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Pathways from Socioeconomic Status to Early Academic Achievement: The Role of Specific Executive Functions

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Abstract

Among the many factors contributing to the SES-achievement gap, executive function (EF) skills have received a considerable amount of attention, given their role in supporting academic skill development. While recent work has demonstrated that global EF constructs mediate SES-achievement relations, less attention has been paid to unpacking the role of specific EF components in linking SES to achievement. Data from the NICHD Study of Early Child Care and Youth Development (N = 1,273) were analyzed to assess direct and indirect associations between SES indicators, preschool EF skills, and first-grade math and reading achievement. Using path analysis, we found parent education and working memory to be uniquely and most predictive of both achievement domains. Further, after controlling for baseline academic skills, verbal ability, and other child- and family-level covariates, only working memory mediated the association between parent education and children's math achievement. These findings offer a comprehensive look at the specific mechanisms through which socioeconomic disadvantage contributes to children's academic development and provide an initial step towards generating more precise targets for policies and interventions aimed at closing the achievement gap.

Keywords

socioeconomic status; executive function; academic achievement; parent education; working memory

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The achievement gap between children of lower- and higher-socioeconomic status (SES) backgrounds and the long-term implications this gap has in shaping children's life trajectories are well-documented (Duncan & Murnane, 2011; Sirin, 2005). Even prior to

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kindergarten entry, children growing up in poverty lag significantly behind their more affluent peers in the cognitive, emotional, and social skills needed to succeed academically (McLoyd, 1998), and these differences persist across primary and secondary schooling (Heckman, 2006; Reardon, 2011). In recent years, efforts to understand the mechanisms underlying the achievement gap have revealed a host of child, family, and schooling factors that contribute to socioeconomic disparities in children's academic development (for a review, see Hackman, Farah, & Meaney, 2010). Among the many factors contributing to the SES-achievement gap, executive function (EF) skills—including response inhibition, attention control, and working memory—have emerged as particularly powerful predictors of academic skill development, especially among children from disadvantaged backgrounds (Blair & Raver, 2014).

Nevertheless, several fundamental questions regarding the role of EF skills in explaining SES-achievement gaps remained unexplored. First, while there is evidence that the global EF construct mediates SES-achievement associations, less attention has been paid to the role of specific EF components in linking SES to achievement. Given recent work demonstrating differential predictions of core EF skills to children's short- and long-term academic outcomes (Ahmed, Tang, Waters, & Davis-Kean, 2019; Nguyen & Duncan, 2019), examining the role of separate EF components can provide a more precise understanding of the cognitive pathways underlying associations between SES and children’s achievement. Second, although differential contributions of SES indicators (i.e., parent education and household income) to children's academic development have been documented (Davis-Kean, 2005; Duncan & Magnuson, 2012), the unique cognitive mechanisms through which distinct markers of socioeconomic disadvantage contribute to disparities in children's academic development remain largely unexplored. Understanding specific child- and family-level contributors to achievement disparities can increase the specificity of our theories and provide more precise targets for policies and interventions aimed at closing the achievement gap. Therefore, in the present study, we build upon prior work by using a large, national dataset to examine the relative contributions of three specific preschool EF skills in mediating associations between distinct SES indicators and children’s first-grade math and reading achievement.

Executive Function

Although definitions vary, there is broad agreement that EF refers to a set of cognitive skills used for purposeful, goal-directed behaviors important for successful functioning in school and beyond (Miyake, Friedman, Emerson, Witzki, & Howerter, 2000; Zelazo & Carlson, 2012). These skills include response inhibition, attention control, and working memory, which emerge in early childhood and continue developing into adulthood (Best & Miller, 2010; Friedman et al., 2016). Response inhibition refers to the ability to suppress impulsive behavioral responses and instead act in more appropriate, goal-oriented ways (Miyake et al., 2000). Attention control involves selectively focusing and maintaining attention on a task while ignoring potential distractions, and shifting attention when necessary (Blair & Diamond, 2008). Working memory includes temporarily holding information in storage while performing mental manipulations (Baddeley, 2003). These skills are associated with concurrent achievement and future academic success (Best, Miller, & Naglieri, 2011;

McClelland, Acock, Piccinin, Rhea, & Stallings, 2013), and long-term outcomes related to health, wealth, and engagement with the criminal justice system (Moffitt et al., 2011).

During the preschool years, children's EF skills undergo rapid development and differentiation (Carlson, 2005; Morrison & Grammer, 2016). While some studies have demonstrated that EF operates as a more unitary construct during this developmental period (e.g., Wiebe, Espy, Charak, 2008; Willoughby, Wirth, & Blair, 2012), others have found the components of EF to be differentiated, statistically loading onto separate factors (e.g., Hughes, 1998; Lonigan, Lerner, Goodrich, Farrington, & Allan, 2016; Miller, Giesbrecht, Müller, Mclnerney, & Kerns, 2012; Simanowski & Krajewski, 2019). Furthermore, evidence of unique associations between different EF skills and children's academic and behavioral outcomes highlights the utility in estimating their effects independently (Morgan, Farkas, Hillemeier, Pun, & Maczuga, 2019).

Executive Function & Academic Achievement

Complex EF skills are particularly useful in a learning environment where children are constantly expected to focus and maintain attention on tasks, remember and follow rules and instructions, and inhibit inappropriate behaviors (Morrison, Cameron Ponitz, & McClelland, 2010). As such, EF is thought to be a critical element of school readiness (Blair, 2002). A large body of research suggests that early EF skills are important for children's academic achievement throughout early childhood (Duncan et al., 2007; McClelland et al., 2014), and this contribution continues into adolescence (Ahmed et al., 2019). These associations endure even after controlling for IQ, prior academic abilities, and indicators of SES (Blair & Razza, 2007; McClelland et al., 2007). Despite the significance of these findings, most studies have only examined the role of a single EF component or have relied on latent or constructed composite EF measures. Moreover, a number of these investigations have focused exclusively on predictions between EF and skills within a single achievement domain (e.g., math). Unfortunately, these analytic approaches do not capture important information regarding how specific EF components may promote academic achievement more so than others, and whether these patterns differ for math and reading.

In an effort to identify aspects of EF that may be especially supportive of academic skill development, a number of studies have taken a componential approach to study associations between EF and achievement in preschoolers. To date, some have found response inhibition to be the strongest unique predictor of early math skills (McClelland et al., 2014; Montoya et al., 2019), whereas others have observed associations between working memory and more complex math skills that require the manipulation of information (Lan, Legare, Ponitz, Li, & Morrison, 2011; Purpura, Ganley, & Schmitt, 2017). Evidence supporting the role of attention control in predicting early math abilities over and above the contribution of other EFs is mixed (Blair & Razza, 2007; Lan et al., 2011; cf. McClelland et al., 2014, Purpura et al., 2017). Results for emerging literacy skills are more variable. For example, in predicting preschool literacy skills, some studies have reported unique contributions of response inhibition (Blair & Razza, 2007), attention control (Lan et al., 2011), and working memory (Montoya et al., 2019), whereas others have reported marginal effects of each EF component (Purpura et al., 2017).

While evidence for associations between EF components and emergent math and literacy skills is mixed, a more consistent pattern of results emerges when examining relations between EF components and math and reading across the years of formal schooling. Although studies generally observe unique associations between multiple EF skills and children’s achievement, recent evidence points to working memory as being the strongest predictor of both math and reading (for a review, see Cortés Pascual, Moyano Muñoz, & Quílez Robres, 2019). For example, one recent investigation used the large, nationally representative Early Childhood Longitudinal Study, Kindergarten Class of 2011 (ECLS-K:2011) dataset to demonstrate the particular strength of kindergarten working memory in predicting third-grade math and reading achievement, even after accounting for other EF skills, baseline achievement, and a host of child- and family-level factors (Nguyen & Duncan, 2019). These findings also extend to adolescent academic outcomes, where preschool working memory has been found to be the sole EF component predicting math (Watts, Duncan, Siegler, & Davis-Kean, 2014) and reading (Ahmed et al., 2019) at age 15—again even after controlling for baseline academic skills and child- and family-level factors. Working memory enables children to engage in higher-order learning through the use of problem-solving and strategic thinking (Cowan, 2014). In fact, working memory has been found to mediate the effects of inhibition and attention on children’s capacity to learn, suggesting that inhibition and attention may constitute working memory (Ropovik, 2014). Thus, working memory appears to play a particularly important role in fostering children’s academic success throughout early childhood and into adolescence.

Socioeconomic Status & Executive Function

Given the role of early EF skills in supporting children’s academic success, recent work has investigated the role of contextual factors in shaping EF development (Hackman et al., 2010). An extensive literature has documented associations between SES and various neighborhood and community characteristics, including exposure to environmental toxins, community violence, and school quality, as well as family-level factors, such as parental beliefs and behaviors (Evans, 2004). As a consistent and robust predictor of an array of developmental outcomes, including children’s achievement, SES serves as a valuable starting point for identifying aspects of the developmental context that are important for shaping EF (McLoyd, 1998).

Numerous investigations have documented associations between SES and EF across various stages of development, such that children of higher-SES backgrounds, on average, demonstrate more advanced EF skills than their lower-SES counterparts (for a review, see Lawson et al., 2018). These disparities are observed when using global measures of EF (e.g., Raver, Blair, & Willoughby, 2013; Rhoades, Greenberg, Lanza, & Blair, 2011), as well as when EF components are included separately (e.g., Hackman, Gallop, Evans, & Farah, 2015; Little, 2017). Yet, few studies to date have simultaneously assessed the relative contribution of different indicators of SES to children’s specific EF skills. Doing so has the potential to provide a more nuanced understanding of the pathways underlying widely reported SES-EF associations, and can generate more specific targets for policy and intervention (Conway, Waldfogel, & Wang, 2018).

To approximate a family's socioeconomic position, studies commonly use composite measures, aggregating information across multiple indicators (Bornstein, Hahn, Suwalsky, & Haynes, 2003). While correlations among SES indicators—such as parent educational attainment and family income—are well-established, relations are often moderate at best (Braveman et al., 2005). Although related, education and income exert independent and unique effects on children through differing mechanisms (Duncan & Magnuson, 2012). Income, for example, provides families with the means to purchase high-quality resources, whereas education benefits children indirectly through non-material investments, like cognitively enriching home environments (for a discussion, see Davis-Kean, Tang, & Waters, 2019). This has led to a call for researchers to place less emphasis on investigating socioeconomic disparities in child outcomes broadly and instead focus on modeling the unique contribution and pathways through which different SES indicators shape children's development (Duncan & Magnuson, 2003). A growing number of studies have adopted this practice, with evidence suggesting that parent educational attainment may be the more powerful predictor of children's cognitive outcomes (e.g., Davis-Kean, 2005; Davis-Kean & Sexton, 2009; Raviv, Kessenich, & Morrison, 2004).

Typically, when multiple SES indicators are included in predicting children's EF skills, independent contributions of each indicator have been observed (Hackman et al., 2015; Sektnan, McClelland, Acock, & Morrison, 2010). However, other studies have reported unique effects solely for parent education (Noble, Norman, & Farah, 2005; Noble, McCandliss, & Farah, 2007) or family income (Piotrowski, Lapierre, & Linebarger, 2013). To disambiguate these findings, Conway and colleagues (2018) recently examined the relative contributions of parent education and family income to children's EF skills at school entry using the ECLS-K:2011 dataset. Results indicated that while unique effects of both parent education and family income on each EF measure were observed, performance gaps were consistently more pronounced across levels of parent education. Together, these findings support theory and research (Davis-Kean et al., 2019) demonstrating the particularly strong contribution of parent education in shaping children's developing EF abilities and highlight pronounced SES-related performance gaps in children's EF skills that are evident at school entry.

Indirect Effects of Socioeconomic Status on Achievement through Executive Function

Due to its association with both SES and academic achievement, EF has been proposed as a candidate for mediating SES-achievement relations. As such, a number of studies have explored the role of EF in explaining SES-related gaps in school readiness (Dilworth-Bart, 2012; Fitzpatrick, McKinnon, Blair, & Willoughby, 2014; Micalizzi, Brick, Flom, Ganiban, & Saudino, 2019), as well as achievement in first grade (Nesbitt, Baker-Ward, & Willoughby, 2013; Sektnan et al., 2010), fifth grade (Crook & Evans, 2014), and in a sample of children ages 6 through 15 (Lawson & Farah, 2017). Results from these investigations provide initial evidence that EF mediates SES-achievement relations across various developmental periods, particularly for math skills (Crook & Evans, 2014; Dilworth-Bart, 2012; Lawson & Farah, 2017; Sektnan et al., 2010). However, several critical questions remain.

First, in most of the work highlighted above, composite measures of EF were used, derived from averaging children’s performance across individual EF tasks or constructing a latent EF variable. While informative for understanding global relations between EF and children’s achievement outcomes, these analytic approaches do not permit the assessment of potential unique effects specific to one or more EF components and how these associations might vary for math and reading. Evidence for differential predictions among core EF skills to children's achievement underscores the importance of estimating their effects independently (Ahmed et al., 2019; Nguyen & Duncan, 2019). Second, extant studies have also relied upon composite measures of SES, ignoring the potential for a single indicator to be more predictive of EF, achievement, or both. Parent education and family income influence children’s development through different mechanisms and, thus, their contribution to children’s EF and achievement should be modeled separately (Davis-Kean et al., 2019; Duncan & Magnuson, 2012). Third, only a few of these studies included control variables such as demographic characteristics or other cognitive factors in their analyses. Failure to account for the influence of such factors can lead to upwardly biased estimates, which in turn places limits on the confidence we have in the validity of our results (Jacob & Parkinson, 2015).

Current Study

The present study aims to address each of these gaps in the literature by using a large, national dataset to chart direct and indirect associations between SES indicators, children’s EF skills, and their emerging academic achievement. Specifically, we examine the role of preschool EF components (response inhibition, attention control, and working memory) as a potential pathway for mediating the association between indicators of SES (parent education and family income-to-needs) and children’s first-grade math and reading achievement. As a robustness check, we also include a rich set of covariates to determine whether the strength of these estimates withstand alternative model specifications. Hence, the present investigation proposes the following research questions and hypotheses:

1. What are the relative contributions of EF components (measured at 54 months) in mediating associations between indicators of SES, including family income-to-needs (averaged from 1 month after birth to 36 months of age) and parent education (measured 1 month after birth), and children’s achievement at first grade? Based on prior work, we hypothesize that unique contributions of each EF component will be observed; however, working memory is expected to account for more variance in both achievement domains than response inhibition or attention control. Secondarily, we anticipate that parent education will explain more variance in all EF and achievement outcomes than family income-to-needs.

2. Are the associations between SES indicators, components of EF, and math and reading achievement attenuated when baseline academic skills are included in the model? While we hypothesize that including prior achievement will reduce

all estimated effects, we expect that working memory will remain a significant mediator of socioeconomic differences in children's achievement.

Method

Participants

Data for this study were drawn from Phases I and II of the National Institute of Child Health and Development Study of Early Child Care and Youth Development (NICHD SECCYD), a prospective longitudinal study that included 10 sites from across the United States. Information regarding participant recruitment, exclusion criteria, enrollment, and data collection can be found online (https://www.icpsr.umich.edu/icpsrweb/ICPSR/series/00233). In total, 1,364 families were enrolled at the initial phase of data collection. Of the families that consented to participate in the study, 80% were White, 13% Black, 2% Asian, and 5% are Pacific Islander or other. For the present study, the sample was restricted to the two largest ethnic groups, White and Black (N = 1,273).

Measures

Socioeconomic status.—In line with our research aims, we examined two indicators of SES: family income-to-needs and parent education. The income-to-needs for each child was calculated as a ratio between their family's total household income divided by the federal poverty threshold for the appropriate family size. Income-to-needs was defined as the average from when the child was 1, 6, 15, 24, and 36 months old (M = 3.39, SD = 2.65). An income-to-needs ratio of less than or equal to 1 indicates that a family is living in poverty (McLoyd, 1998). Parent education represented the total years of education completed by either the head of household or their spouse, measured when the child was 1 month old (M = 14.97 years, SD = 2.61).

Executive function.—For the present analyses, EF was defined as response inhibition, attention control, and working memory, all of which were measured when children were 54 months of age. The Continuous Performance Task (CPT; Rosvold, Mirsky, Sarason, Bransome, & Beck, 1956) was used to measure both response inhibition and attention control. The task involves viewing pictures of common objects on a computer screen and pressing a button when a target stimulus (a chair) appears. Errors were coded across the task so that decrements in performance could be computed as indicators of EF skills. In this study, response inhibition was operationalized as the number of errors of commission made by the child (M = 14.33, SD = 21.65), whereas attention control was reflected in the number of errors of omission (M = 9.13, SD = 7.58). For ease of interpretability, both measures were reverse coded so that higher scores reflect better performance in that domain. The CPT is a commonly used measure of attention control and response inhibition (e.g., Duncan et al., 2007; Watts et al., 2014), and has demonstrated adequate test-retest reliability (rs = .65–.74) and high construct validity (Halperin, Sharma, Greenblatt, & Schwartz, 1991). Working memory was assessed using the Memory for Sentences subtest of the Woodcock-Johnson Revised (WJ-R) Tests of Cognitive Ability (Woodcock & Johnson, 1989). In this task, children listen to words, phrases, and sentences read aloud by an examiner and must repeat each item accurately. The task becomes increasingly difficult over time as memory demands increase. Children earned 2 points for repeating the item precisely, 1 point for responses with one error, and 0 points for responses with two or more errors. W-scores, which are raw scores transformed onto a scale with equal intervals, were used for the present analyses (*M*= 457.20, *SD* = 18.42; α = .84).

Academic achievement.—W-scores from two subtests of the WJ-R Tests of Achievement, a test with high validity and reliability (Woodcock & Johnson, 1989), were used as measures of math and reading achievement. Math achievement was measured using the Applied Problems subscale at 54 months of age (*M* = 424.82, *SD* = 19.24; α = .85) and again at first grade (*M* = 470.09, *SD* = 15.45; α = .92). The Applied Problems subscale required children to perform math calculations in response to problems presented orally and visually. Reading achievement was measured using the Letter-Word Identification subscale at 54 months of age (*M* = 369.33, *SD* = 21.14; α = .86) and again at first grade (*M* = 452.78, *SD* = 23.75; α = .94). The Letter-Word Identification subscale required children to orally identify printed letters and words.

Covariates.—A set of theoretically motivated covariates were included in our models to control for their potentially confounding influence. Given that children's language ability is associated with both their EF and academic skills (Blair & Razza, 2007; Fitzpatrick et al., 2014), children's performance on the Reynell Expressive Language test (*M* = 97.26, *SD* = 14.61; Reynell, 1991), assessed at 36 months, was included as a covariate. Other child-level covariates included age at first testing (*M* = 4.64 years, *SD* = .09), ethnicity (13.83% Black), sex (52% male), the average number of hours spent in center-based care each week from birth to 54 months (*M* = 6.69 hours/week, *SD* = 9.81), and site of data collection.

Analytic Plan

The study sample had a moderate amount of missing data at the 54-month and first-grade assessments (ranging from 22% to 27%; see Table 1). At both time points, children who were Black, from families with lower income and educational backgrounds, and exposed to fewer hours of child care were more likely to have data missing relative to their counterparts. Additionally, boys were more likely to have data missing for the WJ-R battery at 54 months of age, and older children were more likely to have data missing for the first-grade achievement tests. There were also significant differences in missingness by site. In comparison to children from other sites, children from sites 0 and 4 were more likely to have data missing at both time points, and children from site 6 were more likely to have data missing at first grade. All analyses were conducted in Mplus (version 8.1; Muthén & Muthén, 1998-2017). To handle missing data across variables, full information maximum likelihood (FIML) was employed, allowing for the use of all available data. Full information maximum likelihood does not estimate missing data, instead fitting the covariance structure model directly to observed raw data for each participant (Enders, 2001). A set of auxiliary variables, not part of the analyses, were also used to help reduce bias due to missingness and to increase the power of analyses (Graham, 2003). Auxiliary variables included paternal occupation, maternal vocabulary skills, and children's school readiness all measured when children were 36 months of age, as well as children's third- and fifth-grade math and reading achievement. Additionally, MLR estimators were used in all analyses because they are robust to non-normality of observations (Muthén & Asparouhov, 2015).

Path analyses were estimated to examine the hypothesized direct and indirect relationships between SES indicators, EF components, and children's math and reading achievement. Our first step was to investigate the role of specific EF components as potential mediators of the association between SES indicators and children's math and reading achievement. Children's verbal ability, age at testing, ethnicity, sex, time in childcare, and site of data collection were included as covariates. In conjunction with theoretical and empirical guidelines, residuals of each of the three EF components were allowed to correlate. We tested the significance of direct effects from SES indicators to math and reading achievement, the paths from SES indicators to EF components, and the paths from EF components to math and reading achievement. We then tested for mediation by examining the indirect effects of SES indicators on math and reading achievement through separate EF components (MacKinnon, Fairchild, & Fritz, 2007). In order to evaluate the robustness of these findings, a second model was estimated, examining whether the strength and pattern of associations between SES indicators, EF components, and math and reading achievement varied once prior achievement was added to the model. To account for baseline achievement, math and reading scores at first grade were regressed onto their corresponding scores at 54 months and the unstandardized residuals were included as the outcome measures in Model 2. Both Models 1 and 2 were identified and therefore model fit statistics were uninformative. To reduce the possibility of Type I errors, we applied the Bonferonni correction procedure for multiple comparisons.

Results

Descriptive statistics for all study variables are presented in Table 1. Significant correlations provide initial evidence of the hypothesized associations between SES indicators, EF components, and children's math and reading achievement. Below we describe the results of both path models after correcting for multiple comparisons.

Direct Effects

Direct effects from both path models are presented in Table 2. First, direct effects of SES indicators on math and reading achievement were assessed. Results from Model 1 (see Figure 1) indicate that parent education predicted both math (β = 10, p < .01) and reading (β = .13, p < .01) whereas family income-to-needs was only predictive of math (β = .10, p ρ .01). After including baseline achievement in Model 2 (see Figure 2), neither parent education or family income-to-needs predicted either measure of achievement.

Next, direct effects of parent education and family income-to-needs on EF components were examined. Consistent with our hypotheses, results from Model 1 demonstrate that parent education was the stronger predictor of all EF components. Higher parent education was related to greater response inhibition (β = .14, p < .001), attention control (β = .15, p < .001), and working memory (β = .14, p < .001). In contrast, family income-to-needs was only predictive of working memory (β = .09, p < .05). Adding baseline achievement skills to Model 2 did not alter these estimates.

Finally, direct effects of EF components at 54 months on math and reading achievement at first grade were assessed. Also consistent with our hypotheses, results from Model 1 indicate that working memory was the EF component most strongly associated with math ($\beta = .26$, $p < .001$) and reading ($\beta = .16$, $p < .001$). Attention control also predicted math ($\beta = .15$, $p < .001$) and reading ($\beta = .12$, $p < .001$), whereas response inhibition only predicted math ($\beta = .08$, $p < .05$). Once baseline achievement was entered in Model 2, all effects were attenuated. After applying the Bonferonni correction, only the association between working memory and gains in math achievement remained statistically significant ($\beta = .12$, $p < .001$).

Indirect Effects

Indirect effects from both path models are presented in Table 3. First, we examined associations from SES indicators to math achievement through EF components. In Model 1, we found that working memory ($\beta = .02$, $p < .05$) significantly mediated the association between family income-to-needs and math achievement, whereas both working memory ($\beta = .04$, $p < .001$) and attention control ($\beta = .02$, $p < .01$) mediated the association between parent education and children's math. However, once baseline achievement was added to Model 2 and the Bonferonni correction was applied, only the association between parent education and math mediated by working memory remained significant ($\beta = .02$, $p < .05$).

Next, we examined indirect effects of SES indicators on reading achievement through EF components. While no mediated effects were detected for family income-to-needs and reading achievement after the Bonferonni correction was applied, both working memory ($\beta = .02$, $p < .001$) and attention control ($\beta = .02$, $p < .01$) significantly mediated the path from parent education to reading. Counter to the math model, however, once baseline achievement was added to Model 2, all coefficients became non-significant.

Discussion

The primary goal of the present study was to investigate the role of preschool EF skills as potential mechanisms explaining socioeconomic differences in children's early academic achievement. We found that among all EF components, working memory and attention control uniquely mediated associations between parent education and math and reading achievement. Moreover, working memory mediated associations between family income-to-needs and children's math achievement. To evaluate the robustness of these findings, preschool academic skills were then added to the model. Results revealed that, when accounting for children's baseline academic skills, only working memory continued to mediate the association between parent education and math achievement. While a number of recent investigations have explored the ways in which EF mediates links between SES and achievement, few studies to date have explored the relative importance of separate EF components as they relate to achievement, as well as their explanatory role in SES-related achievement gaps. Understanding the specific cognitive mechanisms through which socioeconomic disadvantage contributes to children's academic achievement can provide an initial step towards generating more precise targets for policies and interventions aimed at closing the achievement gap.

Here, we replicate and extend prior research in several important ways. First, we included two distinct indicators of SES—parent education and family income-to-needs ratio—as unique predictors in our analyses to disentangle their relative contributions to children's EF and achievement. Although correlated, parent education and household income each afford distinct resources that benefit children through unique pathways (Duncan & Magnuson, 2012). Davis-Kean (2005), for example, demonstrated that while parent education and income are both related to the resources available in the home environment, parent education exerts a stronger influence on the expectations parents hold for their children's educational success and the behaviors they engage in to realize these ambitions. It is thus unsurprising that parent education has also been found to be more strongly associated with children's outcomes, particularly those related to cognitive development, and that parental beliefs and behaviors mediate these associations (Davis-Kean & Sexton, 2009; Raviv et al., 2004). Consistent with this, we found that parent education was associated with all EF and achievement domains, whereas family-income-to-needs was only related to working memory and math achievement. While efforts to provide families with income supplements as a means of improving children's school success are underway (for a discussion, see Duncan, Magnuson, & Votruba-Drzal, 2014; Shaefer et al., 2018), less attention has been paid to improving parents' educational opportunities to offer the same benefit. Research has demonstrated that pursuing additional schooling after the birth of a child, particularly for mothers with initially low levels of education, can improve the quality of their home environments, as well as their children's language and academic skills (Magnuson, 2007; Magnuson, Sexton, Davis-Kean, & Huston, 2009). Thus, increasing access for parents to advance their education should not be overlooked as a means of supporting children's academic success, especially given that additional schooling is often associated with subsequent increases in income.

Second, many existing studies have operationalized EF as a composite or latent variable. However, recent work has demonstrated that EF components may be detectably differentiated during the preschool period (Lonigan et al., 2016; Simanowski & Krajewski, 2019), and evidence of unique predictions between different EF components and children's academic outcomes is also mounting (Ahmed et al., 2019; McClelland et al., 2014; Morgan et al., 2019). Thus, response inhibition, attention control, and working memory were included as distinct predictors in our analyses to evaluate their unique contributions to math and reading achievement. Our findings are consistent with recent evidence demonstrating that among core EF skills, working memory is most predictive of children's achievement (Cortés Pascual et al., 2019; Nguyen & Duncan, 2019; Watts et al., 2014). Given that working memory has been found to mediate the effects of inhibition and attention on learning (Ropovik, 2014), this skill may play a particularly critical role in fostering children's academic success. While interventions aimed at boosting children's EF generally yield positive effects (e.g., Blair & Raver, 2014; Diamond, Barnett, Thomas, & Munro, 2007; Raver et al., 2011), efforts to specifically improve working memory have produced mixed results (for a review, see Sala & Gobet, 2017). However, quasi-experimental work suggests that simply attending preschool can improve children's working memory and other EF skills (Burrage et al., 2008), especially for children from disadvantaged backgrounds (Weiland & Yoshikawa, 2013). Therefore, increasing access to high-quality preschool programs could significantly reduce SES-related disparities in children's working memory skills evident at kindergarten entry (Little, 2017).

Third, consistent with other studies, we found EF components to more predictive of math than of reading (Cortés Pascual et al., 2019). More specifically, we observed that both working memory and attention control were more strongly associated with math than reading, while response inhibition was solely predictive of math. One explanation for these findings is that math demands a greater level of cognitive control, whereas the cognitive processes required for reading acquisition become increasingly automatic over time (Blair & Razza, 2007). However, it is also possible that EF demands for reading increase as children begin to engage more formally with reading comprehension. The measure of reading used in this study taps children's ability to decode letters and words, a skill that appears to rely less on EF over the school transition period (Fuhs, Nesbitt, Farran, & Dong, 2014). In contrast, EF continues to be implicated in reading comprehension throughout development (for a review, see Follmer, 2018). Although not studied widely, some (e.g., Skibbe, Phillips, Day, Brophy-Herb, & Connor, 2012), but not all (e.g., Cameron et al., 2012) studies have observed associations between EF and growth in comprehension in the early stages of reading development. Thus, more work is needed to clarify the potential role of EF in facilitating the development of reading comprehension.

Fourth, by incorporating baseline academic skills into our final model, we were able to evaluate whether parent education and family income-to-needs predicted gains in math and reading achievement from 54 months to first grade. In our first set of analyses, parent education was uniquely associated with both achievement domains, whereas family income-to-needs was only predictive of reading. However, once prior achievement was added to the model, all effects were attenuated. These results are consistent with work demonstrating that across the first few years of schooling, children from lower- and higher-SES backgrounds make gains in achievement at the same rate (Caro, McDonald, & Willms, 2009; Entwisle et al., 2003) and that SES-related achievement gaps evident at school entry remain fairly stable across schooling (Little, 2017; Reardon, 2011). Therefore, given this relative stability in early achievement, efforts to establish and improve the cognitive skills most supportive of achievement prior to kindergarten entry may prove fruitful in producing the greatest impact on children's long-run academic outcomes.

Fifth, including major confounds such as SES, ethnicity, verbal ability, and prior achievement in our models also enabled us to examine associations between EF components and gains in math and reading, independent of important child- and family-level characteristics. Excluding such variables may upwardly bias estimated associations between EF components and achievement (Jacob & Parkinson, 2015). Results revealed that after controlling for verbal ability, age at testing, ethnicity, sex, time spent in child care, and SES, each EF component was uniquely related to both achievement domains, with the exception of response inhibition being unrelated to reading. Once prior achievement was added to the model, however, only the association between working memory and math remained statistically significant. Furthermore, mediation analysis revealed that among all EF components, only working memory significantly explained variance in the association between parent education and gains in math achievement. Together, these findings demonstrate the unique role of working memory for children's math development, adding to a growing literature documenting the importance of working memory in supporting children's math achievement across schooling (e.g., Lan et al., 2011; Nguyen & Duncan, 2019; Watts et al., 2014). These results also provide an added level of specificity to our understanding of the well-documented roles of SES and EF in shaping children's achievement (Cortes Pascual et al., 2019; Sirin, 2005). For example, constructing a composite or latent measure of SES would have masked the particular contribution of parent education to children's EF skills. Likewise, a global EF variable would have provided no insight into the relative importance of working memory in supporting children's achievement. Including SES indicators and EF components separately and assessing their uniquely predictive relations simultaneously reveals the nuanced relations between these factors and children's developing academic skills.

Limitations & Future Directions

The present study and its findings are not without limitations. First, although we employed a prospective longitudinal design and accounted for a number of potentially confounding influences, the correlational nature of this study does not permit causal inferences. However, experimental work has demonstrated that improvements in EF partially account for gains in school readiness in children from socioeconomically disadvantaged backgrounds, providing preliminary evidence that the relation between EF and achievement may be causal (Raver et al., 2011). Second, while these data are drawn from a large, national sample, they are not nationally representative. As efforts to create a more generalizable science are mounting (see Falk et al., 2013), researchers should aim to replicate these findings in more representative samples, and in other countries. Third, this investigation was limited in the number of EF measures included, as well as the constructs represented. Given the lack of consensus in the conceptualization and measurement of EF skills, particularly for young children (for a discussion, see Morrison & Grammer, 2016), future work should include a more diverse battery of tasks that tap into these and other core EF components, including cognitive flexibility. Fourth, it should be noted that even though many of the coefficients were statistically significant, the standardized effects were relatively small. However, we were specifically interested in isolating the unique effects of individual SES indicators and EF components, which are understandably smaller than the aggregate effects of composite or latent variables. Finally, the present study does not account for all of the influences that contribute to children's academic achievement. Socioeconomic status represents a distal factor that shapes children's cognitive growth, including EF, through more proximal pathways such as parental EF, parenting practices, and the home environment (Bridgett, Burt, Edwards, & Deater-Deckard, 2015; Fay-Stammbach, Hawes, & Meredith, 2014; Valcan, Davis, & Pino-Pasternak, 2018). Future research should incorporate both distal and proximal factors to construct a more complete understanding of the interactive forces shaping children's academic success.

Conclusion

The present study offers a comprehensive investigation of the contribution of SES indicators and EF skills to children's early achievement. We found parent education and working memory to be uniquely and most predictive of both math and reading. Moreover, even after the inclusion of prior achievement and other covariates often omitted in prior work (see Jacob & Parkinson, 2015), working memory remained a significant mediator of the association between parent education and math. Important next steps include replicating and extending these findings using a more representative sample, a diverse battery of EF tasks, and an examination of the proximal processes contributing to socioeconomic differences in children's EF skills. By generating a more complete understanding of the complex relation between the socioeconomic conditions of a family and a child's developing academic skills, we can begin to model the various pathways that may be important for the creation of the achievement gap. Only then will we be in a position to consider interventions that may be useful in reducing this gap.

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Highlights

- Parent education was associated with all EF and achievement domains
- All EFs were more strongly associated with math than reading
- Working memory was EF most predictive of both achievement domains
- Working memory mediated the association between parent education and math

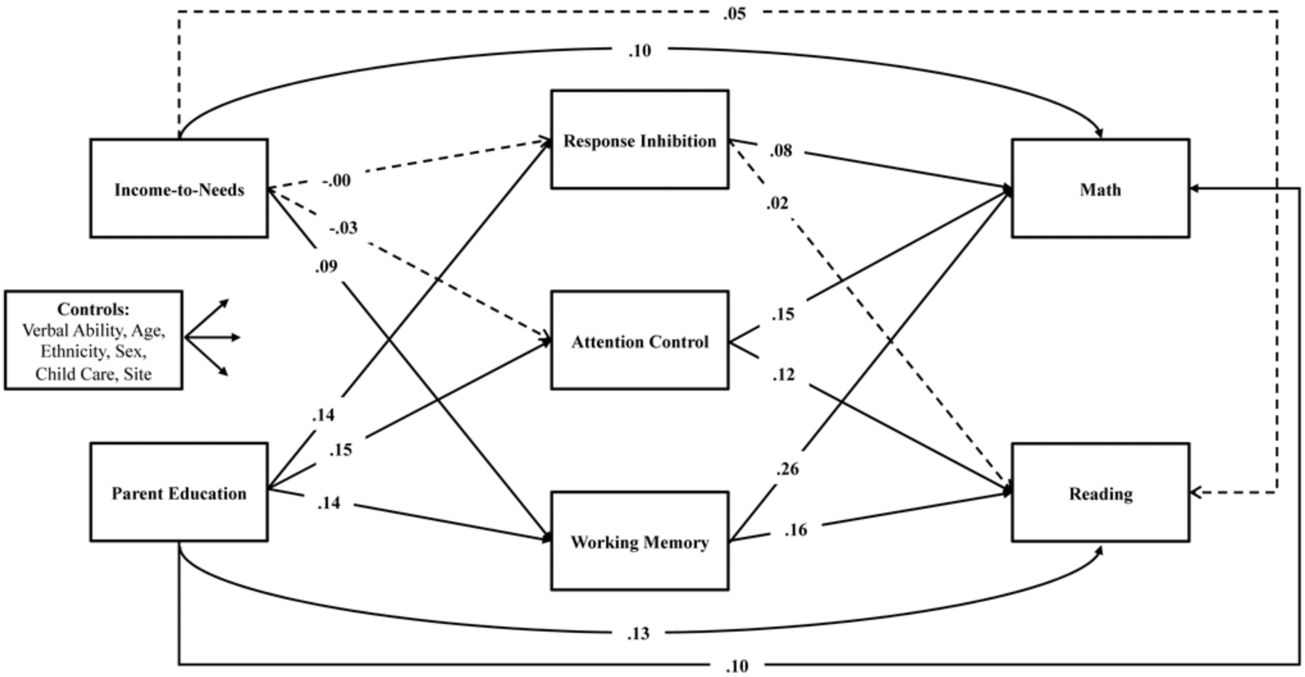

Figure 1.
Path model of the influences of socioeconomic status and executive function on achievement, controlling for children's verbal ability, age at testing, ethnicity, sex, time in child care, and site of data collection (Model 1). All path coefficients are standardized. Solid lines indicate significant coefficients (after Bonferroni correction), dashed lines indicate non-significant coefficients. Estimated error covariances are not shown in the figure.

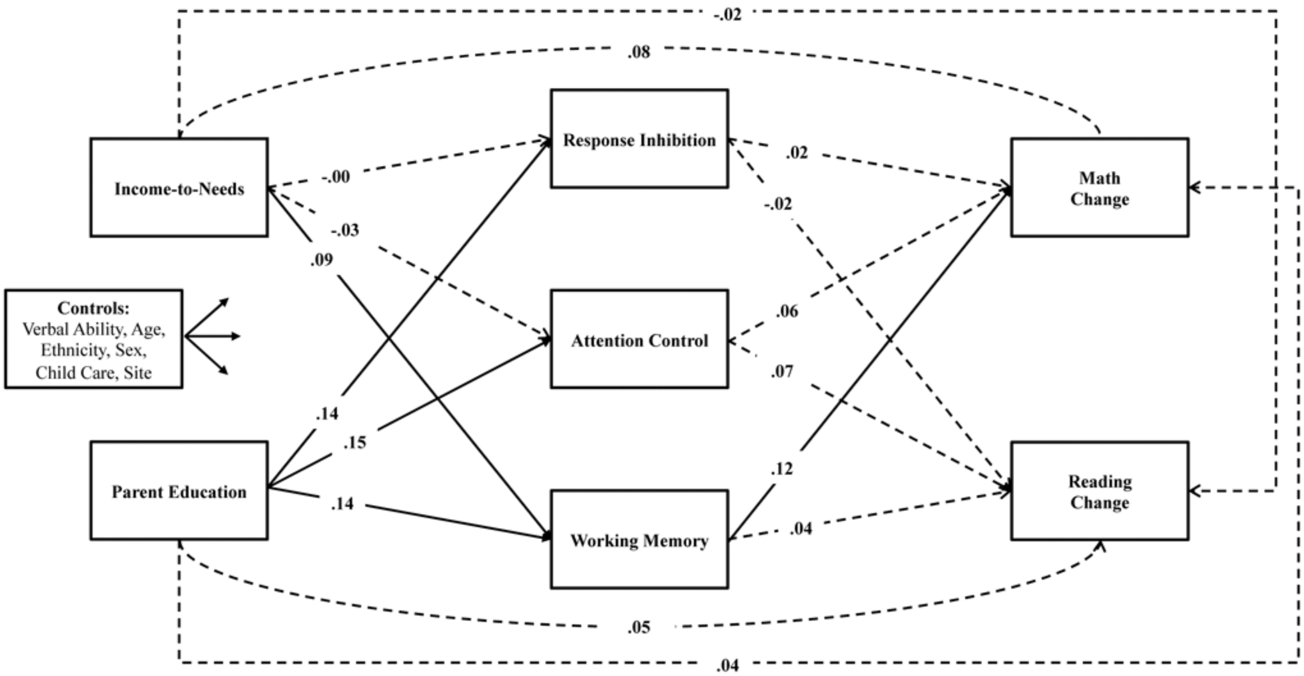

Figure 2.
Path model of the influences of socioeconomic status and executive function on changes in achievement, controlling for children's verbal ability, age at testing, ethnicity, sex, time in child care, and site of data collection (Model 2). All path coefficients are standardized. Solid lines indicate significant coefficients (after Bonferroni correction), dashed lines indicate non-significant coefficients. Estimated error covariances are not shown in the figure.

Table 1

Correlations and Descriptive Statistics for Study Variables

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Income-to-Needs	—													
2. Parent Education	**0.59**	—												
3. Response Inhibition	**0.15**	**0.20**	—											
4. Attention Control	**0.11**	**0.19**	**0.25**	—										
5. Working Memory	**0.25**	**0.29**	**0.21**	**0.24**	—									
6. Math (1st Grade)	**0.32**	**0.36**	**0.23**	**0.28**	**0.43**	—								
7. Reading (1st Grade)	**0.22**	**0.29**	**0.17**	**0.22**	**0.30**	**0.57**	—							
8. Math (Change)	**0.15**	**0.15**	0.04	**0.09**	**0.17**	**0.80**	**0.38**	—						
9. Reading (Change)	0.05	**0.11**	0.05	**0.10**	**0.10**	**0.35**	**0.84**	**0.32**	—					
10. Verbal Ability	**0.25**	**0.33**	**0.14**	**0.18**	**0.35**	**0.34**	**0.26**	**0.08**	**0.09**	—				
11. Child Age (years)	−0.00	−0.02	0.04	0.06	−0.02	−0.05	0.01	**−0.08**	0.01	−0.01	—			
12. Time in Child Care	**0.15**	**0.11**	0.03	−0.06	**0.07**	**0.10**	0.05	**0.07**	0.02	**0.07**	0.03	—		
13. Ethnicity: Black	**−0.28**	**−0.26**	**−0.23**	**−0.14**	**−0.18**	**−0.29**	**−0.20**	**−0.10**	**−0.12**	**−0.20**	0.02	−0.01	—	
14. Male Child	−0.06	−0.03	**−0.23**	−0.06	**−0.07**	**0.08**	−0.06	**0.20**	−0.01	**−0.16**	−0.04	−0.02	−0.01	—
M or %	3.39	14.97	14.33	9.13	457.20	470.09	452.78	0	0	97.26	4.64	6.69	13.83%	52%
SD	2.65	2.61	21.65	7.58	18.42	15.45	23.75	12.29	19.72	14.61	0.09	9.81	—	—
N	1,265	1,273	942	942	990	960	960	924	926	1,062	1,003	1,273	1,273	1,273
Min	0.13	8	0	0	382	408	356	−49.33	−75.13	0	4.51	0	0	0
Max	18.76	21	154	41.07	505	516	514	40.41	58.83	62	5.07	47.71	1	1
% Missing	0.63	0	26	26	22.23	24.59	24.59	27.42	27.26	138	21.21	0	0	0

Note. Max = maximum; Min = minimum. Bolded correlations are significant at $p < .05$.

Table 2

Unstandardized and Standardized Direct Effect Estimates for Models (N = 1,273)

		Model 1 (controls)					Model 2 (controls, achievement change)				
				95% CI					95% CI		
Predictor	**Dependent Variable**	***b***	***SE***	***LL***	***UL***	**β**	***b***	***SE***	***LL***	***UL***	**β**
Income-to-Needs	Math	0.03^{b}	0.01	0.01	0.05	0.10	0.39	0.18	0.04	0.74	0.08
	Reading	0.02	0.02	−0.01	0.05	0.05	−0.17	0.29	−0.74	0.41	−0.02
	Response Inhibition	−0.01	0.27	−0.53	0.52	−0.00	−0.01	0.27	−0.53	0.51	−0.00
	Attention Control	−0.07	0.12	−0.31	0.17	−0.03	−0.07	0.12	−0.31	0.16	−0.03
	Working Memory	0.03^{b}	0.01	0.01	0.06	0.09	0.03^{b}	0.01	0.01	0.06	0.09
Parent Education	Math	0.03^{b}	0.01	0.01	0.05	0.10	0.19	0.19	−0.18	0.58	0.04
	Reading	0.06^{b}	0.02	0.03	0.09	0.13	0.41	0.33	−0.23	1.06	0.05
	Response Inhibition	1.13^{b}	0.29	0.56	1.70	0.14	1.13^{b}	0.29	0.56	1.70	0.14
	Attention Control	0.43^{b}	0.11	0.21	0.64	0.15	0.43^{b}	0.11	0.21	0.64	0.15
	Working Memory	0.05^{b}	0.01	0.02	0.08	0.14	0.05^{b}	0.01	0.02	0.08	0.14
Response Inhibition	Math	0.01^{b}	0.00	0.00	0.01	0.08	0.01	0.02	−0.03	0.06	0.02
	Reading	0.00	0.00	−0.00	0.01	0.02	−0.02	0.03	−0.08	0.05	−0.02
Attention Control	Math	0.02^{b}	0.00	0.01	0.02	0.15	0.10	0.06	−0.01	0.21	0.06
	Reading	0.02^{b}	0.01	0.01	0.03	0.12	0.19	0.20	0.00	0.38	0.07
Working Memory	Math	0.22^{b}	0.03	0.17	0.28	0.26	1.66^{b}	0.48	0.72	2.60	0.12
	Reading	0.21^{b}	0.05	0.12	0.31	0.16	0.91	0.86	−0.79	2.60	0.04
Verbal Ability	Math	0.01^{b}	0.00	0.01	0.01	0.16	0.04	0.03	−0.02	0.10	0.04
	Reading	0.01^{b}	0.00	0.01	0.02	0.13	0.10	0.05	−0.00	0.19	0.07
	Response Inhibition	0.06	0.06	−0.05	0.17	0.04	0.06	0.06	−0.05	0.17	0.04
	Attention Control	0.08^{b}	0.02	0.04	0.11	0.15	0.08^{b}	0.02	0.04	0.12	0.15
	Working Memory	0.02^{b}	0.00	0.01	0.02	0.28	0.02^{b}	0.00	0.01	0.02	0.28

Predictor	Dependent Variable	Model 1 (controls) *b*	*SE*	95% CI *LL*	*UL*	*β*	Model 2 (controls, achievement change) *b*	*SE*	95% CI *LL*	*UL*	*β*
Child Age (years)	Math	−0.34	0.24	−0.80	0.12	−0.04	−8.34	4.25	−16.67	−0.01	−0.06
	Reading	0.20	0.43	−0.64	1.03	0.02	3.32	7.04	−10.48	17.11	0.02
	Response Inhibition	8.29	6.44	−4.33	20.90	0.04	7.94	6.43	−4.66	20.54	0.03
	Attention Control	5.47	2.47	0.63	10.32	0.07	5.26	2.47	0.42	10.10	0.06
	Working Memory	−0.03	0.29	−0.59	0.53	−0.00	−0.02	0.29	−0.58	0.54	−0.02
Time in Child Care	Math	0.00	0.00	−0.00	0.01	0.03	0.05	0.04	−0.03	0.12	0.04
	Reading	0.00	0.00	−0.01	0.01	0.00	0.01	0.07	−0.12	0.14	0.01
	Response Inhibition	0.04	0.06	−0.07	0.15	0.02	0.04	0.06	−0.07	0.15	0.02
	Attention Control	0.03	0.02	−0.01	0.07	0.04	0.03	0.02	−0.01	0.07	0.04
	Working Memory	0.00	0.00	−0.00	0.01	0.04	0.00	0.00	−0.00	0.01	0.04
Ethnicity: Black	Math	-0.32^{b}	0.07	−0.45	−0.19	−0.14	−1.59	1.36	−0.03	0.12	−0.04
	Reading	-0.31^{b}	0.11	−0.53	−0.09	−0.09	-5.39^{b}	2.14	−9.58	−1.19	−0.09
	Response Inhibition	-12.96^{b}	2.86	−18.56	−7.36	−0.21	-12.89^{b}	2.86	−18.49	−7.29	−0.20
	Attention Control	-2.12^{b}	0.87	−3.82	−0.42	−0.10	-2.11^{b}	0.87	−3.82	−0.41	−0.10
	Working Memory	−0.15	0.08	−0.31	−0.00	−0.06	−0.15	0.08	−0.30	0.00	−0.06
Male Child	Math	0.23^{b}	0.04	0.15	0.31	0.15	5.41^{b}	0.79	3.87	6.96	−0.06
	Reading	−0.03	0.07	−0.17	0.11	−0.01	0.30	1.31	−2.26	2.87	0.01
	Response Inhibition	-9.67^{b}	1.33	−12.28	−7.07	−0.22	-9.65^{b}	1.33	−12.25	−7.04	−0.22
	Attention Control	−0.58	0.48	−1.53	0.36	−0.04	−0.57	0.48	−1.52	0.38	−0.04
	Working Memory	−0.05	0.05	−0.16	0.06	−0.03	−0.05	0.05	−0.16	0.06	−0.03
Correlations											
Income-to-Needs & Parent Education		4.04^{b}	0.23	3.59	4.50	0.59	4.04^{b}	0.23	3.59	4.50	0.59
Response Inhibition & Attention Control		28.05^{b}	4.30	19.62	36.47	0.19	28.04^{b}	4.30	19.61	36.48	0.19
Response Inhibition & Working Memory		2.31^{b}	0.52	1.30	3.32	0.14	2.30^{b}	0.52	1.29	3.32	0.14
Attention Control & Working Memory		1.03^{b}	0.21	0.62	1.44	0.17	1.03^{b}	0.21	0.62	1.45	0.17

Predictor	Dependent Variable	Model 1 (controls)					Model 2 (controls, achievement change)				
				95% CI					95% CI		
		b	*SE*	*LL*	*UL*	*β*	*b*	*SE*	*LL*	*UL*	*β*
Math & Reading		0.32[b]	0.03	0.27	0.38	0.47	72.43[b]	8.78	55.22	89.64	0.32

Note. CI = confidence interval; LL = lower bound; UL = upper bound.

[b]Significant after Bonferroni correction.

Table 3

Unstandardized and Standardized Indirect Effect Estimates for Models (N = 1,273)

	Model 1 (controls)					Model 2 (controls, achievement change)				
			95% CI					95% CI		
Predictor → Mediator → Dependent Variable	***b***	***SE***	***LL***	***UL***	***β***	***b***	***SE***	***LL***	***UL***	***β***
Income-to-Needs → Response Inhibition → Math	0.00	0.00	−0.00	0.00	0.00	0.00	0.00	−0.01	0.01	0.00
Income-to-Needs → Attention Control → Math	−0.00	0.00	−0.01	0.00	−0.00	−0.01	0.01	−0.03	0.02	−0.00
Income-to-Needs → Working Memory → Math	0.01[b]	0.00	0.00	0.01	0.02	0.05	0.03	0.00	0.10	0.01
Parent Education → Response Inhibition → Math	0.00	0.00	0.00	0.01	0.01	0.02	0.03	−0.04	0.07	0.00
Parent Education → Attention Control → Math	0.01[b]	0.00	0.00	0.01	0.02	0.04	0.03	−0.01	0.10	0.01
Parent Education → Working Memory → Math	0.01[b]	0.00	0.00	0.02	0.04	0.08[b]	0.03	0.02	0.15	0.02
Income-to-Needs → Response Inhibition → Reading	0.00	0.00	−0.00	0.00	0.00	0.00	0.00	−0.01	0.01	0.00
Income-to-Needs → Attention Control → Reading	−0.00	0.00	−0.01	0.00	−0.00	−0.01	0.02	−0.06	0.03	−0.00
Income-to-Needs → Working Memory → Reading	0.01	0.00	0.00	0.01	0.01	0.03	0.03	−0.03	0.09	0.00
Parent Education → Response Inhibition → Reading	0.00	0.00	−0.00	0.01	0.00	−0.02	0.04	−0.09	0.05	−0.00
Parent Education → Attention Control → Reading	0.01[b]	0.00	0.00	0.01	0.02	0.08	0.05	−0.01	0.17	0.01
Parent Education → Working Memory → Reading	0.01[b]	0.00	0.00	0.02	0.02	0.05	0.05	−0.04	0.13	0.01

Note. CI = confidence interval; LL = lower bound; UL = upper bound.

[b]Significant after Bonferroni correction.