children and structural equation modeling. Unique to the work, we examined administrative records of performance on group-administered, state-mandated achievement tests. These ecologically valid measures may be of greater “real-world” importance, as such testing determines student promotion standards. Consistent with prior work, children from relatively higher-SES homes performed better than their lower-SES peers on assessments of 7th grade reading and math achievement. Furthermore, we found in our primary latent variable analysis that SES disparities in both reading and math achievement are partially mediated by variation in executive function, but not verbal fluency. On average, children from higher-SES families demonstrate stronger EF capacities than their lower-SES peers, and this disparity in EF explains approximately 17% of the SES gap in reading achievement and 37% of the SES gap in math achievement.

Moving beyond composite measures, we also addressed the question of which specific executive function abilities are most implicated in the SES-achievement gap. Results of exploratory analyses evaluating the unique role of each neurocognitive ability highlight the importance of SES-related differences in verbal working memory for explaining gaps in both

reading and math achievement. This relatively high explanatory power of verbal working memory compared to other executive function abilities is clearly apparent in Figure 5, which displays the size of indirect effects for each candidate mediator separately for the two modeling approaches we used. Notably, Figure 5 also highlights the substantially higher explanatory power of our executive function latent variable, which accounts for more than twice as much of the SES-related variance in math and reading scores than the combined effects of the manifest EF variables. To help focus interventions, further research is warranted to determine whether working memory is simply a more reliable measure of EF or if it is indeed the most critical domain of executive function for explaining SES-related differences in achievement.

As a whole, these study results are broadly consistent with work by Lawson and Farah (2017) demonstrating that individual differences in executive function explain a substantial portion of the SES gradient in academic achievement among adolescents. We extend their work by showing that EF mediates SES differences in performance not only on individually administered laboratory tests of achievement, but also on the group-administered assessments of academic proficiency that play an outsized role in contemporary education systems.

Our finding that EF – but not verbal fluency – partially mediates the SES-achievement gap adds an important data point to a literature that is mixed with respect to the role of verbal ability, and suggests that differences in measurement strategy may partially account for divergent findings in the extant literature. In our primary analysis, which evaluated verbal fluency while covarying for a latent measure of EF, we found no evidence for significant pathways through verbal fluency. In exploratory analyses evaluating verbal fluency against four different manifest EF variables, results indicated that verbal fluency partially mediated SES differences in reading scores. The inconsistency of these findings highlights the instability of parameter estimation when modeling the effects of multiple collinear variables using standard manifest variable approaches.

Several methodological strengths of this study bolster our confidence in the robustness of our central finding that executive function is an important mediator of socioeconomic variation in academic achievement. For instance, the use of multiple neurocognitive tasks to measure EF as a latent construct allowed us to minimize measurement error and increase the precision of model estimates. In addition, the longitudinal research design, wherein neurocognitive performance and academic achievement were assessed at different times and in different settings, insured the correct temporal sequence for mediation analysis and reduced the threat of state-level confounds (e.g., sleepiness) inherent when neurocognitive performance and academic achievement are assessed at the same time. Finally, the socioeconomic and ethnic diversity of the study sample, which included roughly equal numbers of European, African, and Latin American families, suggests that study findings are likely relevant to a broad range of student populations and communities.

Despite these strengths, our capacity to identify causal pathways by which socioeconomic factors impact academic achievement is limited due to constraints of study design. Most importantly, we are not able to account for confounds arising from gene-environment correlation; it is possible (indeed, likely) that a substantial portion of SES-related variation in neurocognition and academic performance arises from parental transmission of genetic variants associated with the parents' SES and the child's achievement (Krapohl et al., 2017). However, this uncertainty regarding genetic vs. environmental causation does not necessarily undermine the relevance of the current study findings for educational practice. Whether or not the learning challenges faced by socioeconomically disadvantaged students arise from genetic or environmental causes, which are inextricably intertwined, it remains important for parents, educators, and interventionists to understand these specific challenges when considering options for most effectively supporting student learning.

An additional limitation of the study is its incomplete consideration of alternative

neurocognitive mediators of SES-related variation in achievement. In contrast to our multi-measure assessment of executive function as a latent variable, we assessed verbal ability with only a single verbal fluency task. Given evidence for the mediating role of verbal ability reported in some (but not all) previous studies of the SES-achievement gap (e.g., Fitzpatrick et al., 2014), it is possible that verbal ability would have emerged as a significant mediator in the current study if it were measured with less error. Likewise, there is a need for research that evaluates a more comprehensive range of cognitive abilities as potential mediators, including lower level capacities like processing speed. Although performance on EF tasks depends on these abilities and thus likely captures the variance associated with them, it is not possible to rule out a specific SES-related deficit without explicit model testing. Other high-level processes related to cognitive self regulation (e.g., metacognition) also deserve empirical attention (Roebers, 2017). Approximately 70% of SES-related variation in math and 76% in reading were left unexplained by our latent variable model of education, highlighting the need for more exhaustive research on this question.

Our finding that individual differences in childhood executive function abilities explain a meaningful portion of the SES-achievement gap in adolescence further strengthens the logic model of interventions targeting EF improvement as a pathway to boosting later academic achievement (K. L. Bierman & Torres, 2016). That is, investments in EF skill development during childhood, when plasticity is likely at its highest, may pay dividends in academic achievement gains for years afterward. Although it is well established that EF skills can be taught in much the same way as academic skills (e.g., Diamond & Lee, 2011; Raver et al., 2011), experimental research evaluating the efficacy of EF interventions for improving academic achievement has been conducted primarily with small, clinical samples and has shown mixed results (Bergman Nutley & Söderqvist, 2017; Rabipour & Raz, 2012). However promising, there is need for more definitive evidence of intervention efficacy from large-sample trials of typically developing school-age children before limited school resources are allocated to such training programs.

What else can be done to support the learning of children from disadvantaged backgrounds struggling with the executive function demands of the classroom? Alloway (2006) provided several practical suggestions for modifying classroom practices to support children with poor working memory function based on a careful analysis of their most prevalent points of failure in classroom learning activities. In essence, Alloway argued that, if a substantial segment of the student population does not possess the working memory skills required to learn from a classroom practice, then the practice should be adapted to reduce working memory demands that are preventing learning. For instance, given that children with poor working memory often fail to complete classroom activities simply because they forget what to do next, teachers can increase the odds of successful activity completion by frequently repeating clear, step-by-step instructions and asking children to repeat them aloud. To help children succeed in activities with the most challenging working memory demands, educators can provide training and repeated practice with the use of memory aids like unifix cubes, number lines, and lists of common words. Perhaps most importantly, children can be taught metacognitive strategies for coping with their working memory failures, including asking for forgotten information and engaging in positive self-talk to persist even when they fail.

Despite the challenges that children from low-SES backgrounds may encounter in academic settings, in identifying mediators to the SES-achievement link evidenced by results from high stakes standardized testing, this study provides information that can be used to inform efforts to modify and improve instructional practices for many struggling learners.

Software

We analyzed our data and generated this fully reproducible report using R (Version 3.5.1; R Core Team, 2016) and the R-packages *apaTables* (Version 2.0.5; Stanley, 2017), *bindrcpp* (Version 0.2.2; Müller, 2017), *BiocInstaller* (Tenenbaum & Team, 2016), *broom* (Version 0.5.0; Robinson, 2017), *citr* (Version 0.2.0.9055; Aust, 2016), *corrplot2017* (Wei & Simko, 2017), *cowplot* (Version 0.9.3; Wilke, 2018), *dplyr* (Version 0.7.6; Wickham, Francois, Henry, & Müller, 2017), *Formula* (Version 1.2.3; Zeileis & Croissant, 2010), *ggplot2* (Version 3.0.0; Wickham, 2009), *glue* (Version 1.3.0; Hester, 2017), *gridExtra* (Version 2.3; Auguie, 2017), *haven* (Version 1.1.2; Wickham & Miller, 2017), *Hmisc* (Version 4.1.1; Harrell Jr, Charles Dupont, & others., 2018), *knitr* (Version 1.20; Xie, 2015), *lattice* (Version 0.20.35; Sarkar, 2008), *lavaan* (Version 0.6.3; Y. Rosseel, 2012), *lubridate* (Version 1.7.4; Grolemund & Wickham, 2011), *magrittr* (Version 1.5; Bache & Wickham, 2014), *modelr* (Version 0.1.2; Wickham, 2017a), *pacman* (Version 0.4.6; Rinker & Kurkiewicz, 2017), *papaja* (Version 0.1.0.9842; Aust & Barth, 2018), *psych* (Version 1.8.4; Revelle, 2017), *purrr* (Version 0.2.5; Henry & Wickham, 2017), *readr* (Version 1.1.1; Wickham, Hester, & Francois, 2017), *reshape2* (Version 1.4.3; Wickham, 2007), *semTools* (Version 0.5.1; Jorgensen et al., 2018), *shiny* (Version 1.1.0; Chang, Cheng, Allaire, Xie, & McPherson, 2018), *stringr* (Version 1.3.1; Wickham, 2017b), *survival* (Version 2.42.3; Terry M. Therneau & Patricia M. Grambsch, 2000), *tibble* (Version 1.4.2; Müller & Wickham, 2017), and *tidyr* (Version 0.8.1; Wickham & Henry, 2017).

References

- Albert, D., & Steinberg, L. (2011). Age differences in strategic planning as indexed by the Tower of London. *Child Development, 82*(5), 1501–1517.
- Alloway, T. P. (2006). How does working memory work in the classroom? *Educational Research and Reviews, 1*(4), 134–139.
- Auguie, B. (2017). *GridExtra: Miscellaneous functions for “grid” graphics*. Retrieved from <https://CRAN.R-project.org/package=gridExtra>
- Aust, F. (2016). *Citr: ‘RStudio’ add-in to insert markdown citations*. Retrieved from <https://CRAN.R-project.org/package=citr>
- Aust, F., & Barth, M. (2018). *papaja: Create APA manuscripts with R Markdown*. Retrieved from <https://github.com/crsh/papaja>
- Bache, S. M., & Wickham, H. (2014). *Magrittr: A forward-pipe operator for r*. Retrieved from <https://CRAN.R-project.org/package=magrittr>
- Berg, K., & Byrd, D. (2002). The Tower of London spatial problem-solving task: Enhancing clinical and research implementation. *Journal of Clinical and Experimental Neuropsychology, 24*(5), 586–604. doi:10.1076/jcen.24.5.586.1006
- Bergman Nutley, S., & Söderqvist, S. (2017). How Is Working Memory Training Likely to Influence Academic Performance? Current Evidence and Methodological Considerations. *Frontiers in Psychology, 8*. doi:10.3389/fpsyg.2017.00069
- Beron, K., & Farkas, G. (2004). Oral language and reading success: A structural equation modeling approach. *Structural Equation Modeling, 11*, 110–131.
- Best, J. R., Miller, P. H., & Naglieri, J. A. (2011). Relations between Executive Function and

- Academic Achievement from Ages 5 to 17 in a Large, Representative National Sample. *Learning and Individual Differences*, 21(4), 327–336. doi:10.1016/j.lindif.2011.01.007
- Bierman, K. L., & Torres, M. (2016). Promoting the development of executive functions through early education and prevention programs. In *Executive function in preschool age children: Integrating measurement, neurodevelopment and translational research*. (Vol. 10). Washington, DC: American Psychological Association.
- Blair, C. B., & Razza, R. P. (2007). Relating effortful control, executive function, and false belief understanding to emerging math and literacy ability in kindergarten. *Child Development*, 78(2), 647–663. doi:10.1111/j.1467-8624.2007.01019.x
- Bradley, R., & Corwyn, R. (2002). Socioeconomic status and child development. *Annual Review of Psychology*, 53, 371–399.
- Brock, L., Rimm-Kaufman, S., Nathanson, L., & Grimm, K. (2009). The contributions of ‘hot’ and ‘cool’ Executive function to children’s academic achievement, learning-related behaviors, and engagement in kindergarten. *Early Childhood Research Quarterly*, 24, 337–349.
- Brooks-Gunn, J., & Duncan, G. (1997). The effects of poverty on children. *The Future of Children*, 55–71.
- Bull, R., Espy, K. A., & Wiebe, S. A. (2008). Short-term memory, working memory, and executive functioning in preschoolers: Longitudinal predictors of mathematical achievement at age 7 years. *Developmental Neuropsychology*, 33(3), 205–228. doi:10.1080/87565640801982312
- Casey, B., Getz, S., & Galvan, A. (2008). The adolescent brain. *Developmental Review*, 28,

62–77.

Chang, W., Cheng, J., Allaire, J., Xie, Y., & McPherson, J. (2018). *Shiny: Web application framework for r*. Retrieved from <https://CRAN.R-project.org/package=shiny>

Chein, J., & Morrison, A. (2010). Expanding the mind's workspace: Training and transfer effects with a complex working memory span task. *Psychonomic Bulletin Review*, *17*, 193–199.

Crook, S. R., & Evans, G. W. (2014). The role of planning skills in the income-achievement gap. *Child Development*, *85*(2), 405–411. doi:10.1111/cdev.12129

Cumming, G. (2014). The New Statistics: Why and How. *Psychological Science*, *25*(1), 7–29. doi:10.1177/0956797613504966

Dahl, G., & Lochner, L. (2012). The impact of family income on child achievement: Evidence from the earned income tax credit. *The American Economic Review*, *102*(5), 1927–1956.

Diamond, A., & Lee, K. (2011). Interventions shown to aid executive function development in children 4 to 12 years old. *Science (New York, N.Y.)*, *333*(6045), 959–964. doi:10.1126/science.1204529

Dilworth-Bart, J. (2012). Does executive function mediate SES and home quality associations with academic readiness?. *Early Childhood Research Quarterly*, *27*, 416–425.

Ditlevsen, S., Christensen, U., Lynch, J., Damsgaard, M., & Keiding, N. (2005). The mediation proportion: A structural equation approach for estimating the proportion of exposure effect on outcome explained by an intermediate variable. *Epidemiology*,

16, 114–120.

Duncan, G., Dowsett, C., Claessens, A., Magnuson, K., Huston, A., Klebanov, P., & Sexton, H. (2007). School readiness and later achievement. *Developmental Psychology* 1428, 43.

Duyme, M., Dumaret, A. C., & Tomkiewicz, S. (1999). How can we boost IQs of “dull children”? A late adoption study. *Proceedings of the National Academy of Sciences of the United States of America*, 96(15), 8790–8794.

Evans, G. W. (2004). The environment of childhood poverty. *American Psychologist*, 59, 77–92.

Farah, M. J., Shera, D. M., Savage, J. H., Betancourt, L., Giannetta, J. M., Brodsky, N. L., . . . Hurt, H. (2006). Childhood poverty: Specific associations with neurocognitive development. *Brain Research*, 1110(1), 166–174. doi:10.1016/j.brainres.2006.06.072

Farkas, G., & Beron, K. (2004). The detailed age trajectory of oral vocabulary knowledge: Differences by class and race. *Social Science Research*, 33(3), 464–497.

Fitzpatrick, C., McKinnon, R., Blair, C. B., & Willoughby, M. (2014). Do preschool executive function skills explain the school readiness gap between advantaged and disadvantaged children? *Learning and Instruction*, ., 30, 25–31.

Gottfried, A., Gottfried, A., Bathurst, K., Guerin, D., Parramore, M., In, M., & Mahwah, N. (2003). Socioeconomic status in children’s development and family environment: Infancy through adolescence. *Bornstein R H Bradley Eds Socioeconomic Status Parenting and Child Development Pp Lawrence Erlbaum Associates*, 189–207.

Grolemund, G., & Wickham, H. (2011). Dates and times made easy with lubridate. *Journal*

- of Statistical Software*, 40(3), 1–25. Retrieved from <http://www.jstatsoft.org/v40/i03/>
- Hackman, D., Farah, M. J., & Meaney, M. (2010). Socioeconomic status and the brain: Mechanistic insights from human and animal research. *Nature Reviews Neuroscience* 651, 11.
- Harrell Jr, F. E., Charles Dupont, & others. (2018). *Hmisc: Harrell miscellaneous*. Retrieved from <https://CRAN.R-project.org/package=Hmisc>
- Hart, B., & Risley, T. (2003). The early catastrophe: The 30 million word gap by age 3. *American Educator*, 27, 4–9.
- Haveman, R., & Wolfe, B. (1995). The determinants of children's attainments: A review of methods and findings. *Journal of Economic Literature*, 33, 1829–1878.
- Heaton, R. K., & Pendleton, M. G. (1981). Use of Neuropsychological tests to predict adult patients' everyday functioning. *Journal of Consulting and Clinical Psychology*, 49(6), 807–821.
- Henry, L., & Wickham, H. (2017). *Purrr: Functional programming tools*. Retrieved from <https://CRAN.R-project.org/package=purrr>
- Hester, J. (2017). *Glue: Interpreted string literals*. Retrieved from <https://CRAN.R-project.org/package=glue>
- Hoff, E. (2003). The Specificity of Environmental Influence: Socioeconomic Status Affects Early Vocabulary Development Via Maternal Speech. *Child Development*, 74(5), 1368–1378. doi:10.1111/1467-8624.00612
- Hoff, E., & Tian, C. (2005). Socioeconomic status and cultural influences on language. *Journal of Communication Disorders*, 38(4), 271–278.

doi:10.1016/j.jcomdis.2005.02.003

- Jorgensen, D., T., Pornprasertmanit, S., Schoemann, M., A., . . . Y. (2018). *semTools: Useful tools for structural equation modeling*. Retrieved from <https://CRAN.R-project.org/package=semTools>
- Krapohl, E., Hannigan, L. J., Pingault, J.-B., Patel, H., Kadeva, N., Curtis, C., . . . Plomin, R. (2017). Widespread covariation of early environmental exposures and trait-associated polygenic variation. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(44), 11727–11732. doi:10.1073/pnas.1707178114
- Kurdek, L., & Sinclair, R. (2001). Predicting reading and mathematics achievement in fourth-grade children from kindergarten readiness scores. *Journal of Educational Psychology* *451*, 93.
- Last, B. S., Lawson, G. M., Breiner, K., Steinberg, L., & Farah, M. J. (2018). Childhood socioeconomic status and executive function in childhood and beyond. *PLOS ONE*, *13*(8), e0202964. doi:10.1371/journal.pone.0202964
- Lawson, G., & Farah, M. J. (2017). Executive function as a mediator between SES and academic achievement throughout childhood. *International Journal of Behavioral Development*, *41*, 94–104.
- Lawson, G., Hook, C., & Farah, M. J. (2017). A meta-analysis of the relationship between socioeconomic status and executive function performance among children. *Developmental Science*.
- Lee, C., & Solon, G. (2009). Trends in intergenerational income mobility. *The Review of Economics and Statistics*, *91*(4), 766–772.
- Lonigan, C., Burgess, S., & Anthony, J. (2000). Development of emergent literacy and early

- reading skills in preschool children: Evidence from a latent-variable longitudinal study. *Developmental Psychology* 596, 36(5).
- Luna, B., Padmanabhan, A., & O'Hearn, K. (2010). What has fMRI told us about the development of cognitive control through adolescence? *Brain and Cognition*, 72(1), 101–113. doi:10.1016/j.bandc.2009.08.005
- Mazzocco, M. M. M., & Kover, S. T. (2007). A longitudinal assessment of executive function skills and their association with math performance. *Child Neuropsychology: A Journal on Normal and Abnormal Development in Childhood and Adolescence*, 13(1), 18–45. doi:10.1080/09297040600611346
- Mercy, J., & Steelman, L. (1982). Familial influence on the intellectual attainment of children. *American Sociological Review*, 47, 532–42.
- Mezzacappa, E. (2004). Alerting, orienting, and executive attention: Developmental properties and sociodemographic correlates in an epidemiological sample of young, urban children. *Child Development*, 75(5), 1373–1386. doi:10.1111/j.1467-8624.2004.00746.x
- Müller, K. (2017). *Bindrcpp: An 'rcpp' interface to active bindings*. Retrieved from <https://CRAN.R-project.org/package=bindrcpp>
- Müller, K., & Wickham, H. (2017). *Tibble: Simple data frames*. Retrieved from <https://CRAN.R-project.org/package=tibble>
- Nesbitt, K., Baker-Ward, L., & Willoughby, M. (2013). Executive function mediates socio-economic and racial differences in early academic achievement. *Early Childhood Research Quarterly*, 28, 774–783.
- NICHD Early Child Care Research Network. (2003). Do childrens attention processes

- mediate the link between family predictors and school readiness? *Developmental Psychology*, 39, 581–593.
- Nittrouer, S. (1996). The relation between speech perception and phonemic awareness: Evidence from low-SES children and children with chronic OM. *Journal of Speech and Hearing Research*, 39(5), 1059–1070.
- Noble, K. G., McCandliss, B. D., & Farah, M. J. (2007). Socioeconomic gradients predict individual differences in neurocognitive abilities. *Developmental Science*, 10(4), 464–480. doi:10.1111/j.1467-7687.2007.00600.x
- Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, 40(3), 879–891.
- R Core Team. (2016). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from <https://www.R-project.org/>
- Rabipour, S., & Raz, A. (2012). Training the brain: Fact and fad in cognitive and behavioral remediation. *Brain and Cognition*, 79(2), 159–179. doi:10.1016/j.bandc.2012.02.006
- Raver, C. C., Jones, S. M., Li-Grining, C., Zhai, F., Bub, K., & Pressler, E. (2011). CSRP's Impact on low-income preschoolers' preacademic skills: Self-regulation as a mediating mechanism. *Child Development*, 82(1), 362–378. doi:10.1111/j.1467-8624.2010.01561.x
- Reardon, S., In, R., & York, N. (2011). The widening academic achievement gap between the rich and the poor: New evidence and possible explanations. *Murnane G Duncan Eds Whither Opportunity Rising Inequality and the Uncertain Life Chances of*

- LowIncome Children Pp New Russell Sage Foundation Press*, 91–113.
- Revelle, W. (2017). *Psych: Procedures for psychological, psychometric, and personality research*. Evanston, Illinois: Northwestern University. Retrieved from <https://CRAN.R-project.org/package=psych>
- Rinker, T. W., & Kurkiewicz, D. (2017). *pacman: Package management for R*. Buffalo, New York: University at Buffalo/SUNY. Retrieved from <http://github.com/trinker/pacman>
- Robinson, D. (2017). *Broom: Convert statistical analysis objects into tidy data frames*. Retrieved from <https://CRAN.R-project.org/package=broom>
- Roebers, C. M. (2017). Executive function and metacognition: Towards a unifying framework of cognitive self-regulation. *Developmental Review*, 45, 31–51. doi:10.1016/j.dr.2017.04.001
- Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software*, 48(2), 1–36. Retrieved from <http://www.jstatsoft.org/v48/i02/>
- Rosseel, Y., Oberski, D., Byrnes, J., Vanbrabant, L., Savalei, V., Merkle, E., . . . Jorgensen, T. (2017, February). Lavaan: Latent Variable Analysis.
- Sarkar, D. (2008). *Lattice: Multivariate data visualization with r*. New York: Springer. Retrieved from <http://lmdvr.r-forge.r-project.org>
- Schermelleh-Engel, K., & Moosbrugger, H. (2003). Müller H. *Evaluating the Fit of Structural Equation Models Tests of Significance and Descriptive Goodnessoffit Measures Methods of Psychological Research Online*, 8, 23–74.
- Schmitt, S., McClelland, M., Tominey, S., & Acock, A. (2015). Strengthening school readiness for Head Start children: Evaluation of a self-regulation intervention. *Early*

Childhood Research Quarterly, 30, 20–31.

Shallice, T. (1982). Specific impairments of planning. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences*, 298(1089), 199–209.

St Clair-Thompson, H. L., & Gathercole, S. E. (2006). Executive functions and achievements in school: Shifting, updating, inhibition, and working memory. *Quarterly Journal of Experimental Psychology (2006)*, 59(4), 745–759. doi:10.1080/17470210500162854

Stanley, D. (2017). *ApaTables: Create american psychological association (apa) style tables*. Retrieved from <https://CRAN.R-project.org/package=apaTables>

Stroop. (1935). Studies of interference in serial verbal reactions. *Journal of Experimental Psychology*, 18, 643–662.

Tenenbaum, D., & Team, B. (2016). *BiocInstaller: Install/update bioconductor, cran, and github packages*.

Terry M. Therneau, & Patricia M. Grambsch. (2000). *Modeling survival data: Extending the Cox model*. New York: Springer.

Thompson-Schill, S. L., Jonides, J., Marshuetz, C., Smith, E. E., D’Esposito, M., Kan, I. P., ... Swick, D. (2002). Effects of frontal lobe damage on interference effects in working memory. *Cognitive, Affective & Behavioral Neuroscience*, 2(2), 109–120.

Waber, D. P., De Moor, C., Forbes, P. W., Almli, C. R., Botteron, K. N., Leonard, G., ... Brain Development Cooperative Group. (2007). The NIH MRI study of normal brain development: Performance of a population based sample of healthy children aged 6 to 18 years on a neuropsychological battery. *Journal of the International Neuropsychological Society: JINS*, 13(5), 729–746. doi:10.1017/S1355617707070841

Wei, T., & Simko, V. (2017). *R package “corrplot”: Visualization of a correlation matrix*.

Retrieved from <https://github.com/taiyun/corrplot>

Welsh, J. A., Nix, R. L., Blair, C. B., Bierman, K. L., & Nelson, K. E. (2010). The Development of Cognitive Skills and Gains in Academic School Readiness for Children from Low-Income Families. *Journal of Educational Psychology, 102*(1), 43–53. doi:10.1037/a0016738

Wickham, H. (2007). Reshaping data with the reshape package. *Journal of Statistical Software, 21*(12), 1–20. Retrieved from <http://www.jstatsoft.org/v21/i12/>

Wickham, H. (2009). *Ggplot2: Elegant graphics for data analysis*. Springer-Verlag New York. Retrieved from <http://ggplot2.org>

Wickham, H. (2017a). *Modelr: Modelling functions that work with the pipe*. Retrieved from <https://CRAN.R-project.org/package=modelr>

Wickham, H. (2017b). *Stringr: Simple, consistent wrappers for common string operations*. Retrieved from <https://CRAN.R-project.org/package=stringr>

Wickham, H., & Henry, L. (2017). *Tidyr: Easily tidy data with 'spread()' and 'gather()' functions*. Retrieved from <https://CRAN.R-project.org/package=tidyr>

Wickham, H., & Miller, E. (2017). *Haven: Import and export 'spss', 'stata' and 'sas' files*. Retrieved from <https://CRAN.R-project.org/package=haven>

Wickham, H., Francois, R., Henry, L., & Müller, K. (2017). *Dplyr: A grammar of data manipulation*. Retrieved from <https://CRAN.R-project.org/package=dplyr>

Wickham, H., Hester, J., & Francois, R. (2017). *Readr: Read rectangular text data*. Retrieved from <https://CRAN.R-project.org/package=readr>

Wilke, C. O. (2018). *Cowplot: Streamlined plot theme and plot annotations for 'ggplot2'*.

Retrieved from <https://CRAN.R-project.org/package=cowplot>

Woodcock, R., McGrew, K., Mather, N., Woodcock-Johnson, I., & Itasaca, I. (2001).

Riverside Publishing.

Woods, S. P., Delis, D. C., Scott, J. C., Kramer, J. H., & Holdnack, J. A. (2006). The

California Verbal Learning Test second edition: Test-retest reliability, practice effects, and reliable change indices for the standard and alternate forms. *Archives of Clinical Neuropsychology*, 21(5), 413–420. doi:10.1016/j.acn.2006.06.002

Xie, Y. (2015). *Dynamic documents with R and knitr* (2nd ed.). Boca Raton, Florida:

Chapman; Hall/CRC. Retrieved from <https://yihui.name/knitr/>

Zeileis, A., & Croissant, Y. (2010). Extended model formulas in R: Multiple parts and multiple responses. *Journal of Statistical Software*, 34(1), 1–13.

doi:10.18637/jss.v034.i01

Table 1

Demographic characteristics of analytic sample

Variable	%	Mean	SD
Male	50.2	—	—
European American	32.5	—	—
African American	33.5	—	—
Latin American	34.0	—	—
Single Parent	23.8	—	—
Family Income	—	44,500.0	28,460.8
Education	—	13.3	3.8
Child Age (Y1)	—	8.6	0.6
Child Age (Y2)	—	9.6	0.6
Child Age (Y3)	—	10.6	0.7
Child Age (Y4)	—	13.2	0.4

Note. Families were coded as single-parent if the parent reported the absence of a partner in the home at both of the years 1 and 2 assessments.

Family Income was estimated from parent reports at years 2 and 3 on a scale with income range response options. For each report, we estimated income as the midpoint of the response range, and computed the mean from the two reports.

Education was estimated as the mean of parent reports at years 1-3 of the number of “years of formal education” attained by oneself and one’s spouse or partner, if applicable.

Table 2

Means, standard deviations, and correlations with confidence intervals

Variable	M	SD	1	2	3	4	5	6	7
1. SES	-0.00	0.93							
2. Reading	50.10	32.45	.65** [.56, .72]						
3. Math	48.86	31.92	.57** [.46, .65]	.79** [.74, .84]					
4. Verbal Fluency	9.78	2.59	.50** [.38, .60]	.50** [.38, .61]	.43** [.30, .54]				
5. Verbal WM	6.05	1.28	.27** [.13, .40]	.40** [.27, .52]	.46** [.33, .57]	.41** [.28, .53]			
6. Spatial WM	4.51	1.40	.07 [-.08, .21]	.18* [.03, .32]	.28** [.14, .41]	.21** [.06, .35]	.29** [.14, .42]		
7. Planning	0.34	0.11	.20** [.05, .34]	.22** [.08, .36]	.33** [.19, .46]	.17* [.02, .31]	.27** [.13, .40]	.26** [.11, .39]	
8. Inhibition	-0.09	0.13	.20** [.05, .34]	.16* [.01, .30]	.15* [.00, .30]	.16* [.01, .31]	.19* [.04, .33]	.04 [.11, .19]	.14 [.01, .29]

Note. Note. M and SD are used to represent mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval. The confidence interval is a plausible range of population correlations that could have caused the sample correlation (Cumming, 2014). * indicates $p < .05$. ** indicates $p < .01$. SES = Socioeconomic status. WM = Working Memory. All study variables except SES are described here on their original scales. SES is the average of standardized (Mean = 0; SD = 1) scores for Education and Income.

Table 3

Factor loadings for latent variable model of executive function

	Std. Beta	Raw Beta	SE
Verbal WM	0.68	1.00	0.00
Spatial WM	0.43	0.63	0.15
Planning	0.43	0.64	0.15
Response Inhibition	0.24	0.35	0.13

Note. WM = Working Memory. Standardized factor loadings are reported as Std. Beta. For scale identification, the raw loading for Verbal WM was set to 1.

Table 4

Model 1 coefficient estimates

Path	Estimate	CI (low)	CI (high)	SE	z	p
SES->Reading	17.17	12.83	21.51	2.21	7.76	<0.001
SES->Math	13.66	8.70	18.63	2.53	5.39	<0.001
SES->Verbal	0.51	0.39	0.64	0.06	7.96	<0.001
SES->EF	0.27	0.13	0.40	0.07	3.93	<0.001
Verbal->Reading	3.03	-1.50	7.55	2.31	1.31	0.190
EF->Reading	14.39	4.21	24.58	5.20	2.77	0.006
Verbal->Math	-2.89	-8.73	2.94	2.98	-0.97	0.331
EF->Math	27.01	12.21	41.81	7.55	3.58	<0.001

Note. SES = Socioeconomic Status. Verbal = Verbal Fluency. EF = Executive Function. CI (low) and CI (high) represent the lower and upper bounds of the 95% confidence interval for the point estimate, respectively. SE = Standard Error.

Table 5

Model 1: Direct and Indirect Effects of SES on Reading and Math Scores

Effect	Beta	CI (low)	CI (high)	Mediation Ratio
Direct (SES->Reading)	17.17	12.03	21.39	0.76
SES->EF->Reading	3.87	1.26	10.00	0.17
SES->Verbal->Reading	1.56	-1.47	4.08	0.07
Total (SES->Reading)	22.60	19.47	25.59	—
	—	—	—	—
Direct (SES->Math)	13.66	7.49	18.57	0.70
SES->EF->Math	7.26	3.36	16.72	0.37
SES->Verbal->Math	-1.49	-6.52	1.22	-0.08
Total (SES->Math)	19.44	15.93	22.75	—

Note. SES = Socioeconomic Status. Verbal = Verbal Fluency. EF = Executive Function. CI (low) and CI (high) represent the lower and upper bounds of the bias-corrected bootstrap confidence intervals (95% CIs), based on 5000 draws with replacement; effects are deemed significant if the CI does not include zero. Mediation Ratio was calculated by dividing the effect estimate (Beta) by the total SES-to-achievement effect.

Table 6

Model 2 coefficient estimates

Path	Estimate	CI (low)	CI (high)	SE	z	p
SES->Reading	18.16	13.99	22.33	2.13	8.53	<0.001
SES->Math	15.40	11.23	19.57	2.13	7.24	<0.001
SES->Verbal WM	0.28	0.14	0.42	0.07	3.86	<0.001
SES->Verbal Fluency	0.51	0.39	0.64	0.06	7.96	<0.001
SES->Inhibition	0.21	0.07	0.35	0.07	2.95	0.003
SES->Spatial WM	0.06	-0.08	0.20	0.07	0.87	0.386
SES->Planning	0.21	0.06	0.36	0.08	2.69	0.007
Verbal WM->Reading	5.55	1.44	9.66	2.10	2.64	0.008
Verbal Fluency->Reading	5.23	1.64	8.82	1.83	2.85	0.004
Inhibition->Reading	-0.47	-4.08	3.13	1.84	-0.26	0.798
Spatial WM->Reading	1.57	-2.65	5.80	2.16	0.73	0.466
Planning->Reading	1.02	-2.62	4.66	1.86	0.55	0.583
Verbal WM->Math	7.71	3.61	11.82	2.09	3.69	<0.001
Verbal Fluency->Math	1.68	-2.67	6.04	2.22	0.76	0.449
Inhibition->Math	-0.64	-3.97	2.69	1.70	-0.38	0.705
Spatial WM->Math	4.37	0.01	8.74	2.23	1.96	0.050
Planning->Math	4.32	0.50	8.15	1.95	2.21	0.027

Note. SES = Socioeconomic Status. WM = Working Memory. CI (low) and CI (high) represent the lower and upper bounds of the 95% confidence interval for the point estimate, respectively. SE = Standard Error.

Table 7

Model 2: Direct and Indirect Effects of SES on Reading and Math Scores

Effect	Beta	CI (low)	CI (high)	Mediation Ratio
Direct (SES->Reading)	18.16	13.72	22.19	0.80
SES->Verbal->Reading	2.69	0.87	5.19	0.12
SES->VWM->Reading	1.54	0.37	3.51	0.07
SES->SWM->Reading	0.10	-0.15	0.96	0.00
SES->Planning->Reading	0.21	-0.50	1.29	0.01
SES->Inhibition->Reading	-0.10	-1.03	0.63	0.00
Total (SES->Reading)	22.60	19.50	25.54	—
	—	—	—	—
Direct (SES->Math)	15.40	11.02	19.53	0.79
SES->Verbal->Math	0.87	-1.42	3.18	0.04
SES->VWM->Math	2.14	0.78	4.32	0.11
SES->SWM->Math	0.27	-0.24	1.34	0.01
SES->Planning->Math	0.89	0.08	2.37	0.05
SES->Inhibition->Math	-0.13	-1.05	0.52	-0.01
Total (SES->Math)	19.44	16.01	22.71	—

Note. SES = Socioeconomic Status. Verbal = Verbal Fluency. VWM = Verbal Working Memory. SWM = Spatial Working Memory. CI (low) and CI (high) represent the lower and upper bounds of the bias-corrected bootstrap confidence intervals (95% CIs), based on 5000 draws with replacement; effects are deemed significant if the CI does not include zero. Mediation Ratio was calculated by dividing the effect estimate (Beta) by the total SES-to-achievement effect.

Figure 1. Latent variable model of direct and indirect effects of SES on academic achievement. SES = Socioeconomic status. WM = Working Memory. EF = Executive Function. Variance parameters are omitted for visual clarity but are reported in Supplemental Materials.

Figure 2. Manifest variable model of direct and indirect effects of SES on academic achievement. SES = Socioeconomic status. WM = Working Memory. Variance parameters are omitted for visual clarity but are reported in Supplemental Materials.

Figure 3. Associations between SES, Executive Function, and Reading and Math scores. Executive function (EF) scores are extracted factor scores from the measurement model illustrated in Figure 1. SES = Socioeconomic status.

Figure 4. Comparison of effect sizes for neurocognitive pathways linking SES to reading and math achievement. Effect estimates (i.e., beta coefficients) are represented by dots; 95% confidence intervals are represented by dashed lines. Panel A depicts the size of effects linking SES to each neurocognitive ability, controlling for all other neurocognitive abilities; coefficients indicate the number of standard deviations each neurocognitive ability is expected to change given a one standard deviation change in SES. Panel B depicts the size of effects linking each neurocognitive ability to an academic achievement score, controlling for SES and all other neurocognitive abilities; coefficients indicate the number of percentile points that a reading or math score is expected to change given a one standard deviation change in a given neurocognitive ability. Panel C depicts the size of indirect effects from SES to achievement through each neurocognitive ability; coefficients indicate the number of percentile points that a reading or math score is expected to change given a one standard deviation change in SES, attributable to a given neurocognitive ability.

Figure 5. Relative magnitude of neurocognitive mediation effects estimated from latent (Model 1) and manifest (Model 2) variable models of SES-related variation in academic achievement. Each bar represents the total number of percentile points that a reading or math score is expected to change given a one standard deviation change in SES, due to the effects of SES on neurocognitive ability variables in the model. The portion of the indirect effect attributable to a given neurocognitive ability variable is indicated by bar color. SES = Socioeconomic status. WM = Working Memory.

Appendix
Supplemental Materials

Table A1

Model 1 parameter estimates (coefficients, variances, and covariances)

Parameter	Variable(s)	Estimate	CI (low)	CI (high)	SE	z	p
Coefficients	SES->Reading	17.17	12.83	21.51	2.21	7.76	<0.001
	SES->Math	13.66	8.70	18.63	2.53	5.39	<0.001
	SES->Verbal	0.51	0.39	0.64	0.06	7.96	<0.001
	SES->EF	0.27	0.13	0.40	0.07	3.93	<0.001
	Verbal->Reading	3.03	-1.50	7.55	2.31	1.31	0.190
	EF->Reading	14.39	4.21	24.58	5.20	2.77	0.006
	Verbal->Math	-2.89	-8.73	2.94	2.98	-0.97	0.331
	EF->Math	27.01	12.21	41.81	7.55	3.58	<0.001
Variances	Verbal WM	0.53	0.26	0.80	0.14	3.84	<0.001
	Inhibition	0.94	0.64	1.23	0.15	6.30	<0.001
	Spatial WM	0.81	0.60	1.02	0.11	7.55	<0.001
	Planning	0.81	0.60	1.02	0.11	7.58	<0.001
	Reading	498.94	395.24	602.65	52.91	9.43	<0.001
	Math	433.35	281.64	585.05	77.40	5.60	<0.001
	Verbal	0.75	0.55	0.96	0.10	7.20	<0.001
	EF	0.39	0.16	0.63	0.12	3.33	<0.001
	SES	0.86	0.86	0.86	0.00	—	NA
Covariances	Math<->Reading	283.45	168.89	398.01	58.45	4.85	<0.001
	Verbal<->EF	0.24	0.13	0.36	0.06	4.04	<0.001

Note. SES = Socioeconomic Status. Verbal = Verbal Fluency. EF = Executive Function. WM = Working Memory. CI (low) and CI (high) represent the lower and upper bounds of the 95% confidence interval for the point estimate, respectively. SE = Standard Error.

Table A2

Model 2 parameter estimates (coefficients, variances, and covariances)

Parameter	Variable(s)	Estimate	CI (low)	CI (high)	SE	z	p
Coefficients	SES->Reading	18.16	13.99	22.33	2.13	8.53	<0.001
	SES->Math	15.40	11.23	19.57	2.13	7.24	<0.001
	SES->Verbal WM	0.28	0.14	0.42	0.07	3.86	<0.001
	SES->Verbal Fluency	0.51	0.39	0.64	0.06	7.96	<0.001
	SES->Inhibition	0.21	0.07	0.35	0.07	2.95	0.003
	SES->Spatial WM	0.06	-0.08	0.20	0.07	0.87	0.386
	SES->Planning	0.21	0.06	0.36	0.08	2.69	0.007
	Verbal WM->Reading	5.55	1.44	9.66	2.10	2.64	0.008
	Verbal Fluency->Reading	5.23	1.64	8.82	1.83	2.85	0.004
	Inhibition->Reading	-0.47	-4.08	3.13	1.84	-0.26	0.798
	Spatial WM->Reading	1.57	-2.65	5.80	2.16	0.73	0.466
	Planning->Reading	1.02	-2.62	4.66	1.86	0.55	0.583
	Verbal WM->Math	7.71	3.61	11.82	2.09	3.69	<0.001
	Verbal Fluency->Math	1.68	-2.67	6.04	2.22	0.76	0.449
	Inhibition->Math	-0.64	-3.97	2.69	1.70	-0.38	0.705
	Spatial WM->Math	4.37	0.01	8.74	2.23	1.96	0.050
	Planning->Math	4.32	0.50	8.15	1.95	2.21	0.027
Variances	Reading	529.90	438.42	621.37	46.67	11.35	<0.001
	Math	545.12	450.98	639.25	48.03	11.35	<0.001
	Verbal WM	0.92	0.73	1.12	0.10	9.26	<0.001
	Verbal Fluency	0.75	0.55	0.96	0.10	7.19	<0.001
	Inhibition	0.95	0.66	1.24	0.15	6.45	<0.001
	Spatial WM	0.99	0.80	1.18	0.10	10.21	<0.001
	Planning	0.96	0.73	1.19	0.12	8.12	<0.001
	SES	0.86	0.86	0.86	0.00	—	NA
Covariances	Math<->Reading	345.16	254.54	435.78	46.24	7.47	<0.001
	Verbal Fluency<->Verbal WM	0.28	0.17	0.39	0.06	4.90	<0.001
	Inhibition<->Verbal Fluency	0.06	-0.04	0.17	0.06	1.16	0.248
	Spatial WM<->Verbal Fluency	0.18	0.05	0.30	0.06	2.70	0.007

Planning<->Verbal Fluency	0.06	-0.06	0.19	0.06	1.01	0.314
Inhibition<->Verbal WM	0.14	0.00	0.27	0.07	2.01	0.045
Spatial WM<->Verbal WM	0.26	0.11	0.42	0.08	3.32	<0.001
Planning<->Verbal WM	0.22	0.05	0.39	0.09	2.52	0.012
Spatial WM<->Inhibition	0.03	-0.14	0.20	0.09	0.36	0.722
Planning<->Inhibition	0.12	-0.03	0.26	0.08	1.51	0.132
Planning<->Spatial WM	0.24	0.10	0.39	0.07	3.34	<0.001

Note. SES = Socioeconomic Status. WM = Working Memory. CI (low) and CI (high) represent the lower and upper bounds of the 95% confidence interval for the point estimate, respectively. SE = Standard Error.