SOCIOECONOMIC STATUS AND THE CO-DEVELOPMENT OF EXECUTIVE FUNCTION AND ACADEMIC ACHIEVEMENT IN ELEMENTARY SCHOOL STUDENTS

by

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DISSERTATION ABSTRACT

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Title: Socioeconomic Status and the Co-Development of Executive Function and Academic Achievement in Elementary School Students

This study used latent growth curve modeling to examine the co-development of executive function and academic achievement in students who progressed from Kindergarten to Grade 4. It also examined (a) growth trajectories of students with high and low initial levels of working memory, (b) the associations of seven common indicators of socioeconomic status with executive function and academic achievement growth factors, and (c) the growth trajectories of students form different levels of household poverty.

The first analysis found that higher initial status on the EF measures was, on average, associated with higher initial status on the achievement measures. Faster growth on the EF measures was also, on average, associated with faster growth on the achievement measures, except for attentional shifting in Grades 2-4. However, higher initial working memory and achievement was associated with slower growth on both the EF and achievement measures. The first analysis also examined within-person associations. It found that within-person associations tended to be small, but the size and direction of associations differed across the sample and subsamples.

The second analysis investigated the association between socioeconomic status and the co-development of executive function and academic achievement. Specifically, it examined the associations of seven common indicators of socioeconomic status with executive function and academic achievement initial status and growth. It found that lower socioeconomic status was generally associated with lower initial status but faster growth in executive function and academic achievement. However, variation patterns across indicators that choice of SES indicator can have important consequences for research and decision-making. The relative merits of the different indicators are discussed. The study also tested co-developmental models of executive function and academic achievement on students from households with different poverty levels. It found that covariance structures and within-person effects differed according to student poverty-level, highlighting the need for more research on the causes and characteristics of SES-related differences in growth.

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CHAPTER I: INTRODUCTION

Executive function (EF) is an umbrella term for fundamental cognitive processes, such as working memory and attentional shifting. For decades, there has been intense interest in accelerating the development of EF in children, slowing the decline of EF in the elderly, and improving EF through interventions in virtually all age groups (Diamond & Ling, 2016). Various approaches to intervention have been tested, including martial arts (Lakes et al., 2013), yoga (Gothe et al., 2013), aerobic exercise (Best, 2010), mindfulness training (Moynihan et al., 2013), computer games (Schwaighofer et al., 2015), and academic interventions that incorporate one or more of the former approaches into more traditional academic interventions (Jacob & Parkinson, 2015). More recently, there has been increased interest in intervening on EF through social programs that reduce poverty (e.g., Amso & Lynn, 2017; Blair et al., 2011; Farah, 2017) and supporting parenting practices thought to be related to EF development (e.g., Distefano, Galinsky, McClelland, Zelazo, & Carlson, 2018; Korucu, Rolan, Napoli, Purpura, & Schmitt, 2019). For example, the Chan Zuckerberg Initiative and Bill and Melinda Gates Foundation recently committed $50 million over five years to fund "breakthrough solutions" in EF interventions (Bill and Melinda Gates Foundation, 2019a).

Enthusiasm for EF interventions is often based on evidence that EF predicts a wide array of important life outcomes. For example, the Chan Zuckerberg Initiative cited evidence that EF predicts academic performance, income, physical health, drug problems, criminal behavior, and school readiness as justification for its initiative (Bill and Melinda Gates Foundation, 2019b). Another $15 million study funded was undertaken to test the effect of unconditionally providing $4,000 per year to mother's living in poverty in order to improve their children’s EF, memory, language, and social-emotional behavior (Teacher’s College Newsroom, 2018). The president of Columbia University’s Teacher College has claimed that the study could “change the course of education and social policy” (Teacher’s College Newsroom, 2018).

Although there is intense interest in intervening on EF, there is also an awareness among researchers and funding agencies that a number of important questions about EF remain to be fully answered (Bill and Melinda Gates Foundation, 2019b; Friedman & Miyake, 2017). Is EF a singular construct, and if so, what is its structure? To what extent are common EF measures valid and reliable in children over time? To what extent is EF distinct from other important constructs, such as general intelligence? To what extent is the development of EF affected by environmental factors? Such question not only bare on the causal mechanisms and the substantive interpretations that may emerge from intervention research, but they should also inform the measurement approaches used therein. For example, if EF were a unitary emergent construct, there would be inherent limitations in studying the cognitive processes from which it was derived on a piecemeal basis (Barbey, 2018; Miyake & Friedman, 2012; Willoughby, 2016), as is often done in practice (Jacob & Parkinson, 2015). Similarly, if EF is in some sense fundamental or foundational to abstract thinking, questions about task purity become important for differentiating EF components from each other (Miyake, Emerson, et al., 2000) and for understanding the relation between EF and outcome measures, such as measures of academic achievement and intelligence (Barbey, 2018).

Given that there is no lack of EF-related intervention research (e.g., De Simoni & von Bastian, 2018; Jacob & Parkinson, 2015; Melby-Lervåg, Redick, & Hulme, 2016;

Redick, 2019; Schwaighofer et al., 2015), short-term progress in understanding EF is apt to be made from studies that give consideration to developmental trajectories of EF, as well as studies that consider measurement challenges in the study of EF. This dissertation focuses the former subject, noting potential measurement challenges throughout. Specifically, the dissertation utilizes the *Early Childhood Longitudinal Study, Kindergarten Class of 2010-11* dataset (ECLS-K: 2011) and latent growth curve modeling (LCM) to estimate the co-development of executive function (EF) and academic achievement. It also examines how socioeconomic status (SES) relates to the co-development of EF and academic achievement.

Chapter 1, entitled, “The Co-Development of Executive Function and Academic Achievement in Grades K-4” reports the result of analysis where latent change modeling (LCM) was used to examine longitudinal associations between EF and academic achievement. The first step of the analysis consisted of fitting univariate models of working memory, attentional shifting, reading achievement, and mathematics achievement. These constructs were respectively measured by the Numbers Reversed task, the Dimensional Card Sorting task, and two researcher-developed achievement measures based on the National Assessment for Educational Progress framework. The best fitting univariate models were then combined into bivariate models that estimate how each type of EF relates to each type of academic achievement. Because the best-fitting models tended to be LCMs with auto-regressed structured residuals (LCM-SR), the analysis was able to examine both between-person and within-person associations for most measures. All models were then re-tested on subsamples of students with low and high working memory in order to consider whether patterns in growth trajectories differed for students with different initial ability levels.

The primary finding from Chapter 1 was that average associations between EF and achievement tended to be large (β's = .22 – .86), but within person associations tended to be small (β's = |.05| – |.36|). Furthermore, after accounting for previous academic achievement and the covariance between working memory and academic achievement at each point in time, there were no significant cross-lagged associations across constructs, except for small negative associations between working memory in the fall of Kindergarten and spring mathematics and reading achievement. However, when the models were tested on subsamples of students disaggregated by kindergarten working memory level, the patterns in cross-lagged associations changed. For students with low initial working memory, there were significant and positive cross-lags between working memory and mathematics achievement in Kindergarten and Grade 1 and significant and positive cross-lags between working memory and reading in Grade 1. For students with high working memory, a pattern emerged whereby reading achievement tended to predict subsequent working memory during Kindergarten and Grade 1. These findings extend previous research by highlighting (a) the small size of within person EF contributions to achievement, and (b) the extent to associations between EF and academic achievement growth can depend on student characteristics. The findings also buttress arguments that school-based EF interventions are not a practical means of improving academic achievement (e.g., Jacob & Parkinson, 2015; Redick, 2019; Schwaighofer et al., 2015), unless perhaps, they are carefully designed to work in conjunction with academic interventions and/or target specific deficits (e.g., Cirino et al., 2019; Fuchs, Fuchs, Malone, Seethaler, & Craddock, 2019). Finally, the findings highlight need for more research on how to longitudinally measure EF in young children.

Chapter 2 entitled, "Socioeconomic Status and Co-Development of Executive Function and Academic Achievement in Grades K-4" extends Chapter 1 by examining how seven indicators of SES (i.e., adult food insecurity, household income, poverty level, parent education level, parent occupational prestige, free and reduced priced lunch status, and an SES composite) relate to the intercepts and slopes of the bivariate models that were tested in Chapter 1. It also tested the unconditional bivariate models on subsamples of students below, at or above, and 200% above the poverty level. Results suggest that SES composites and parental education levels are most likely to associate with initial status and growth in cognitive and academic ability. Following these two indicators, household income, poverty level, and free and reduced priced lunch status associated with the most growth factors. Adult food insecurity and parental occupational prestige tended to associate with initial status but not growth. The relative merits of the different indicators are discussed in terms of these findings.

Subsample analyses considered whether patterns in growth differed for students from different levels of poverty. Important differences were found across groups. Specifically, there was a general pattern whereby cross-construct associations tended to be larger for students in higher SES brackets, while within-person effects tended to decrease, but this pattern was not consistent across subsamples or measures. The inconsistent results lend partial support to the argument that economic advantage facilitates mutual support between early EF development and academic achievement, but also presents counter-evidence (Peng & Kievit, 2019). The results highlight the need for more research on the nature and causes of SES-related differences in status and achievement.

Chapter 3 concludes the dissertation by synthesizing findings from the Chapters 1 and 2. It highlights unanswered questions that should be considered in future research. It also considers the place of EF research in the field of education. Interest using cognitive and neuropsychological measures has waxed and waned in educational research over the decades. The renewed interest in EF has been met with concern by some researchers, who see it as a potentially costly and harmful distraction (Bowers, 2016; Burns, 2016). Though faddishness may explain some of the renewed research interest in EF, the final chapter suggests that the interest in EF probably reflects a growing demand for educators to engage more with psychological research in general. Policymakers and educator preparation programs should consider providing preservice educators with more formalized training in attention and memory, especially in states that are revising how educators are trained to provide reading instruction.

CHAPTER II: THE CO-DEVELOPMENT OF EXECUTIVE FUNCTION AND ACADEMIC ACHIEVEMENT IN GRADES K-4

EF is an umbrella term for fundamental cognitive processes thought to be used in a variety of tasks, but especially those that require planning and effortful, goal-directed behaviors (Friedman & Miyake, 2017). A large body of research has documented associations between EF and academic achievement (Jacob & Parkinson, 2015), and EF deficits with poor school performance (P. L. Morgan et al., 2016, 2019), obesity (Yang et al., 2018), antisocial behavior (M. Miller et al., 2012; A. B. Morgan & Lilienfeld, 2000), and various psychopathologies (Snyder et al., 2015). Despite the extensive research on EF as a predictor of important outcomes, relatively little research has been conducted on developmental trajectories of EF. In the context of education, it is important to understand the developmental trajectory of EF because there is widespread interest in developing interventions that either improve EF (Chan Zuckerberg Initiative, 2018; Jacob & Parkinson, 2015) or provide compensatory strategies to reduce difficulties associated with low EF (e.g., Cirino et al., 2019; Fuchs, Fuchs, Malone, Seethaler, & Craddock, 2019). Without a firmer understanding of how, when, and why EF relates to life outcomes, it will be difficult to identify the most efficacious intervention strategies. This study therefore examines the co-development of EF and academic achievement in elementary school students in the United States.

What is Executive Function?

EF is generally thought to be a domain-general ability associated with activity in the frontal-parietal network (Friedman & Miyake, 2017). It is similar to (and perhaps overlapping with) fluid intelligence (Barbey, 2018; J. Duncan, Johnson, Swales, & Freer, 1997; Friedman et al., 2006). The study of EF's structure, which has been called "perplexing" (Friedman & Miyake, 2017), is complicated by several factors, including (a) task impurity across EF measures, (b) low reliability within EF measures (e.g., due to strategy use), (c) developmental change (Demetriou & Spanoudis, 2015; Friedman & Miyake, 2017), (d) inconsistent use of EF measures across studies (e.g., Jacob & Parkinson, 2015), and (e) varying interpretations of what constructs and abilities EF measures tap (e.g., Redick & Lindsey, 2013). Though research on the structure of EF is ongoing, a consistent theme in the literature is that the organization of EF shows a pattern of "unity and diversity." That is, individual EF measures typically show low but robust intercorrelations (i.e., unity) that are not well-represented by unitary factor models (i.e., diversity; Karr et al., 2018; Miyake, Friedman, et al., 2000).

Friedman and Miyake (2017) have advocated for a bifactor model of EF, with an EF factor that is common to all EF tasks, and *working memory updating* factor and *attentional shifting* factors that capture the remaining correlations between tasks of similar type. Working memory is a limited capacity storage space used in an variety of cognitive processes (Baddeley, 1992; Daneman & Carpenter, 1980). It is theorized to (a) override pre-potent and automatic responses, and (b) facilitate the maintenance and retrieval of information, especially in the presence of irrelevant stimuli (Roberts & Pennington, 1996; Unsworth et al., 2014). In the Friedman and Miyake (2017) model, response inhibition, which is sometimes described as an EF (Jacob & Parkinson, 2015), is largely subsumed by the working memory. Attentional shifting (sometimes called cognitive flexibility or attentional control; Vaghi et al., 2017) is the ability to shift attention among sets, trials, strategies, or rules (van der Sluis et al., 2004), or between different features of a stimulus (Stoet & Snyder, 2004).

The bifactor model of EF is fairly well-established in adults, but evidence for a bifactor model is mixed in studies of children. There is a tendency across studies to see more evidence of EF unity at earlier ages (Karr et al., 2018). For instance, in a study of children age 7 to 9, Brydges et al., (2012) found that a unitary factor model of EF fit the data better than Friedman and Miyake's bifactor model, and that the unitary model was strongly related to fluid and crystallized intelligence (in about equal proportions). However, other studies have found evidence of a two-factor model, including studies of preschool children (e.g., M. R. Miller, Giesbrecht, Müller, McInerney, & Kerns, 2012), where evidence for a unitary construct should have been stronger if bifurcation occurs with age. It has been suggested that the divergence between child and adult EF structures reported in the scientific research may be the result of fewer construct-specific tests being administered to children within the typical study, which would limit the amount of construct-specific variance present in resulting models (Karr et al., 2018). Given that studies of children typically test complex models in low power conditions, firm conclusions about the structure of EF in children cannot yet be drawn (Karr et al., 2018).

Executive Function and Academic Achievement

Educational research on childhood EF is driven in largely by EF's well-established association with academic achievement e.g., (Jacob & Parkinson, 2015; Malanchini et al., 2019). EF is thought to be needed for reading and mathematics achievement because academic problem-solving often requires simultaneous processing and storage of information. In reading, individuals must visually process words, decode them, develop mental models of their semantic content, and then flexibly attend to their models as they answer comprehension questions (Peng, Barnes, et al., 2018a). Similarly, mathematics problems frequently require individuals to hold and retrieve numbers and intermediate steps as they progress through a series of mental computations (e.g., multi-digit calculations; Peng, Namkung, Barnes, & Sun, 2016). Meta-analytic estimates of the average relation between WM and achievement range from .29 (Peng, Barnes, et al., 2018a) to .37 for reading (Jacob & Parkinson, 2015) and from .31 (Jacob & Parkinson, 2015) to .35 for mathematics (Peng et al., 2016). The average strength of working memory's relation with reading is similar across areas of reading (e.g., vocabulary, decoding), but is more closely related to reading before Grade 4 (Peng, Barnes, et al., 2018a). The average strength of working memory's relation with mathematics varies by domain of working memory, type of mathematics problem and age (Peng et al., 2016). The averages correlation for shifting and reading range from .29 (Yeniad et al., 2013) to .42 (Jacob & Parkinson, 2015), and from .21 (Yeniad et al., 2013) to .34 for mathematics achievement. To my knowledge, moderators of shifting's relation with academic achievement have not been documented.

Meta-analytic estimates of EF's relation with academic achievement are essentially zero order correlations that do not account for potentially important covariates and interactions. Recent research on EF and academic achievement has begun to probe interactions and unique variance contributions. A confirmatory factor analysis by Cirino et al., (2018) recently extended the literature by comprehensively measuring EF and then examining its unique contributions to an array of reading-related constructs. In the study, 23 EF measures were completed by over 800 late elementary school students, oversampled for reading difficulties. The team extracted a bifactor model consisting of a common EF factor, and specific factors of (a) working memory span; (b) working memory updating; (c) fluency; (d) metacognitive behavioral report; and (d) self-regulated learning. In a follow-up analysis, the researchers examined the model's relation to various reading outcomes, including component skills from the Simple View of Reading (i.e., word reading and listening comprehension; Hoover & Gough, 1990). Predictive models were tested to sequentially account for (1) all demographic, language and cognitive covariates, (2) EF, and (3) potential interactions between EF and covariates.

For single word reading, the non-EF predictor variables explained 57% of the variance, with EF factors adding ~ 3% to the models, most of which came from the behavioral/self-regulation ratings. For single word reading fluency, the final model explained 55% of variance, and there were unique effects for multiple EF components, including the common EF factor, working memory span, fluency and the behavioral/self-regulation ratings. Collectively, the EF measures explained an additional ~ 3% variance. For both single-word reading and fluency, interactive effects of EF with language did not improve the model. The reading comprehension models, meanwhile, explained more variance overall (pseudo-R^2 = 67% and 75%), with EF continuing to add about ~ 3%, variance. Interestingly, the authors also reported evidence of several two- and three-way interactions involving the Simple View of Reading. For instance, for low levels of common EF, reading comprehension was driven by linguistic factors that interacted with one another (e.g., phonological awareness X fluency), in line with the Simple View. However, at higher levels of EF, the relation of listening comprehension to reading comprehension was strong, suggesting EF can act to partially compensate for lower decoding skill.

The findings from Cirino et al., (2019) are important for educational research for at least three reasons. First, they suggest that, even when many EF measures are administered, their unique variance contribution is apt to be small after accounting for more proximal constructs (e.g., prior achievement) and student background. Furthermore, they suggest that longitudinal researchers should give some attention to the changing content of typical achievement measures, which tend to focus on basic and sometimes informal skills in early elementary and with less able students, but more advanced skills in later grades or with more able students (see Namkung, Peng, Goodrich, & Molfese, 2019 for a mathematics example). Finally, it appears that EF is useful for different types of learning in different ways (see also Barnes et al., 2019). That is, the oft-mentioned EF "bottleneck" that can constrain whether and how tasks are completed may act differentially across tasks and students with different levels of ability and development.

The Development of Executive Function and Academic Achievement

Studies that examine change in EF and academic achievement have also contributed to a fuller picture of nature of the association between EF and achievement. Longitudinal studies that address change have regularly reported that EF is related to change in academic achievement (e.g., Jerman, Reynolds, & Swanson, 2012; Swanson, 2006, 2011c, 2011a), sometimes in a complex manner (Ribner, Willoughby, & Blair, 2017). For instance, Ribner et al., (2017) recently examined the longitudinal relation between EF and academic achievement with children from high poverty regions of the United States. The authors reported that EF at age 5 strongly predicted grade 5 math and reading. Moreover, a significant interaction between early EF and early math (both measured at age 5 before school entry) suggested that the magnitude of the association between early and later math varied as a function of early EF. Noting that children who began with high EF and low math ability scores at age 5 were able to "catch-up" to their higher ability peers by fifth grade, the authors concluded that EF is critical for early academic learning.

Studies of academic *growth* have also provided indirect evidence of a complex relation between EF and achievement. Peng et al., (2019) explored the developmental trajectories and predictors of word reading and reading comprehension among 185 young at-risk readers. In fall of first grade, students completed domain-general measures of working memory, nonverbal reasoning, and processing speed, as well as measures of phonological awareness, letter knowledge, vocabulary, word reading, and comprehension. They were then reassessed on word reading and comprehension every spring through Grade 4. Individual growth curve modeling showed that the children demonstrated decelerated growth on word reading (i.e., upside-down U) and linear growth on reading comprehension. After controlling for word reading and reading comprehension in first grade, letter knowledge predicted growth in word reading; and vocabulary and nonverbal reasoning predicted growth in reading comprehension. Working memory was not a unique predictor for either outcome. It should be noted, however, that the sample average was low according to national norms on most measures. Thus, the findings are consistent with the idea that working memory's relation to early reading may be context dependent, and that it may differ from its relation to early mathematics learning (Barnes et al., 2019).

Finally, there is evidence for the reverse causal path, namely, that change in academic achievement can predict change in EF (Fuhs et al., 2014; Fuhs & Day, 2011; Nesbitt et al., 2018; Schmitt et al., 2017). Evidence of bidirectional relations have been reported from preschool (Fuhs, Nesbitt, Farran, & Dong, 2014; Schmitt, Geldhof, Purpura, Duncan, & McClelland, 2017) into first grade (Nesbitt et al., 2018). Evidence of bidirectional relations is stronger for mathematics achievement than for reading achievement. To my knowledge, only one study has reported bidirectional associations for reading achievement (Willoughby et al., 2019). Results for early oral and verbal ability are mixed (Fuhs & Day, 2011; Fuhs et al., 2014; Nesbitt, Fuhs, & Farran, 2018; cf. Weiland & Yoshikawa, 2013; Welsh, Nix, Blair, Bierman, & Nelson, 2010). In a review of the effect of literacy acquisition on brain structure and function, Dehaene, Cohen, Morais, and Kolinsky (2015) hypothesized that the onset of schooling, but not the acquisition of literacy, would lead to improvements in simple EF tasks, such as digit span performance. Thus, there is at least some theoretical support of unidirectional relations between EF and reading achievement.

Regarding the bidirectional associations reported in oral/verbal skills studies, the authors of the aforementioned studies generally explain these findings by suggesting that cognitively demanding activities during early childhood may improve EF. For instance, Hughes et al., (2009) found that verbal ability at age 4 predicted change in EF by age 6 such that students with lower verbal ability grew faster in EF than students with higher ability. The authors considered this dynamic evidence of a “catch-up effect” whereby less verbally able children grew faster in EF upon entry into a school environment. Because low verbal ability children still lagged behind high verbal ability children in terms of verbal ability growth, the authors suggest that the relationship between verbal ability and EF is characterized by a non-linear threshold function where a certain level of verbal competence is required for performance on EF tasks, but subsequent gains in verbal competence have little impact on EF performance. More recent predictions allow that early academic gains may facilitate EF development, but specify that bidirectionality may depend on a match between initial student ability and the learning environment (Peng & Kievit, 2019). Specifically, EF and achievement may only reinforce each other when learning experiences elicit and sustain the use of cognitive ability over time. Under this prediction, bidirectional relations may be more evident in higher ability students, who gain earlier and more frequent access to higher quality learning experiences (Peng & Kievit, 2019).

The Co-Development of Executive Function and Academic Achievement

An increasingly popular approach to studying the relation between EF and achievement over time is to use latent growth curve modeling (LCM) to test hypotheses about intraindividual change and interindividual differences in intraindividual change (Bainter & Howard, 2016; Curran & Bollen, 2001; Grimm et al., 2012; Petscher et al., 2016). In an LCM, observed repeated measures are treated as indicators of a latent growth process. Sampled individuals contribute a set of repeated measures that estimate their individual trajectories, usually through an intercept and slope that respectively describe an initial status and rate of growth over time. Deviations from the average intercept and slope are modeled through disturbance terms thereby providing estimates of the unique trajectory for each individual in the sample. LCMs allow researchers to consider whether initial status is related to growth, but the growth process is not dynamic:

each individual growth process is fixed. Times-specific variability is treated as error and within-person change is confounded with between-person change.

Extensions of LCMs provide researchers unique affordances in the study of developmental change. In latent curve modeling with structured residuals (LCM-SRs), residuals are autoregressed such that within-person correlations can be estimated, while preserving the between-person intercepts and slopes (Curran et al., 2014). By contrast, latent change score models (LCSs) do not isolate within-person variance, but they are parametrized such that the intercept and slope model *latent change* using estimates of change between adjacent timepoints. In this case, change represents the combination of a constant change over time and autoregressive change that is proportional to change at the previous occasion. Like LCMs, both LCM-SRs and LCS can be adapted to multivariate contexts in a straightforward manner. After fitting trajectories for two developmental processes, the correlation between their growth factors can be examined. Because the residuals represent individual deviations in LCM-SRs, cross-lags and cross-construct covariances can also be added to bivariate models to estimate patterns in intraindividual change (Bainter & Howard, 2016).

Recently, Willoughby, Wylie, and Little (2019) used LCM-SR to examine the co-development of EF and academic achievement. Their analysis used the *Early Childhood Longitudinal Study-Kindergarten 2011* (ECLS-K: 2011) dataset to estimate between- and within-person associations in a nationally representative sample of students as they progressed from Kindergarten through Grade 2. They also tested the robustness of their models on a subsample of students who qualified for free and reduced-price lunch. Their primary finding was that although the between-person associations between EF and achievement were large (β's = .55 – .91), the within-person associations were small (β's = .10 – .25). This pattern held for the free and reduced-priced lunch subsample.

In terms of cross-lags and bidirectional associations, the authors reported that working memory led spring mathematics achievement in Kindergarten, $\beta = -.06$ $p < .05$, and Grade 1, $\beta = -.06$ $p < .05$; and spring working memory in Grade 1 led mathematics achievement in the fall of Grade 2, $\beta = .06$, $p < .05$. They also reported that mathematics achievement in the fall of Grade 2 lead working memory in the spring of Grade 2, $\beta = .07$ $p < .05$. However, these cross-lags were not significant for the free and reduced priced lunch subsample. For reading, the authors reported that fall working memory led spring achievement in Grade 1, β (SE) = .06 $p < .01$ and Grade 2 β (SE) = .03 $p < .05$. Achievement led working memory from the fall of Grade 1 to the end of Grade 2, with standardized β's ranging from .08 to .23. Results held for the free and reduced-price lunch subsample, except for the cross-lag from Spring Grade 1 working memory to fall Grade 2 achievement.

The authors also examined longitudinal associations between attentional shifting and achievement in Kindergarten and Grade 1. They reported that attention shifting led mathematics achievement, β's (.03-.06), and reading achievement, β's (.04-.10), at all time points for the whole sample, but for the free and reduced priced lunch sample, it only led reading in the fall of Kindergarten and Grade 1. Meanwhile, reading achievement led attentional shifting for both samples in the spring of Kindergarten and the fall of Grade 1 β's (.05-.15). Overall, these findings are important because they may constitute the first attempt to separate the within-person longitudinal associations between EF and achievement from the between-person longitudinal associations in elementary school children.

The Present Study

The present study contributes to research by re-analyzing the ECLS-K: 2011 dataset, following a similar set of procedures to those used in Willoughby et al., (2019). It extends the findings of the previous study by examining an additional timepoints (i.e., Grades 2-4 for attentional shifting and Grades 3 and 4 for all other measures). It also tests its models against subsamples of students with low and high working memory in the fall of kindergarten rather than free and reduced lunch status. Examining subsamples of students with different initial-levels of working memory is informative because previous studies have reported that the association between EF and academic achievement may depend on either the specific task, student ability level, or both.

Method

Data for this study came from the publicly-available ECLS-K:2011 dataset for grades K to 4 (*N* = 18,174). This dataset was selected because it is the only current nationally-representative, longitudinal dataset that contains direct measures of EF in school-age children as well as measures of academic achievement. The dataset follows students from 1,352 schools (300 private) from kindergarten to grade 4, with most measures having been collected in the fall and spring of each year in Grades K-2, and in the spring in Grades 3-4. Analyses for this study used a subsample of students who were eligible for data collection at all timepoints and who passed the fall language screener (*N* = 5,890). Students who did not pass the fall language screener were excluded because the test of working memory they were administered was on a different scale from the other students. Students were 52% male and 48 % female; and 38% White, 11.5% Black, 35% Hispanic, 8% Asian, .6% Native Hawaiian/Pacific Islander, 2.0 American Indian/Alaska Native, and 4.1% multiracial non-Hispanic.

Analyses were also performed with two subsample of students who were respectively 1.5 SDs below (*n* = 1,910) and 1.5 SDs above the mean (*n* = 540) on the Numbers Reversed task in the fall of kindergarten. The subsamples were similar in terms of developmental age at each time of assessment. For the whole sample, the mean age at the time of first assessment was 67.16 months. For the low and high working memory subsamples, the mean ages were 68.33 and 65.86 months respectively, suggesting mean differences in working memory were not artifacts of the test administration schedule. Assessment occurred at regular intervals across the three groups (i.e., about every 6 months in Grades K-2 and about every 12 months thereafter). The largest cross-group difference in age at time of assessment was between the high working memory group (6.11 months) and the whole sample (6.95 months) from Fall to Spring of Grade 1, suggesting that differences in growth patterns were not artifacts of the test administration schedule. Students in the low working memory subsample were 55% male and 45% female; and 26.6% White, 13.9% Black, 40.4% Hispanic, 5.5% Asian, .5% Native Hawaiian/Pacific Islander, 2% American Indian/Alaska Native, and 3.6% multiracial and Non-Hispanic. Students in the high working memory subsample were 48% male and 52% female; and 49.9% White, 7.6% Black, 18.6% Hispanic, 12.5% Asian, .6% Hawaiian/Pacific Islander, 1.3% American Indian/Alaska Native, and 5.9% multiracial and Non-Hispanic.

Measures

Working memory. Working memory was measured with the Woodcock Johnson III's Numbers Reversed task (McGrew & Woodcock, 2001). In the Numbers Reversed task, children were presented a digit span and asked to repeat the numbers in the reverse sequence in which they were presented. All children were given five two-number sequences. If the child got three consecutive two-number sequences incorrect, the test ended. Otherwise, the child progressed to sequences of greater length. The largest number of items administered to a child was 30. Raw scores were used to calculate a W score. The W score is an equal interval scale (M = 500, SD = 100) normed so that most children under 10 would score below 500, and most older children score about 500. Scores range from 403 to 603. The WJ III manual reports that Numbers Reversed has a median test-retest reliability of .87 across ages in a nationally representative norming sample of children and adults (McGrew & Woodcock, 2001). Validity evidence is reported at the test-level rather than for this specific subtest.

Attentional shifting K-1. In the fall and spring of grades K and 1, attentional shifting was measured by the Dimensional Change Card Sorting Task (DCSS; Zelazo, 2006). In this task, children were asked to sort 22 picture cards into one of two trays according to different rules. In the first part of the assessment, students sorted cards by color. In the second part, students sorted cards by shape. If students successfully completed the first two trials, they performed the Border Game where cards were sorted by color or shape according to the presence or absence of a border on the card. For this study, I followed the test publisher's recommendation of analyzing the combined scores produced by these tasks. Combined scores may range from 0 to 18. Higher scores indicate greater ability. Zelazo et al.'s, (2014) validation study with adults reported that the DCSS has a test-retest reliability of .85; and convergent validity with the Delis-Kaplan Executive Function System's inhibition subtest (*r* = .55) as well as the National Institute of Health Toolbox flanker (*r* = .71).

Attentional shifting grades 2-4. Beginning in fall of grade 2, attentional shifting was measured with a variation of the DCSS. The ECLS: 2011 manual indicates that the version of the DCCS used in kindergarten and grade 1 would have been too easy for the majority of the study children in grade 2. Consequently, participants were administered a new, age-appropriate, computerized version of the DCCS in which the "cards" are presented on a computer screen and children sort them into virtual "piles" on the screen using keys on the keyboard to indicate where to place each card. Sorting took place in 30 mixed block trials. One sorting rule (color or shape; randomly determined) was presented more frequently than the other across trials. Only children who successfully completed the practice trials completed the mixed block trials. Practice trials ranged between 8 and 24 trials, depending on rate of successful completion. The computerized version of the test accounted for both accuracy and reaction time, whereas the K-1 version only measures accuracy. Because the comparability of scores from the two versions of the test is uncertain (*User's Manual for the ECLS-K:2011Kindergarten-First Grade Data File and Electronic Codebook, Public Version*, 2015), it was treated as a distinct measure.

Mathematics achievement. In the fall and spring of each grade level in Grade K-2 and in the spring thereafter, mathematics achievement was measured with a series of adaptive assessments developed specifically for the study. The assessments included questions assessing number sense, properties, operations, measurement, geometry, spatial sense, data analysis, probability, algebra, and functions. All of the assessments used IRT and were based on the NAEP standards and assessments. Thus, the reading test assessed areas such as number sense, operations, and geometry. Each test contained between 50 and 70 items. Detailed information on the content of these assessments, and evidence of their technical adequacy can be found in the ECLS-K psychometric report (Najarian et al., 2011). The analyses used the theta scores, which were derived using the same methods described under reading achievement measure. Theta ranges from -8 to 8 with higher scores indicating greater ability. There is limited published evidence of the math assessment's validity. The ECLS manual notes that expert panels developed the questions based on the NAEP 1996 mathematics framework. The item pool was reviewed by expert educators and administrators for design, accuracy, and clarity. A field test was conducted in which the best functioning items were identified for use. However, the results of the field test are not publicly available. The ECLS manual describes reliability for the mathematics assessment as ranging from .92 in the fall of kindergarten to .94 to the spring of second grade.

Reading achievement. In the fall and spring of each grade level in Grade K-2 and in the spring thereafter, reading achievement with a series of adaptive assessments developed specifically for the study. The assessments included questions measuring basic literacy skills (rhyme, letter recognition), vocabulary, and reading comprehension. All of the assessments used IRT and were based on NAEP standards and assessments. Thus, the reading test assessed areas such as vocabulary, initial and developing understanding, and personal reflection. Each test contained between 50 and 70 items. Detailed information on the content of these assessments, and evidence of their technical adequacy can be found in the ECLS-K psychometric report (Najarian et al., 2011). In brief, two methods were used to calculate scores. For scores within a grade, a concurrent calibration model was applied where, for each domain, fall and spring data were pooled and calibrated together. A chain-linking approach was then used to place ability estimates (i.e., theta) and item parameters for the within-grade scores on the same scale in order to link the scores across grades. Theta ranges from -8 to 8 with higher scores indicating greater ability. There is limited published evidence of the reading assessment's validity. The ECLS manual notes that expert panels developed the questions based on the NAEP Reading Framework 2009. The item pool was reviewed by expert educators and administrators for design, accuracy, and clarity. A field test was conducted in which the best functioning items were identified for use. However, the results of the field test are not available. The ECLS manual describes reliability for the reading assessment as ranging from .91 in spring of second grade to .95 for fall of kindergarten.

Analysis

Analyses were performed with the main sample, and two subsample of students who were respectively 1.5 SDs below and 1.5 SDs above the mean on the Numbers Reversed task in the fall of kindergarten. The primary analysis consisted of four main steps that are typically recommended for growth modeling (e.g., Duncan & Duncan, 2009; Muthén & Muthén, 2006). In Step One, descriptive statistics from a null model of each measure, as well as plots of growth trajectories for randomly selected students, were examined. Descriptive statistics were compared to those from an identical two-level model in which students were clustered within schools. To evaluate the risk of bias due to dependent observations, design effects were calculated according to Lai and Kwok's (2015) formula:

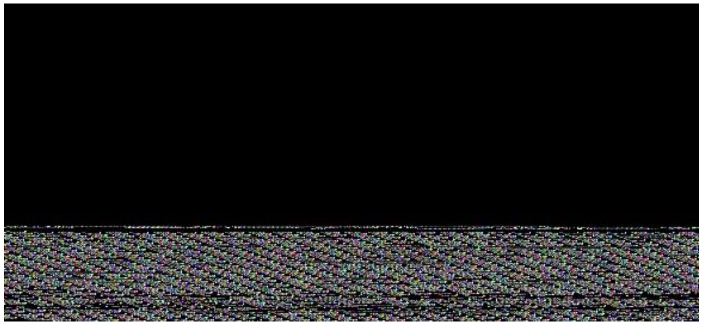
$$deff = 1 + (c - 1) \text{ X ICC}$$

where c is the cluster size and ICC is the intraclass coefficient. Data visualizations were also examined to gain insight into patterns in mean and individual growth trajectories. Finally, Mardia's test was performed in R (R Core Team, 2018) using MVN package on each measure (Korkmaz et al., 2019).

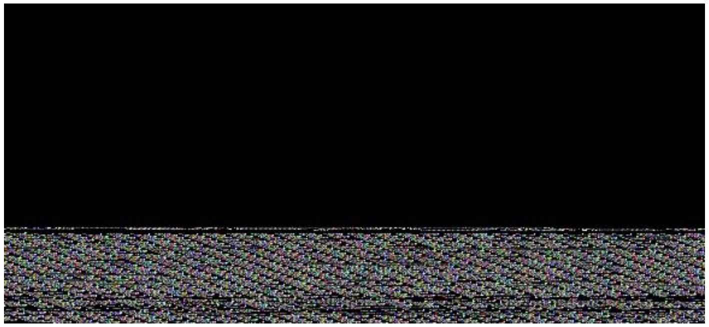
In Step Two, univariate growth models were fit for each measure (i.e., Numbers Reversed, Dimensional Card Sorting K-1, Dimensional Card Sorting 2-4, Mathematics Achievement, and Reading Achievement). An intercept-only, linear growth, quadratic growth, and freely estimated model were fit for each measure. For models with fixed time scores, the time scores represented the fall-spring assessment intervals in grades K-2 and the spring-only assessment interval in grades 3 and 4. Model fit was evaluated using recommended cut-offs for χ^2, CFI, RMSEA, and SRMR (Kenny, 2015), and χ^2 difference testing (Satorra & Bentler, 2010).

In Step Three, the best fitting models from Step Two were used to estimate LCM-SRs for each measure. In Step Four, the final univariate models were combined into bivariate models estimating the co-development of an executive function and either mathematics of reading achievement, as well as bivariate models with cross-lagged paths from each EF assessment to the subsequent achievement assessment, and vice versa (Figures 1 and 2). Because there were potentially meaningful differences in the demographic composition of the working memory subsamples, the final bivariate models were re-run with the subsamples, including sex and race/ethnicity as covariates. Differences in results were negligible. Consequently, the results of the more parsimonious models are reported here.

All analyses were conducted in Mplus (Muthén & Muthén, 2017). Alpha was set to .01 because the sample was powered to detect even trivially significant correlations. CFI, RMSEA, and SRMR were examined to assess goodness-of-fit. To address the non-independence of observations due to clustering of students, school ID in the fall of kindergarten was used with Mplus's cluster option. MLR estimation was used to address missingness, skew, and kurtosis, and potential violations of the assumption of multivariate normality detected by Mardia's test (B.O. Muthén & Asparouhov, 2002). Sample weights were used to address design effects. For the sake of illustration, latent change score models (LCSMs) were also fit in Mplus, and to the extent possible, all univariate models were re-run in Latent Growth Model Comparisons in R (LGMComp; Torgesen & Petscher, 2018), a new web-based application that utilizes the RAMpath package (Zhang et al., 2016) to quickly fit and compare growth models with different specifications. LGMComp is a useful tool because of the speed with which it can fit models.



Step 1A-D: Univariate Model



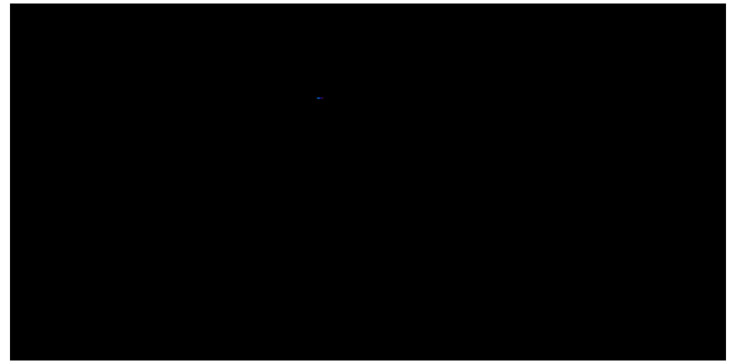
Step 2: Univariate Model with Structured Residuals

Step 3: Bivariate Model

Step 4: Bivariate Model with Cross Lagged Paths

Figure 1. Intended model-building process for working memory and academic achievement measures.

Step 1A-D: Univariate Model



Step 2: Univariate Model with Structured Residuals

Step 3: Bivariate Model

Step 4: Bivariate Model with Cross Lagged Paths

Figure 2. Intended model-building process for attentional shifting and achievement measures in K-1.

After uploading a .csv file and specifying the observed variables, LGMComp automatically fits a (a) no growth, (b) linear growth, (c) quadratic growth, (d) freely estimated, (e) latent change

score model, and (f) when applicable, bivariate latent change score model. It also outputs descriptive statistics, model fit indices (χ^2, CFI, TLI, RMSEA), select parameter estimates, and several data visualizations. LGMComp was not used in place of Mplus because it unable to utilize sample weights and cluster variables, and modifications to models cannot be made, such as the addition of structured residuals.

Results

The first step of the analysis consisted of an examination of the descriptive statistics from a null model of each measure (Table 1). Descriptive statistics were compared to those from an identical two-level model in which students were clustered within schools (Appendix 1). To evaluate the risk of bias due to dependent observations, design effects were calculated. As illustrated in Appendix 1, design effects were large. However, there were over 400 clusters with an average size greater than 10, suggesting that clustering was ignorable provided that school-level variables were not examined (Lai & Kwok, 2015). Furthermore, the use of Mplus' complex analysis and cluster options with single-level estimation produced nearly identical descriptive statistics to those from the multi-level models (Appendix 1). Consequently, a single-level modeling approach was used for subsequent analyses. Select univariate models were run in a two-level framework for comparison and no substantive differences were detected (Appendix 2).

To evaluate patterns in mean and individual growth, plots of the assessment data were inspected. Unweighted violin plots (Figure 3) suggested

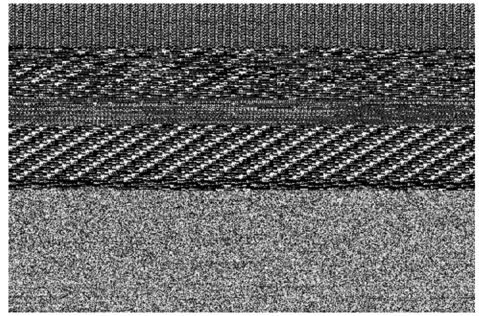
Table 1

Weighted Descriptive Statistics for Kindergarten through Grade 4 (Type Complex Null Model)

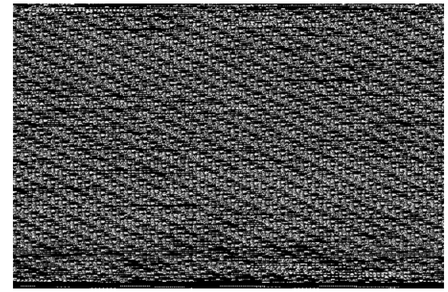
Measure and Time	*N*	*M* (*SD*)	Skew/Kurtosis
Numbers reversed			
Grade K fall	4,970	436.59 (29.77)	0.18 / -1.38
Grade K spring	5,510	452.70 (28.96)	-0.45 / -0.80
Grade 1 fall	5,020	459.98 (27.12)	-0.71 / -0.09
Grade 1 spring	5,150	471.97 (23.27)	-0.73 / 1.46
Grade 2 fall	4,530	475.26 (22.66)	-0.88 / 1.67
Grade 2 spring	4,890	482.07 (21.14)	-0.65 / 1.87
Grade 3 spring	4,660	490.99 (20.21)	-0.68 / 2.83
Grade 4 spring	5,510	497.99 (20.26)	-0.24 / 1.40
Dimensional card sorting			
Grade K fall	4,970	14.42 (3.05)	-1.75 / 2.60
Grade K spring	5,510	15.42 (2.44)	-2.07 5.79
Grade 1 fall	5,020	15.90 (2.23)	-2.27 / 7.68
Grade 1 spring	5,150	16.31 (2.07)	-2.35 / 7.68
Grade 2 fall	4,510	6.46 (1.34)	-1.47 / 2.00
Grade 2 spring	4,880	7.00 (1.11)	-1.63 / 3.75
Grade 3 spring	4,630	7.32 (0.85)	-1.54/ 5.42
Grade 4 spring	4,470	7.72 (0.89)	-1.38 / 5.70
Mathematics achievement			
Grade K fall	4,970	-0.36 (0.84)	-0.47 / 0.91
Grade K spring	5,510	0.49 (.070)	-0.92 / 3.33
Grade 1 fall	5,020	1.00 (0.81)	0.16 / 0.22
Grade 1 spring	5,150	1.73 (0.79)	-0.23 / 0.57
Grade 2 fall	4,530	1.98 (0.78)	-0.81 / 2.25
Grade 2 spring	4,890	2.51 (0.74)	-1.13 / 3.66
Grade 3 fall	4,660	3.12 (0.71)	-0.52 / -0.03
Grade 4 spring	4,510	3.48 (0.70)	-0.76 / 0.83
Reading achievement			
Grade K fall	4,990	-0.40 (0.80)	0.34 / 0.37
Grade K spring	5,520	0.55 (0.72)	-0.45 / 1.02
Grade 1 fall	5,020	0.95 (0.76)	0.17 / 0.09
Grade 1 spring	5,160	1.70 (0.71)	-0.36 / 0.51
Grade 2 fall	4,530	1.90 (0.65)	-0.26 / 0.02
Grade 2 spring	4,890	2.27 (0.63)	-0.31 / 0.37
Grade 3 spring	4,660	2.66 (0.60)	-0.07 / 0.09
Grade 4 spring	4,510	2.94 (0.58)	-0.46 / 1.42

Note. Means for Numbers Reversed, Reading Achievement, and Mathematics Achievement are weighted with W8CF8P_80. Dimensional Card Sorting is weighted with W4CF4P_20 in grades K-1 and W8CF8P_80 in 2-4. Students were clustered in 438 classes for Numbers Reversed, Mathematics Achievement, and Dimensional Card Sorting Grade K-1, 439 classrooms for Reading Achievement, and 400 classrooms for Dimensional Card Sorting Grade 2-4. Sample sizes rounded to the nearest 10 per National Center on Education Statistics convention.

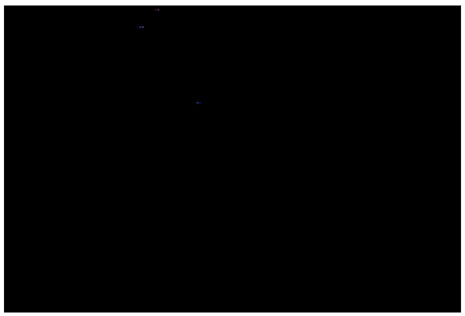
Numbers Reversed



Dimensional Card Sort K-1



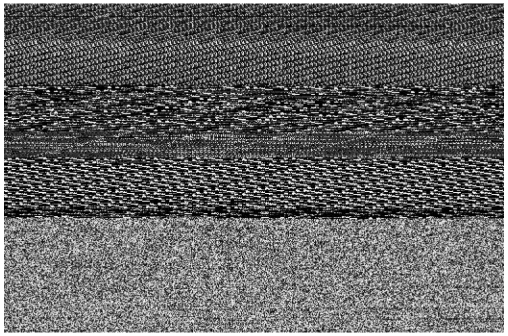
Dimensional Card Sort 2-4



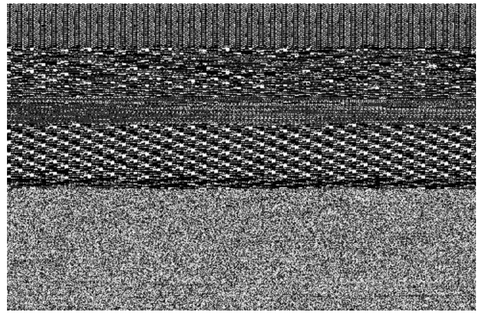
Mathematics Achievement

Reading Achievement

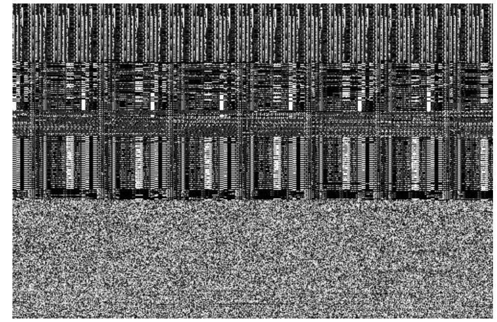
Figure 3. Unweighted violin plots for executive function and achievement measures produced using LGMComp.



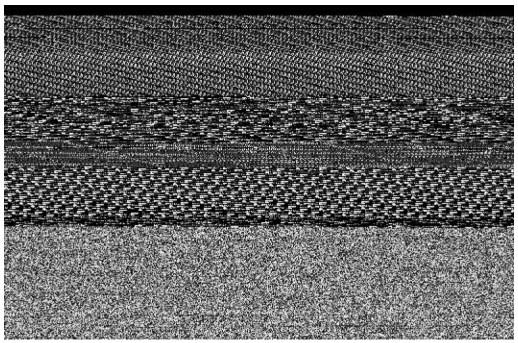
Numbers Reversed



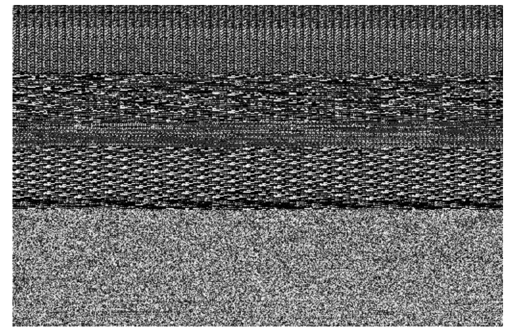
Dimensional Card Sort K-1



Dimensional Card Sort 2-4



Mathematics Achievement



Reading Achievement

Figure 4. Unweighted trellis plots for executive function and achievement measures produced using LGMComp.

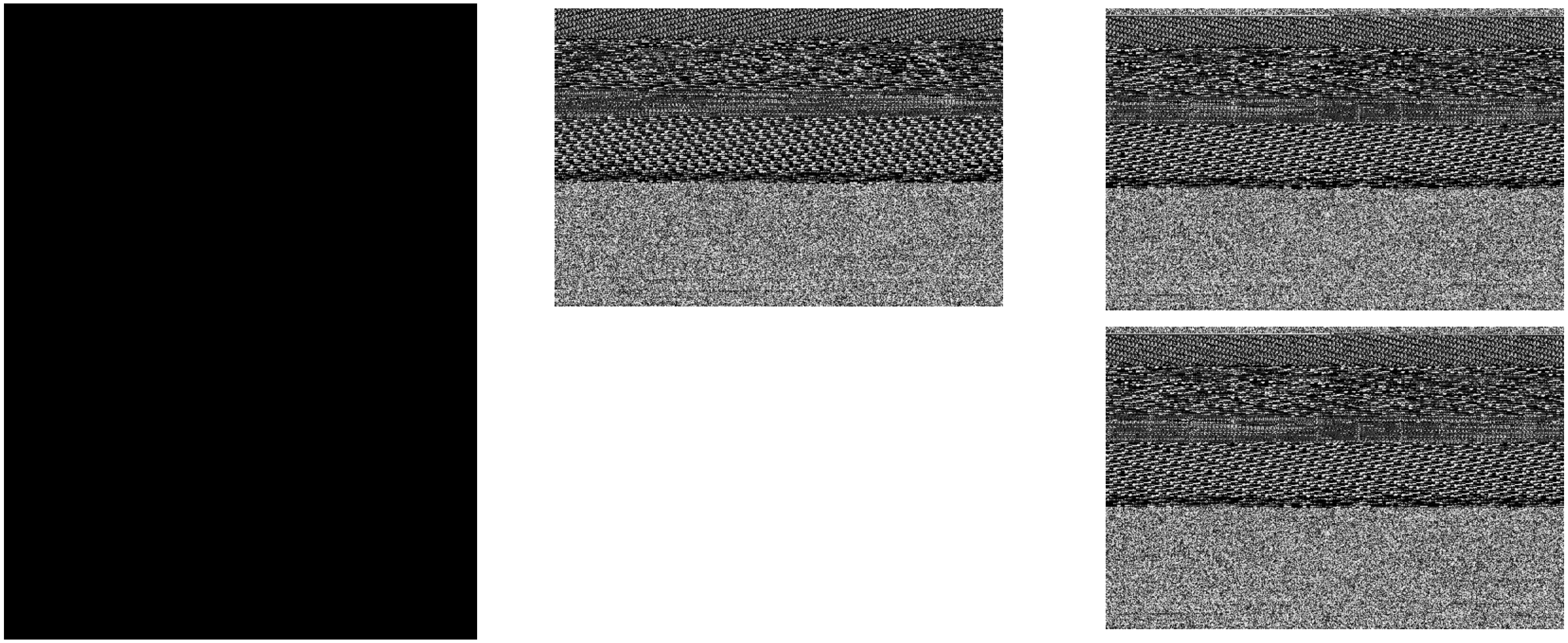


Figure 5. Unweighted overlaid trajectories for executive function and achievement measures produced using LGMComp.

Figure 6. Observed mean and individual growth trajectories for a random sample of 75 students on Numbers Reversed. Scores are weighted with W8CF8P_80.

Figure 7. Observed mean and individual growth trajectories for a random sample of 75 students on Dimensional Card Sort (K-1). Scores are weighted with W4CF4P_20.

Figure 8. Observed mean and individual growth trajectories for a random sample of 75 students on Dimensional Card Sort (2-4). Scores are weighted with W8CF8P_80.

Figure 9. Observed mean and individual growth trajectories for a random sample of 75 students on Mathematics Achievement. Scores are weighted with W8CF8P_80.

Figure 10. Observed mean and individual growth trajectories for a random sample of 75 students on Reading Achievement.

Scores are weighted with W8CF8P_80.

possible floor effects on the Kindergarten Numbers Reversed task and possible ceiling effects on the Dimensional Card Sorting task in Spring of Grade 1. They also illustrate that the range in scores greatly dipped for the Grade 3 Dimensional Card sort due to a greater number of students getting very low scores, but the cause of the dip is unclear. The dip does not coincide with the change in test administration procedures. Consistent with prior research, trellis plots (Figure 4) and overlaid trajectories (Figure 5) suggested that the EF measures were “noisier” than the achievement measure, with scores being somewhat erratic from one time point to another; and that patterns in growth may differ by initial level of ability. Visual inspection of mean and individual growth trajectories (Figures 6-10) suggested that the growth of working memory, reading achievement, and mathematics achievement were characterized by a curvilinear pattern in accordance with prior research (e.g., Willoughby, Wylie, & Little, 2019; Zelazo, Craik, & Booth, 2004). The trajectories of the attentional shifting measures were more ambiguous. In both cases, the overall trajectory was relatively flat, but the slope from first to second measurement occasion appeared steeper. Additionally, there appeared to be little variation in individual trajectories across students by Grades 2-4.

Univariate Model Results

Fit indices for the unconditional univariate models are presented in Table 2. For the working memory and achievement measures, model fit tended to improve as more parameters were estimated. The freely estimated model exhibited the best fit according to all fit indices with the exception of SRMR for Numbers Reversed (.133), which was negligibly higher than the quadratic growth model with structured residuals (.130). Results for Dimensional Card Sort were ambiguous. None of the fixed time score models

Table 2
Fit Indices for Unconditional Univariate Growth Models in Mplus and LGMComp

		Mplus					LGComp		
Model	Description	*N*	χ^2 (df)	CFI	RMSEA	SRMR	χ^2 (df)	CFI	RMSEA
	Numbers Reversed								
1	No Growth	5,820	5,482.58* (34)	.000	.116	1.912	—	—	—
2	Linear Growth	5,820	847.59* (31)	.791	.067	0.318	—	—	—
3	Quadratic Growth	5,820	172.93* (27)	.963	.030	0.170	NA	NA	NA
4	Quadratic Growth SR	5,820	139.92* (23)	.970	.030	0.130	NA	NA	NA
5	Freely Estimated	5,820	130.35* (25)	.973	.027	0.156	17,579.94* (32)	.000	.402
6	**Freely Estimated SR**	**5,820**	**73.12* (24)**	**.987**	**.019**	**0.133**	**NA**	**NA**	**NA**
7	Latent Change Score	5,820	792.24* (38)	.807	.058	.662	—	—	—
	Dimensional Card Sorting Grades K-1								
8	No Growth	5,800	428.07* (8)	.000	.095	0.203	2,686.07* (11)	.000	.244
9	Linear Growth	5,800	31.55* (5)	.933	.030	0.037	595.67* (8)	.624	.134
10	Quadratic Growth	5,800	6.81* (1)	.985	.032	0.013	162.36* (4)	.899	.098
11	Linear Growth SR	5,800	34.74* (2)	.918	.053	0.035	NA	NA	NA
12	**Freely Estimated**	**5,800**	**5.57* (3)**	**.994**	**.012**	**0.028**	**231.91* (6)**	**.856**	**.096**
13	Freely Estimated SR	5,800	Just-identified				NA	NA	NA
14	Latent Change Score	5,800	85.11* (8)	.769	.041	0.248	243.82* (7)	.849	.091
	Dimensional Card Sorting Grades 2-4								
15	No Growth	5,020	713.61* (8)	.000	.133	0.560	4,658.80* (11)	.000	.317
16	Linear Growth	5,020	47.39* (5)	.933	.044	0.096	509.02* (8)	.865	.125
17	Quadratic Growth	5,020	56.069* (1)	.767	.105	0.044	151.43* (4)	.960	.096
18	Linear Growth SR	5,020	24.28* (2)	.906	.047	0.028	NA	NA	NA
19	**Freely Estimated**	**5,020**	**0.830* (3)**	**1.00**	**> .001**	**0.020**	**420.39* (6)**	**.888**	**.132**
20	Freely Estimated SR	5,020	Just-identified				NA	NA	NA
21	Latent Change Score	5,020	61.44* (8)	.923	.036	.163	460.68* (7)	.878	.128

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Table 2 (continued)

Model	Description	Mplus					LGMComp		
		N	χ^2 (df)	CFI	RMSEA	SRMR	χ^2 (df)	CFI	RMSEA
	Mathematics Achievement								
22	No Growth	5,820	12,400.80* (34)	.000	.250	1.867	67,923.52* (41)	.000	.699
23	Linear Growth	5,820	3,467.16* (31)	.651	.138	0.227	7,385.764* (38)	.790	.239
24	Quadratic Growth	5,820	607.15* (27)	.941	.061	0.065	4,248.38* (34)	.879	.191
25	Quadratic Growth SR	5,820	836.139* (23)	.917	.078	0.076	NA	NA	NA
26	Freely Estimated	5,820	391.30* (25)	.963	.050	0.065	2,126.99* (32)	.940	.139
27	**Freely Estimated SR**	**5,820**	**177.03* (24)**	**.984**	**.033**	**0.061**	**NA**	**NA**	**NA**
28	Latent Change Score	5,820	1,869.27 (38)	.814	.091	.111	4,521.16* (37)	.872	.189
	Reading Achievement								
29	No Growth	5,820	12,597.89* (34)	.000	.252	1.743	66,000.44* (41)	.000	.688
30	Linear Growth	5,820	6,867.68* (31)	.359	.195	0.331	14,238.40* (38)	.575	.332
31	Quadratic Growth	5,820	1,358.15* (27)	.875	.092	0.090	5,360.06* (34)	.840	.215
32	Quadratic Growth SR	5,820	1,266.55* (23)	.883	.096	0.083	NA	NA	NA
33	Freely Estimated	5,820	619.35* (25)	.944	.064	0.092	2,842.47* (32)	.916	.161
34	**Freely Estimated SR**	**5,820**	**273.45* (24)**	**.977**	**.042**	**0.083**	**NA**	**NA**	**NA**
35	Latent Change Score	5,820	4,470.66* (38)	.585	.142	0.183	5,193.21* (37)	.846	.202

Note. LGMComp indices are with unweighted measures and all paths are fixed. For MPLUS models, LCSMs are specified to estimate constant change. Bold text indicates the final model for each measure. NA = the model is not provided as part of LGMComp's automated output. — = LGMComp returned an error message for this model. * = $p < .001$.

Figure 11. Estimated growth trajectories for a random sample of 75 students on Numbers Reversed.

Figure 12. Estimated growth trajectories for a random sample of 75 students on Dimensional Card Sort (K-1). Scores are weighted with W4CF4P_20.

[redacted]

Figure 13. Estimated growth trajectories for a random sample of 75 students on Dimensional Card Sort. Scores are weighted with W8CF8P_80. Scores are weighted with W8CF8P_80 in 2-4.

Figure 14. Estimated growth trajectories for a random sample of 75 students on Mathematics Achievement Reversed. Scores are weighted with W4CF4P_20.

Figure 15. Estimated growth trajectories for a random sample of 75 students on Reading Achievement Reversed. Scores are weighted with W4CF4P_20.

Table 3

Fit Indices for Unconditional Univariate Growth Models with Low and High Working Memory Subsamples

		Low WM				High WM			
Model	Description	χ^2 (df)	CFI	RMSEA	SRMR	χ^2 (df)	CFI	RMSEA	SRMR
	Numbers Reversed								
1	No Growth	3,531.91* (34)	.000	.232	22.50	641.84* (34)	.000	.181	3.017
2	Linear Growth	1,960.7* (31)	.000	.180	9.399	139.42* (31)	.719	.080	1.194
3	Quadratic Growth	395.60* (27)	.684	.084	.535	85.80* (27)	.843	.063	.467
4	Freely Estimated	310.65* (25)	.755	.077	.714	62.54* (25)	.899	.053	1.302
5	**Freely Estimated SR**	**191.628* (24)**	**.856**	**.060**	**.549**	**55.89* (24)**	**.915**	**.049**	**1.025**
6	Latent Change Score	1,553.35* (38)	.000	.144	8.10	213.32* (38)	.531	.092	3.307
	Dimensional Card Sorting Grades K-1								
7	No Growth	168.21* (8)	.000	.102	.193	82.27* (8)	.000	.131	.204
8	Linear Growth	14.03* (5)	.931	.031	.050	9.30* (5)	.882	.040	.056
9	Quadratic Growth	7.19* (1)	.952	.057	.020	3.93* (6)	1.00	.000	.066
10	Linear Growth SR	13.99* (2)	.908	.056	.036	7.18* (2)	.858	.069	.048
11	**Freely Estimated**	**4.39* (3)**	**.989**	**.016**	**.042**	**1.78 (3)**	**1.00**	**.000**	**.062**
13	Latent Change Score	36.26* (8)	.671	.043	.251	21.31* (8)	.224	.055	.517
	Dimensional Card Sorting Grades 2-4								
14	No Growth	408.56* (8)	.000	.175	.712	68.464* (8)	.000	.125	.618
15	Linear Growth	31.13* (5)	.928	.057	.928	6.21* (5)	.977	.022	.073
16	Quadratic Growth	18.52* (4)	.960	.047	.064	5.63* (4)	.969	.029	.074
17	Linear Growth SR	49.357* (5)	.670	.074	.185	49.36* (5)	.670	.074	.185
18	**Freely Estimated**	**.867* (3)**	**1.00**	**.000**	**.017**	**2.28* (3)**	**1.00**	**.000**	**.118**
20	Latent Change Score	27.63* (8)	.946	.039	.210	7.60* (8)	1.00	.000	.364

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Table 3 (continued)

Model	Description	Low WM χ^2 (df)	CFI	RMSEA	SRMR	High WM χ^2 (df)	CFI	RMSEA	SRMR
	Mathematics Achievement								
21	No Growth	5,571.17* (34)	.000	.292	2.02	2,450.82* (34)	.000	.362	3.10
22	Linear Growth	1,202.92* (31)	.614	.141	.266	831.20*	.495	.218	.413
23	Quadratic Growth	257.82* (27)	.924	.067	.075	169.63* (27)	.910	.099	.133
24	Freely Estimated	154.86* (25)	.957	.052	.065	127.76* (25)	.935	.087	.142
25	**Freely Estimated SR**	**77.13* (24)**	**.982**	**.034**	**.054**	**89.73* (24)**	**.959**	**.071**	**.140**
26	Latent Change Score	741.33* (38)	.768	.098	.125	1,613.28* (38)	.730	.144	.215
	Reading Achievement								
27	No Growth	4,428.54* (34)	.000	.260	2.34	1,768.04* (34)	.000	.306	2.03
28	Linear Growth	2,204.51* (31)	.291	.191	.414	865.11* (34)	.194	.223	.406
29	Quadratic Growth	481.16* (27)	.852	.094	.105	211.33* (27)	.822	.112	.127
30	Freely Estimated	256.81* (25)	.924	.070	.113	100.66* (25)	.927	.075	.124
31	**Freely Estimated SR**	**100.72* (24)**	**.975**	**.041**	**.089**	**65.61* (24)**	**.960**	**.057**	**.120**
32	Latent Change Score	1,500.28* (38)	.523	.142	.204	646.40* (38)	.412	.172	.310

Note. Samples sizes for the Low and High Working Memory groups were respectively 1,910 and 540. Bold text indicates the final model.

* = $p < .001$.

exhibited very good fit in grades 2-4. For both grade intervals, fit improved considerably as the models became more complicated, with the freely estimated model exhibiting the best fit, despite the observed trajectories being relatively flat and uniform. However, the quadratic and freely estimated models left insufficient *df* to model structured residuals due to fewer measurement occasions. Because the fit indices suggested that a linear model was misspecified, the freely estimated model *without* structured residuals was selected as the final model, which precluded an examination of within individual variation for this measure. For all measures, there was a significant negative correlation between intercepts and slopes, implying that, on average, students who begin kindergarten with lower ability levels tended to grow faster than their peers.

Working memory subsamples. Fit indices for the unconditional univariate models with the low and high working memory subsample are presented in Table 3. Overall, fit indices followed the same pattern as that found for the whole sample, with the freely estimated model with structured residuals exhibiting the best fit for all measures except for Dimensional Card Sort, which lacked the *df* necessary to estimate the additional parameters. For the low working memory groups, fit indices for the Numbers Reversed were below recommended cut-offs (Kenny, 2015). The source of misspecification was likely related to the fact that most students in this subsample received the lowest possible score on the measure in the fall of kindergarten, resulting in low variance in the intercept. Because there was no better-fitting model, the freely estimated model was provisionally accepted as the final model, and the variance of the intercept was fixed to 0 in subsequent steps.

Bivariate Models

Table 4

Fit Indices for Bivariate Growth Models

Model	Base Models	*N*	χ^2 (df)	CFI	RMSEA	SRMR
32	Numbers Reversed with Mathematics	5,820	367.03* (106)	.985	.021	.085
33	Numbers Reversed with Reading	5,820	472.07*(106)	.979	.024	.086
34	Dimensional Card Sorting K-1 with Mathematics K-4	5,820	218.40* (55)	.986	.023	.045
35	Dimensional Card Sorting K-1 with Reading K-4	5,820	311.96* (55)	.977	.028	.062
36	Dimensional Card Sorting 2-4 with Mathematics K-4	5,820	239.55* (55)	.985	.024	.046
37	Dimensional Card Sorting 2-4 with Reading K-4	5,820	332.99* (55)	.978	.029	.059
	Bivariate Models with Autoregressive Cross-Lagged Residuals					
38	Numbers Reversed with Mathematics With ARCL K-4	5,820	360.13* (103)	.985	.021	.085
39	Numbers Reversed with Mathematics With ARCL K-1	5,820	358.16* (103)	.985	.021	.086
40	Numbers Reversed with Reading with ARCL K-4		Not identified			
41	Numbers Reversed with Reading with ARCL K-1	5,820	461.90* (103)	.979	.024	.086

Note. * = $p < .001$.

Table 5

Fit Indices for Bivariate Growth Models for the Working Memory Subsamples

		Low WM				High WM			
Model	Base Models	χ^2 (df)	CFI	RMSEA	SRMR	χ^2 (df)	CFI	RMSEA	SRMR
42	Numbers Reversed with Mathematics	412.29* (110)	.940	.038	.397	253.64* (109)	.931	.049	.636
43	Numbers Reversed with Reading	404.76* (111)	.941	.037	.349	203.29* (109)	.944	.040	.597
	Attentional Shifting K-1 with Mathematics K-4	108.50* (55)	.985	.023	.049	124.12* (55)	.956	.048	.111
	Attentional Shifting K-1 with Reading K-4	136.76* (55)	.976	.028	.072	100.78* (55)	.963	.039	.099
	Attentional Shifting 2-4 with Mathematics K-4	118.37* (55)	.981	.025	.044	126.11* (55)	.955	.049	.109
	Attentional Shifting 2-4 with Reading K-4	148.11* (55)	.972	.030	.069	110.51* (55)	.956	.043	.101
	Bivariate Models with Autoregressive Cross-Lagged Residuals								
44	Numbers Reversed with Mathematics K-4	Unidentified				240.53* (103)	.935	.050	.624
45	Numbers Reversed with Mathematics K-1	401.49* (107)	.941	.038	.395	247.69* (106)	.933	.050	.604
46	Numbers Reversed with Reading with ARCL K-4	Unidentified				Unidentified			
47	Numbers Reversed with Reading with ARCL K-1	391.56* (108)	.943	.037	.340	194.63* (106)	.947	.039	.605

Note. For the low working memory group, the intercept of the numbers reversed model was fixed to zero due to low variance. For the high working memory group, cross-construct covariances were fixed to zero in the ARCL models, except for the covariance of the intercepts.

Table 6

Select Parameters for Bivariate Growth Models of Working Memory and Academic Achievement

Parameter	NMRV with Math	NMRV with Math and K-1 ARCL	NMRV with Math and K-4 ARCL	NMRV with Read	NMRV with Read and K-1 ARCL
Working memory					
Mean intercept $\mu_{y\alpha}$	**436.71 (1.01)**	**436.74 (1.01)**	**436.73 (1.01)**	**436.62 (1.01)**	**436.63 (1.01)**
Mean Slope $\mu_{y\beta}$	**60.57 (0.98)**	**60.55 (0.98)**	**60.56 (0.981)**	**60.66 (0.98)**	**60.63 (0.98)**
Intercept variance ψ_{11}	**494.85 (23.61)**	**490.75 (24.57)**	**493.26 (24.58)**	**502.84 (23.92)**	**512.56 (23.92)**
Slope variance ψ_{22}	**320.57 (9.17)**	**319.21 (35.81)**	**320.26 (35.92)**	**324.39 (35.12)**	**333.07 (34.54)**
Intercept slope covariance ψ_{21}	**-286.929 (23.85)**	**-283.78 (24.73)**	**-285.34 (24.77)**	**-294.04 (24.02)**	**-302.94 (23.89)**
Residual variance $\sigma^2_{\varepsilon y}$	**448.72 (23.02)**	**445.86 (22.85)**	**446.55 (27.74)**	**435.67 (24.74)**	**433.30 (24.53)**
Achievement					
Mean intercept $\mu_{z\alpha}$	**-0.36 (0.03)**	**-0.36 (.03)**	**-0.36 (0.03)**	**-0.40 (0.03)**	**-0.40 (.03)**
Mean slope $\mu_{z\beta}$	**3.83 (0.02)**	**3.83 (.02)**	**3.83 (0.02)**	**3.33 (0.03)**	**3.30 (0.03)**
Intercept variance ψ_{33}	**0.51 (0.03)**	**0.52 (.03)**	**0.52 (0.03)**	**0.52 (.03)**	**0.52 (0.03)**
Slope variance ψ_{44}	**0.14 (0.02)**	**0.14 (.02)**	**0.14 (0.02)**	**0.10 (0.02)**	**0.19 (0.02)**
Intercept slope covariance ψ_{43}	**-0.10 (0.02)**	**-0.10 (.02)**	**-0.10 (0.02)**	**-0.21 (.55)**	**-0.21 (.02)**
Residual variance $\sigma^2_{\varepsilon z}$	**0.22 (0.02)**	**.22 (.02)**	**0.22 (0.02)**	**0.23 (.014)**	**0.23 (.01)**
Standardized Cross-construct covariances					
Intercept$_{wm}$ to intercept$_{achiev}$ ψ_{31}	**.85 (.02**	**.87 (.02)**	**.86 (.02)**	**.74 (.02)**	**.75 (.24)**
Slope$_{wm}$ to slope$_{achiev}$ ψ_{42}	**.38 (.07)**	**.45 (.07)**	**.43 (.07)**	**.37 (.07)**	**.40 (.07)**
Intercept$_{wm}$ to Slope$_{achieve}$ ψ_{41}	**-.28 (.06)**	**-.33 (.06)**	**-.31 (.06)**	**-.34 (.05)**	**-.36 (.06)**
Intercept$_{Achiev}$ to slope$_{wm}$ ψ_{32}	**-.55 (.05)**	**-.57 (.05)**	**-.72 (.02)**	**-.51 (.05)**	**-.52 (.05)**
Within-person effect					
Contemporaneous $\sigma_{\varepsilon zy}$	**0.37 (0.05)**	**.35 (.05)**	**0.36 (0.06)**	**0.25 (0.05)**	**0.23 (.05)**
WM autoregression ρ_{yy}, $\rho_{\varepsilon yy}$	**0.11 (0.02)**	**.12 (.02)**	**0.11 (0.02)**	**0.12 (0.02)**	**0.12 (0.02)**
Achievement autoregression ρ_{zz}, $\rho_{\varepsilon zz}$	**0.24 (0.02)**	**.24 (.02)**	**0.24 (0.02)**	**0.30 (0.02)**	**0.30 (0.02)**
WM on Achieve cross-lag	—	-1.83 (.94)	0.001 (0.00)	—	0.16 (1.06)
Achieve on WM cross-lag	—	>**-0.01 (.00)**[g]	-0.80 (0.64)	—	>**-0.01 (0.00)**[i]

Table 7

Select Parameters for Bivariate Growth of Working Memory and Mathematics Achievement by Initial Working Memory

	NMRV with Math		NMRV with Math and K-1 ARCL	
Parameter	Low WM	High WM	Low WM	High WM
Working memory				
Mean intercept $\mu_{y\alpha}$	**404.96 (.27)**	**479.83 (.70)**	**404.96 (.27)**	**479.83 (.69)**
Mean Slope $\mu_{y\beta}$	**84.74 (.95)**	**30.05 (1.52)**	**84.75 (.95)**	**30.04 (1.51)**
Intercept variance ψ_{11}	**0.00**	**44.68 (11.37)**	**0.00**	**42.29 (11.12)**
Slope variance ψ_{22}	**215.08 (25.57)**	**107.94 (35.82)**	**214.63 (25.67)**	**106.45 (35.90)**[c]
Intercept slope covariance ψ_{21}	**0.00**	**44.12 (9.92)**	**0.00**	**45.20 (9.69)**
Residual variance $\sigma^2_{\varepsilon y}$	**33.71 (6.52)**	**62.51 (8.84)**	**33.71 (6.52)**	**62.40 (9.05)**
Achievement				
Mean intercept $\mu_{z\alpha}$	**-0.82 (.04)**	**.27 (.05)**	**-0.82 (.04)**	**.27 (.05)**
Mean slope $\mu_{z\beta}$	**3.92 (.04)**	**3.65 (.05)**	**3.92 (.04)**	**3.65 (.05)**
Intercept variance ψ_{33}	**0.34 (.04)**	**.25 (.04)**	**0.32 (.04)**	**.24 (.04)**
Slope variance ψ_{44}	**0.14 (.03)**	**.25 (.04)**	**0.14 (.03)**	**.11 (.04)**
Intercept slope covariance ψ_{43}	-0.02 (.03)	-.05 (.03)	-0.01 (.03)	-.05 (.02)
Residual variance $\sigma^2_{\varepsilon z}$	**.283 (.04)**	**.14 (.02)**	**.285 (.04)**	**.14 (.02)**
Standardized Cross-construct covariances				
Intercept$_{wm}$ to intercept$_{achiev}$ ψ_{31}	**0.00**	**.65 (.06)**	**0.00**	**.62 (.06)**
Slope$_{wm}$ to slope$_{achiev}$ ψ_{42}	**.34 (.10)**	0.00	**.38 (.11)**	0.00
Intercept$_{wm}$ to Slope$_{achieve}$ ψ_{41}	**0.00**	0.00	**0.00**	0.00
Intercept$_{Achiev}$ to slope$_{wm}$ ψ_{32}	**.61 (.07)**	0.00	**.60 (.07)**	0.00

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Table 7 (continued)

Parameter	NMRV with Math		NMRV with Math and K-1 ARCL	
	Low WM	High WM	Low WM	High WM
Within-person effect				
Contemporaneous $\sigma_{\varepsilon zy}$	**.50 (10)**	**.62 (.15)**	**.52 (.11)**	**.67 (.16)**
WM autoregression ρ_{yy}, $\rho_{\varepsilon yy}$	**.24 (.03)**	.10 (.04)	**.24 (.03)**	.10 (.04)
Achievement autoregression ρ_{zz}, $\rho_{\varepsilon zz}$	**.25 (.04)**	**.26 (.05)**	**.26 (.04)**	**.27 (.05)**
WM on Achieve cross-lag			.95 (2.0)	4.32 (2.44)
Achieve on WM cross-lag			**>.01 (>.01)**	>.01 (>.01)

Table 8

Select Parameters for Bivariate Growth Models of Working Memory and Reading Achievement by Initial Working Memory

	NMRV with Reading		NMRV with Reading and K-1 ARCL	
Parameter	Low WM	High WM	Low WM	High WM
Working memory				
Mean intercept $\mu_{y\alpha}$	**404.97 (.27)**	**479.86 (.69)**	**405.00 (.28)**	**479.85 (.69)**
Mean Slope $\mu_{y\beta}$	**84.85 (.94)**	**30.04 (1.51)**	**84.87 (.94)**	**30.04 (1.50)**
Intercept variance ψ_{11}	0.00	**41.80 (10.31)**	0.00	**41.68 (36.82)**
Slope variance ψ_{22}	**208.65 (25.91)**	**107.56 (37.18)**[d]	**205.38 (25.86)**	**107.25 (.04)**
Intercept slope covariance ψ_{21}	0.00	**49.11 (10.94)**	0.00	**50.53 (11.04)**
Residual variance $\sigma^2_{\varepsilon y}$	**33.70 (6.52)**	**63.36 (9.35)**	**26.13 (6.35)**	**64.26**
Achievement				
Mean intercept $\mu_{z\alpha}$	**-0.79 (.04)**	**.23 (.06)**	**-0.79 (.04)**	**.24 (.06)**
Mean slope $\mu_{z\beta}$	**3.43 (.04)**	**3.07 (.05)**	**3.43 (.04)**	**3.06 (.05)**
Intercept variance ψ_{33}	**0.33 (.04)**	**.38 (.04)**	**0.32 (.03)**	**.38 (.04)**
Slope variance ψ_{44}	**0.16 (.04)**	**.20 (.04)**	**0.16 (.04)**	**.20 (.04)**
Intercept slope covariance ψ_{43}	**-0.12 (.03)**	**-.21 (.04)**	**-0.12 (.03)**	**-.20 (.04)**
Residual variance $\sigma^2_{\varepsilon z}$	**0.21 (.02)**	**.21 (.03)**	**0.21 (.03)**	**.21 (.03)**
Standardized Cross-construct covariances				
Intercept_{wm} to $\text{intercept}_{achiev}$ ψ_{31}	.00	**.65 (.23)**	.00	**.38 (.08)**
Slope_{wm} to slope_{achiev} ψ_{42}	.00	.00	.00	.00
Intercept_{wm} to $\text{Slope}_{achieve}$ ψ_{41}	.00	.00	.00	.00
$\text{Intercept}_{Achiev}$ to slope_{wm} ψ_{32}	**.56 (.05)**	.00	**.55 (.05)**	.00
Within-person effect				
Contemporaneous $\sigma_{\varepsilon zy}$	**.40 (.09)**	**.62 (.15)**	**.44 (.09)**	**.42 (.14)**[b]

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Table 8 (continued)

	NMRV with Reading		NMRV with Reading and K-1 ARCL	
Parameter	Low WM	High WM	Low WM	High WM
WM autoregression ρ_{yy}, $\rho_{\varepsilon yy}$	**.25 (.03)**	.10 (.04)	**.25 (.03)**	.11 (.05)
Achievement autoregression ρ_{zz}, $\rho_{\varepsilon zz}$	**.36 (.04)**	**.26 (.05)**	**.37 (.04)**	**.20 (.04)**
WM on Achieve cross-lag			2.31 (1.85)	**5.50**[g]
Achieve on WM cross-lag			**>.01 (>.01)**	.00 (>.01)

In Step Three the univariate models were combined into bivariate growth models. In Step Four, cross-lags were added to the models involving working memory. Fit was good for all bivariate models with the whole sample (Table 4). The bivariate model of working memory and reading with cross-lagged residuals was unidentified when cross-lags were added for the entire Kindergarten through Grade 4 span. Consequently, the model was simplified to specify cross-lags for Kindergarten through Grade 1 only, which better reflects findings from previous research (Fuhs et al., 2014; Fuhs & Day, 2011; Nesbitt et al., 2018; Schmitt et al., 2017). For the sake of comparison across achievement measures, a bivariate model of working memory and mathematics with cross-lags from (a) Kindergarten through Grade 1 and (b) Kindergarten through Grade 4 are also reported.

Working memory subsamples. For the working memory subsamples, fit was adequate to good for all models. However, for the low working memory subsample, the bivariate model of working memory and mathematics with cross-lags from Kindergarten to Grade 4 was unidentified. Consequently, cross-lags were specified for Kindergarten and Grade 1. Cross-lags were not added to the attentional shifting models because the final univariate models did not include structured residuals. Table 5 describes the fit statistics for the bivariate models with working memory subsamples. Tables 6, 7, 8, and 9 describes select parameters for each model.

Working memory and mathematics achievement. In the final bivariate model of working memory and mathematics achievement, all paths and covariances were significant except for the cross-lagged paths. Intercepts and slopes covaried positively across constructs, indicating that students who had higher initial levels on one measure also tended to have higher initial levels on the other measure; and that growth on one measure was related to growth on the other measure across students. Across constructs, intercepts and slopes covaried negatively, indicating that higher initial levels on one construct was related to less growth on the other construct. For the cross-lags, working memory in the fall of kindergarten led spring mathematics achievement, but the association was small and negative, β (SE) = -.08, p = .006. These results suggest that, between students, there is an average association between initial status and growth on working memory and mathematics achievement measures. However, working memory is not associated with subsequent mathematics achievement within students after accounting for their previous mathematics achievement and the covariance between working memory and academic achievement at a given point in time, except at the start of Kindergarten. Similarly, mathematics achievement is not associated with subsequent working memory after accounting for previous working memory and the covariance between working memory and academic achievement.

Working memory subsamples. Results differed for the working memory subsamples. For the low working memory subsample, intercepts of the working memory measure were fixed to zero due to low variance. Consequently, any covariances that included the intercept were not estimated, implying that variation in initial working memory status is not associated with growth in working memory or mathematics between students. Furthermore, fall Kindergarten working memory was associated with spring mathematics, β (SE) = .05, p = .002; and spring Kindergarten working memory associated with fall of Grade 1 mathematics, β (SE) = .15, p = .001. For the high working memory group, neither the cross-construct covariances nor the cross-lags were significant, implying that initial status and growth on working memory and mathematics achievement were unrelated between and within students.

Working memory and reading achievement. Similar to the mathematics models, all paths were significant in the working memory and reading achievement models except for the cross-lagged paths. Intercepts and slopes covaried positively across constructs, indicating that students who had higher initial levels on one measure also tended to have higher initial levels on the other measure; and that growth on one measures was related to growth on the other measure across students. Across-constructs, intercepts and slopes covaried negatively, indicating that higher initial levels on one construct was related to slower growth on the other construct. For the cross-lags, spring working memory in Kindergarten led reading achievement in the fall of Grade 1, but the association was small and negative, β (SE) = -.05, p = .009. These results suggest that, between students, there is an average association between initial status and growth on working memory and reading achievement measures. However, working memory was not associated with subsequent reading achievement within students after accounting for previous reading achievement and the covariance between working memory and reading achievement, except from the spring of Kindergarten to the fall of Grade 1. Similarly, reading achievement was not associated with working memory after accounting for previous working memory and the covariance between working memory and reading achievement.

Working memory subsamples. Results differed for the working memory subsamples. For the low working memory subsample, intercepts of the working memory measure were fixed to zero due to low variance. Consequently, any covariances that included the intercept were not estimated, implying that variation in initial working memory status is not associated with growth in working memory or reading between students. Working memory in the fall of Grade 1 was associated with the reading in the spring of Grade 1, β (SE) = .14, $p < .001$. Among students with high working memory, the association between reading in the fall of Kindergarten and working memory in the spring trended toward significance, β (SE) = .16, $p = .010$. Reading in the spring of Kindergarten was associated with working memory in the fall of Grade 1, β (SE) = .13, $p = .001$), and reading in the fall of Grade 1 was associated with working memory in the spring of Grade 1, β (SE) = .13, $p = .009$. The cross-lags between working memory and reading achievement were not significant.

Attentional shifting and mathematics achievement. In the final bivariate models of attentional shifting and mathematics achievement, all paths and covariances were significant in the Kindergarten and Grade 1 model. However, in the Grade 2-4 model, the covariance of the slopes was not significant, and the intercept of attentional shifting was not associated with the slope of mathematics achievement. Thus, students who had higher initial levels on one measure also tended to have higher initial levels on the other measure; but growth on one measure was only related to growth on the other measure in Grades K-1. Across-constructs, intercepts and slopes covaried negatively in Grade K-1, indicating that higher initial levels on one construct was related to less growth on the other construct. However, initial status in attentional shifting in Grades 2-4 was not significantly related to growth in achievement. The within-person effect of previous mathematics achievement was β (SE) = .24, $p < .001$. The final models did not estimate within-person effects for attentional shifting.

Table 9

Select Parameters for Bivariate Growth Models of Attentional Shifting and Academic Achievement

Parameter	DCSS K-1 with Math K-4	DCSS 2-4 with Math K-4	DCSS K-1 with Read K-4	DCSS 2-4 with Read K-4
Attentional Shifting				
Mean intercept $\mu_{y\alpha}$	**14.43 (0.11)**	**6.45 (.04)**	**14.43 (.11)**	**6.45 (.04)**
Mean Slope $\mu_{y\beta}$	**1.90 (0.11)**	**1.26 (.04)**	**1.90 (.11)**	**1.26 (.04)**
Intercept variance ψ_{11}	**2.94 (.56)**	**1.05 (.12)**	**3.00 (.60)**	**1.03 (.12)**
Slope variance ψ_{22}	**1.72 (.61)[e]**	**.68 (.12)**	**1.80 (.64)[e]**	**.65 (.13)**
Intercept slope covariance ψ_{21}	**-1.48 (.54)[g]**	**-.63 (.11)**	**-1.55 (58)[h]**	**-.61 (.11)**
Achievement				
Mean intercept $\mu_{z\alpha}$	**-.36 (.03)**	**-.36 (.03)**	**-.40 (.03)**	**-.40 (.03)**
Mean slope $\mu_{z\beta}$	**3.81 (.02)**	**3.83 (.02)**	**3.33 (.03)**	**3.33 (.03)**
Intercept variance ψ_{33}	**.52 (.03)**	**.52 (.03)**	**.52 (.03)**	**.52 (.03)**
Slope variance ψ_{44}	**.14 (.02)**	**.13 (.02)**	**.19 (.02)**	**.19 (.02)**
Intercept slope covariance ψ_{43}	**-.09 (.02)**	**-.09 (.02)**	**-.21 (.02)**	**-.21 (.02)**
Residual variance $\sigma^2_{\varepsilon z}$	**.22 (.02)**	**.22 (.02)**	**.22 (.01)**	**.23 (.01)**
Standardized Cross-Construct Covariances				
Intercept_{attn} to $\text{intercept}_{achiev}$ ψ_{31}	**.70 (.05)**	**.63 (.03)**	**.55 (.06)**	**.48 (.04)**
Slope_{attn} to slope_{achiev} ψ_{42}	**.36 (.12)[b]**	.15 (.07)	**.28 (.10)[d]**	.18 (.08)
Intercept_{attn} to $\text{Slope}_{achieve}$ ψ_{41}	**-.39 (.08)**	-.08 (.06)	**-.31 (.06)**	-.15 (.06)
$\text{Intercept}_{Achiev}$ to slope_{attn} ψ_{32}	**-.28 (.12)[b]**	**-.43 (.05)**	**-.22 (.08)[g]**	**-.38 (.06)**
Within-person effect				
Achievement autoregression ρ_{zz}, $\rho_{\varepsilon zz}$	**.24 (.02)**	**.24 (.02)**	**.30 (.02)**	**.30 (.02)**

a = p = .001
b = p = .002
…
h = p = *.008*

Table 10

Select Parameters for Bivariate Growth Models of Attentional Shifting and Academic Achievement for the Working Memory Subsamples

	DCSS K-1 with Math K-4		DCSS K-1 with Read K-4	
Parameter	Low WM	High WM	Low WM	High WM
Attentional Shifting				
Mean intercept $\mu_{y\alpha}$	**13.62 (.17)**	**15.40 (.19)**	**13.65 (0.17)**	**15.37 (0.18)**
Mean Slope $\mu_{y\beta}$	**2.10 (.19)**	**1.51 (.21)**	**2.09 (0.20)**	**1.44 (0.22)**
Intercept variance ψ_{11}	**3.27 (1.21)[g]**	.37 (.58)	**2.97 (1.12)[h]**	.43 (0.97)
Slope variance ψ_{22}	2.17 (1.54)	.40 (.89)	1.87 (1.49)	.41 (1.23)
Intercept slope covariance ψ_{21}	-1.77 (1.34)	-.06 (.70)	-1.46 (1.27)	-.13 (1.09)
Achievement				
Mean intercept $\mu_{z\alpha}$	**-.82 (.04)**	**.27 (.05)**	**-0.79 (0.04)**	**.24 (0.06)**
Mean slope $\mu_{z\beta}$	**3.92 (.04)**	**3.65 (.05)**	**3.43 (0.04)**	**3.06 (0.05)**
Intercept variance ψ_{33}	**.36 (.04)**	**.27 (.04)**	**0.32 (0.04)**	**.38 (0.04)**
Slope variance ψ_{44}	**.15 (.03)**	**.14 (.04)**	**0.16 (0.04)**	**.20 (0.04)**
Intercept slope covariance ψ_{43}	-.03 (.03)	**-.07 (.03)[i]**	**-0.12 (0.03)**	**-.20 (0.04)**
Residual variance $\sigma^2_{\varepsilon z}$	**.28 (.04)**	**.14 (.02)**	**0.20 (0.02)**	**.20 (0.03)**
Standardized Cross-Construct Covariances				
Intercept_{attn} to $\text{intercept}_{achiev}$ ψ_{31}	**.63 (.12)**	.46 (.41)	**.38 (0.13)[c]**	.77 (0.76)
Slope_{attn} to slope_{achiev} ψ_{42}	.34 (.18)	1.36 (1.44)	.46 (.25)	1.47 (2.02)
Intercept_{attn} to $\text{Slope}_{achieve}$ ψ_{41}	.30 (.12)	-1.03 (.78)	-.30 (.14)	-.71 (.72)
$\text{Intercept}_{Achiev}$ to slope_{attn} ψ_{32}	-.26 (.18)	> -.01 (.44)	-.08 (0.18)	-.88 (1.20)
Within-person effect				
Achievement autoregression ρ_{zz}, $\rho_{\varepsilon zz}$	**.24 (.04)**	**.23 (.05)**	**0.38 (0.04)**	**.21 (0.03)**

a = p = .001
b = p = .002
…
h = p = *.008*

Table 11

Select Parameters for Bivariate Growth Models of Attentional Shifting and Academic Achievement for the Working Memory Subsamples

	DCSS 2-4 with Math K-4		DCSS 2-4 with Read K-1	
Parameter	Low WM	High WM	Low WM	High WM
Attentional Shifting				
Mean intercept $\mu_{y\alpha}$	**6.05 (.08)**	**7.02 (.07)**	**6.05 (.08)**	**7.02 (.07)**
Mean Slope $\mu_{y\beta}$	**1.51 (.07)**	**.88 (.09)**	**1.50 (.07)**	**.88 (.09)**
Intercept variance ψ_{11}	**1.76 (.26)**	**.38 (.10)**	**1.75 (.27)**	**.37 (.09)**
Slope variance ψ_{22}	1.11 (.24)	**.61 (.20)**[c]	**1.10 (.27)**	**.62 (.09)**[b]
Intercept slope covariance ψ_{21}	-1.17 (.22)	-.29 (.13)	**-1.16 (.24)**	-.28 (.13)
Achievement				
Mean intercept $\mu_{z\alpha}$	**-.82 (.04)**	**.27 (.05)**	**-.79 (.04)**	**.24 (.06)**
Mean slope $\mu_{z\beta}$	**3.92 (.04)**	**3.65 (.05)**	**3.43 (.04)**	**3.06 (.05)**
Intercept variance ψ_{33}	**.36 (.04)**	**.27 (.04)**	**.32 (.04)**	**.38 (.04)**
Slope variance ψ_{44}	**.14 (.03)**	**.14 (.04)**	**.16 (.04)**	**.21 (.04)**
Intercept slope covariance ψ_{43}	-.03 (.03)	**-.07 (.03)**[i]	**-.11 (.03)**	**-.20 (.04)**
Residual variance $\sigma^2_{\varepsilon z}$	**.29 (.04)**	**.14 (.02)**	**.21 (.02)**	**.20 (.03)**
Standardized Cross-Construct Covariances				
Intercept_{attn} to $\text{intercept}_{achiev}$ ψ_{31}	**.56 (.04)**	**.36 (.09)**	**.39 (.05)**	**.29 (.10)**[c]
Slope_{attn} to slope_{achiev} ψ_{42}	-.03 (.10)	.19 (.20)	-.06 (.11)	.13 (.16)
Intercept_{attn} to $\text{Slope}_{achieve}$ ψ_{41}	.13 (.09)	-.28 (.18)	.05 (.10)	-.05 (.13)
$\text{Intercept}_{Achiev}$ to slope_{attn} ψ_{32}	-.42 (.06)	-.03 (.11)	**-.31 (.07)**	-.22 (.12)
Within-person effect				
Achievement autoregression ρ_{zz}, $\rho_{\varepsilon zz}$	**.24 (.04)**	**.24 (.05)**	**.37 (.04)**	**.19 (.04)**

a = *p* = .001
b = *p* = .002
…
h = *p* = *.008*

Working memory subsample. Results differed for the working memory subsamples. For the low working memory group and high working memory group, intercept and slope variance of attentional shifting was not significant. Further, covariances involving these parameters were not significant except for the covariance between the intercepts in the low working memory Kindergarten Grade 1 model, β (SE) = .63, $p < .001$, the Grade 2-4 model, β (SE) = .56, $p < .001$; and the high working memory Grade 2-4 model, β (SE) = .36, $p < .001$. The within-person effect of previous achievement was in the .20-.30 range for both grade spans and subgroups.

Attentional shifting and reading achievement. In the final bivariate model of attentional shifting and mathematics achievement, all paths and covariances were significant in the Kindergarten and Grade 1 model. However, in the Grade 2-4 model, the covariance of the slopes was not significant, and the intercept of attentional shifting was not associated with the slope of mathematics achievement. Thus, students who had higher initial levels on one measure also tended to have higher initial levels on the other measure; but growth on one measure was only related to growth on the other measure in Grades K-1. Across-constructs, intercepts and slopes covaried negatively in Grade K-1, indicating that higher initial levels on one construct was related to less growth on the other construct. However, initial status in attentional shifting in Grades 2-4 was not significantly related to growth in achievement. The final models did not estimate within-person effects for attentional shifting. The within-person effect of previous reading achievement was β (SE) = .30, $p < .001$. achievement (Tables 7 and 8).

Working memory subsample. Results differed for the working memory subsamples. For the low working memory group, the variance for the attentional shifting slope and the covariance between the slope and intercept were not significant for either timespan or achievement measure, except for Grade 2-4 reading. Cross-construct covariances were not significant for either grade span except for the covariance between intercepts (both grades spans), and the attentional shifting intercept's covariance with the slope of reading achievement (Grades 2-4 only). For the high working memory group, the variance of attentional shifting's intercept, slope, and their covariance were not significant for either grade span or achievement measures. Cross-construct covariances were not significant for either grade span. The within-person effect of previous achievement ranged from .37 to .38 for the low working memory group, and .19 to .21 for the high working memory group.

Discussion

There is a moderate unconditional association between EF and academic achievement across grade levels (Jacob & Parkinson, 2015; Peng et al., 2016), but relatively little research has been conducted on the unique contributions of EF to academic achievement over time. LCM-SR is a new method for examining the within-person associations between two constructs over time. Willoughby et al., (2019) recently used LCM-SR to examine the co-development of EF and academic achievement in the ECLS-K:2011 sample for students with different free and reduced priced lunch status. This study replicated the main analytic strategy used in Willoughby et al., (2019) after adding the Grade 3 and 4 timewaves to the dataset, but used (a) a refined sample, (b) a lower alpha, and (c) a maximum likelihood robust estimator, all of which facilitate more conservative estimates to those from the prior study. The present study also disaggregated results by student working memory level rather than free and reduced lunch status.

Overall, the within-person results reported here are quantitatively similar to those in Willoughby et al., (2019), but there are some important substantive differences. The primary finding in Willoughby et al., (2019) was that although the between-person associations between EF and achievement were large (β's = .55 – .91), the within-person associations were small (β's = .10 – .25), a pattern which held for the free and reduced priced lunch subsample. This overall pattern held for the present study, with large between person effects (β's = .22 – .86), and small within person effects (β's = $|.05|$ – $|.36|$) in the whole sample. However, the present study did not examine within-person effects for attentional shifting due limited *df* and difficulties identifying the correct functional form. The two studies differed in terms of their between-person covariances, number of cross-lagged effects, and in some cases, directions of cross-lagged effects.

Differences in Covariances

The present study added an additional timewaves to the ECLS-K: 2011 dataset, which resulted in changes to the intercepts and slopes of all models. In this case, an important feature of the additional time waves is that they were from spring test administrations. In the earlier grade levels, growth is less robust from the spring to fall, likely due to the so-called summer slide (Gershenson, 2013; Zvoch & Stevens, 2015). The addition of the Grades 3 and 4 timepoints resulted in smoother estimated trajectories for those timepoints, and by extension, changes to the latent growth factors. The univariate model parameters are not reported in Willoughby et al., (2019), but it can be inferred from the differences in covariance structures in the bivariate models that there are some differences between the two study's univariate models.

For working memory and mathematics achievement, Willoughby et al. (2019) reported that intercepts were positively associated, β (SE) = .82, $p < .001$; the working memory intercept and slope were negatively associated, β (SE) = -.71, $p < .001$; the working memory intercept and math slope were positively associated, β (SE) = .23 , $p < .001$; the math intercept and working memory slope were negatively related, β (SE) = -.50, $p < .001$; and the slopes were not significantly related. In contrast, all covariances were significant in the present study, and the direction of the relations were such that higher initial ability on *either* construct was always associated with less growth on *both* constructs. Meanwhile, slopes were positively associated, indicating that growth on one construct was generally associated with growth on the other. For working memory and reading achievement, the variance of the reading slope was not significant in Willoughby et al. (2019), thus, covariances involving the reading slope were not estimated. In contrast, the variance was significant in the present study. Otherwise, the covariances were identical in terms of direction, and broadly similar in terms of magnitude in the two studies.

The present study also examined low and high working memory subsamples. For the low working memory group, the variance of the working memory intercept was not significant in the models involving mathematics. Consequently, covariances involving the intercept were not estimated. Working memory and math slopes positively covaried. The math and reading achievement intercepts positively related to working memory growth, which is the opposite direction reported for the whole sample in this study, but the same as Willoughby et al., (2019) mathematics model. For the high working memory group, no cross-construct covariance was significant except the covariance of the intercepts.

Patterns in attentional shifting and academic achievement covariances also differed. In Willoughby et al.'s (2019) final model, the variance of the attentional shifting slope was not significant in either bivariate model. For the reading achievement model, the attentional shifting intercept and reading achievement slope were also not significant. Consequently, estimates involving these parameters are not reported. The remaining parameters covaried positively. In the present study, the variance of the growth factors were significant, likely because structured residuals were not estimated. Covariances were such that higher initial ability on *either* construct was always associated with less growth on *both* constructs, except in Grades 2-4, where the slope of achievement was not significant in any cross-construct parameters. For the working memory subsamples, covariances were generally not significant, with the exception of covariances between intercepts, which were positive except for the low working memory group in Grades K-1, which was not significant. Achievement intercepts and slopes had small negative covariances, and were not significant for the low working memory group. In Grades 2-4, the reading achievement intercept negatively covaried with the attentional shifting slope.

Differences in Cross-Lagged Effects

Another area of difference that emerged involved the cross-paths between constructs and the working memory subsamples. Willoughby et al., (2019) found an array of small cross-construct associations between the EF and achievement measures for the whole sample, some of which held for the free and reduced priced lunch subsample. With two exceptions, these associations did not hold for the whole sample in the present study.

However, follow-up analyses with the working memory subsamples found several within-person cross-construct associations. Some of these associations corresponded to those reported in Willoughby et al., (2019). Other associations were in the opposite directions as those reported in Willoughby et al., (2019) as well as those reported in the present study's whole sample analyses.

Willoughby et al., (2019) found small cross-lagged effects with fall working memory leading spring mathematics in Kindergarten, β (SE) = -.06 p < .05. Spring of Kindergarten working memory did not lead and fall Grade 1 achievement, but fall working memory led spring achievement in Grade 1, β (SE) = -.06 p < .05; and spring working memory in Grade 1 led mathematics achievement in the fall of Grade 2, β (SE) .06, $p < .05$. The study also found that mathematics achievement in the fall of Grade 2 led working memory in the spring of Grade 2, β (SE) = .07 $p < .05$. In the present study, these paths were not significant for the whole sample, except working memory in the fall of Kindergarten, which negatively led spring mathematics achievement, β (SE) = -.08, $p = .006$. However, for students with low working memory, fall Kindergarten working memory *positively* led spring mathematics, β (SE) = .05, $p = .002$; and spring Kindergarten working memory positively led fall of Grade 1 mathematics, β (SE) = .15, $p = .001$. There were no significant cross-lagged effects for the high working memory group.

For reading, Willoughby et al., (2019) reported that fall working memory led spring achievement in Grade 1 and Grade 2, β (SE) = .03 - .06, and reading achievement led working memory from the fall of Grade 1 to the end of Grade 2 β (SE) = .08 - .23. Results held for the free and reduced-price lunch subsample, except for the cross-lag from Spring Grade 1 working memory to fall Grade 2 achievement. The present study found that, for the whole sample, the cross-lags were not significant with the exception of spring working memory in Kindergarten leading reading achievement in the fall of Grade 1, but in this case, the association was small and negative, β (SE) = -.05, p = .009. This latter finding also substantively differs from Peng et al., (2019) which did not find that working memory was a unique predictor of reading in Grade 1 at-risk readers. However, Peng et al., (2019) accounted for a greater variety of domain-general and domain-specific abilities per model and intentionally lowered the floor of their working memory test by giving feedback on the first three recall items. Furthermore, the correlation reported in the present study is quite small.

Willoughby et al., (2019) also reported that reading achievement led working memory at all time points for the free and reduced priced lunch sample, and all time points except for the fall of Kindergarten for the whole sample (significant *β's* ranging from .08 to .25). In the present study, these cross-lags were not significant for the whole sample, but for students with high working memory, the association between reading in the fall of Kindergarten and working memory in the spring trended toward significance, β (SE) = .16, p = .010. Reading in the spring of Kindergarten was associated with working memory in the fall of Grade 1, β (SE) = .13, p = .001), and reading in the fall of Grade 1 was associated with working memory in the spring of Grade 1, β (SE) = .13, p = .009. The cross-lags between working memory and reading achievement were not significant.

The results of the reading cross-lags are surprising for three reasons. First, previous studies have not documented bidirectional relations between EF and reading *achievement* (except for Willoughby 2019). The associations reported here have the closest analogs in studies examining EF and verbal skills (e.g., Fuhs et al., 2014) and studies suggesting that formal education may improve fluid intelligence (Ritchie & Tucker-Drob, 2018). Secondly, the present study did not find evidence that working memory facilitates more advanced reading strategies (cf. Cirino et al., 2019). To the contrary, results are consistent with the idea that the acquisition of literacy improves EF. One explanation for the finding is that Cirino et al., (2019) measured working memory with discrimination scores from four *n*-back paradigm tasks, which presumably taps capacity and updating in different proportions from the Numbers Reversed task due to the latter's lack of an interference component. Another possibility is that children who are more cognitively and academically able benefit more from classroom instruction due to more and/or higher quality student-teacher interactions (Peng & Kievit, 2019).

Another surprising difference is that the cross-lagged models in Willoughby et al.'s, (2019) free and reduced priced lunch subsample resemble those from the high working memory subsample in the present study, though one might except the free and reduced priced lunch subsample to more closely resemble the low working memory group given that SES-gaps in achievement and working memory have been described in this dataset (Little, 2017). The resemblance between the free and reduced priced lunch subsample and the high working memory subsample is difficult to explain, but two points are noteworthy. First, the mean differences in scores between the whole sample free and reduced priced lunch subsample were relatively small in Willoughby et al., (2019). Working memory and reading scores tended to be within 2 points of each other on scales that respectively ranged from 403 to 603 and 0 to about 140. In contrast, the mean differences between the working memory subsamples and the whole sample were very large across all measures. Secondly, theta scores at different ends of the spectrum often reflect different abilities. For instance, students in the low working memory group may have tended to derive their reading achievement scores by utilizing their word-level abilities on the assessment whereas students with higher scores may have derived their higher scores from sentence and passage reading, or even comprehension. Relatedly, it is likely that students in these groups received different types of classroom instruction due to their large difference in early reading ability. Thus, it may be the case that the use of advanced reading skills may facilitate minor gains to working memory in the first years of school, and that heterogeneity in previous research findings reflect the use of measures that (a) tap different reading-related abilities and (b) analyze samples of students with different ability levels.

Implications for Practice and Future Research

The results of the present study have implications for educational practice. Both Willoughby et al., (2019) and the present study found that, although there is a large between-person association between EF and achievement, the within person associations tend to be quite small. When the small association is considered in conjunction with literature documenting small effect sizes for educational interventions in general (Lortie-Forgues & Inglis, 2019), a lack of causal evidence that school-based EF interventions can improve academic achievement (Jacob & Parkinson, 2015), and mounting evidence that EF training programs can improve specific EFs, but generally do not transfer to more distal abilities or improve global EF (e.g., Melby-Lervåg et al., 2016; Redick, 2019; Schwaighofer et al., 2015), it can be concluded that school-based EF interventions are not an efficient use of resources in Tier 1 or whole-class contexts. Because within-person effects seem to depend on initial ability level, small-group and individualized EF interventions may be a better use of resources, especially if the EF intervention is part of a broader intervention aimed at improving academics (e.g., Fuchs et al., 2019), or other important attributes, such as physical fitness (e.g., Gearin & Fien, 2016), behavior and self-regulation (Flook et al., 2015), or compensatory strategies for students with EF and achievement difficulties (Titz & Karbach, 2014).

That said, further research is needed to better understand how to design EF intervention and measure its effects (see also Peng & Kievit, 2019). One finding from the present study is that the within-person relation between performance on the Numbers Reversed task and future mathematics achievement may differ for students of different ability levels. Further interpreting these results is complicated by two aspects of the study: (a) the sparse measurement net within timepoints, and (b) the floor effects on the Numbers Reversed task documented in the fall of Kindergarten. Typically, early mathematics ability is thought to reflect a combination of number-specific and domain general abilities (Hornung et al., 2014). One longitudinal study of Kindergarteners reported that numerical knowledge mediated ($k^2 = .09$) the relation between number sense and arithmetic, even after controlling for age, IQ, visual attention, working memory, visuospatial processing, and inhibition (Peng et al., 2017). Though it is possible the relation between working memory and achievement reported here reflects differences in working memory capacity, it is also possible that numerical knowledge drove the differences in performance on both the Numbers Reversed and achievement measures. Previous studies have reported that phonological decoding, verbal knowledge, visuo-spatial memory, and spatial ability may work in tandem with general EF in explaining variation in early mathematics achievement (see also Szűcs, Devine, Soltesz, Nobes, & Gabriel, 2014). It is possible that students with little or no formal knowledge of numbers may have struggled to recall the digits in the Numbers Reversed task due to lack of familiarity with even the names of the numbers (e.g., Poppenk, Köhler, & Moscovitch, 2010; Savi, Marsman, van der Maas, & Maris, 2019) and subsequently achieved differently from their higher ability peers.

A related limitation concerns the measurement of childhood EF. The use of only two EF measures in the ECLS-K: 2011 dataset proved to be a limitation for the present study because (a) an EF factor model could not be empirically tested, and (b) the measures exhibited floor and ceiling effects. Clarification is needed about how to most efficiently measure EF in early childhood. It is not feasible to comprehensively measure EF, as was done in Cirino et al., (2018) in every study of elementary school children. It is also difficult to find tasks that are easy enough for preschool students to complete but challenging enough to create a normal distribution of scores for elementary school students. Unfortunately, discrepancies between the previous studies (Peng et al., 2019; Willoughby et al., 2019) and the present one seem to suggest that modest differences in measurement approaches may result in different substantive conclusions about EF's relation to academic achievement. When designing future studies, researchers should consider replicating measurement nets from comparable studies in order to gauge the extent to which bivariate relations or lack thereof depend on the choice of measure.

CHAPTER III: SOCIOECONOMIC STATUS AND THE CO-DEVELOPMENT OF EXECUTIVE FUNCTION AND ACADEMIC ACHIEVEMENT

The socioeconomic status (SES) academic achievement gap refers to the average difference in academic achievement among students from different SES backgrounds. This gap manifests as soon as children begin school and narrows only slightly thereafter (Little, 2017). There is a parallel SES-gap in cognitive ability of about equal magnitude (Hackman, Gallop, Evans, & Farah, 2015a; Little, 2017). Though probably less well-known than the Black-White achievement gap, the SES academic achievement gap is actually the larger of the two when comparing students from the highest and lowest SES quintiles (Little, 2017). There is some evidence that the SES-achievement gap has been growing since the 1970s. Reardon (2011), for example, found that for children born in 2001, the gap between households at the 90th percentile of income and households at the 10th percentile of income was 30 to 40 percent larger than for children born twenty-five years earlier. This shift coincided with growing levels of income inequality in the United States, and a decline in achievement gaps between White students and Black and Hispanic students (Reardon, 2011).

The SES academic achievement gap, and the possible growth thereof, has important policy implications. Children facing SES-hardship enter high school with average literacy skills about five years behind those of their wealthier peers (Reardon et al., 2012). They are more likely to drop out of high school (National Center for Education Statistics, 2014), and less likely to obtain a bachelor's degree by the age of 24 (U.S. Census Bureau, 2000). These trends are alarming because education has long been considered a "great equalizer" of social class, and a "balance wheel" of the nation's social machinery (Mann, 1868). Former Secretary of Education Arne Duncan, for instance, frequently championed the idea that education equalize differences in social class (A. Duncan, 2009, 2011), and even argued that "[t]he only way to increase social mobility and strengthen the middle class is through high-quality education" (A. Duncan, 2012). However, if differences in academic achievement and educational attainment substantially reflect SES-related factors that schools are not addressing, different social strategies may be necessary for addressing SES disparities. It is therefore important that researchers and policymakers develop a nuanced understanding of the causes, characteristics, and indicators of the SES academic achievement gap.

In order to better understand SES differences in academic achievement, this study examines the association between seven common indicators of SES and the co-development of executive function (EF) and academic achievement in elementary school students. It also examines whether growth trajectories differ for students below, at, or above the poverty level. In so doing, it helps paint a fuller picture of the SES-achievement gap over time. It also elucidates some of the strengths and weaknesses of common SES-indicators for predicting cognitive and academic growth, which can improve future research and data-based decision-making.

What is Socioeconomic Status?

SES is a widely-studied but anamorphous concept (Sirin, 2005). Since at least the 1970s, researchers from different disciplines have been interested in understanding the in-school and out-school processes that contribute to differences in academic achievement (Becker, 1962; Coleman, 1988; Greg J. Duncan et al., 1994; Gottfried, 1985; White, 1982). SES is usually discussed as a contextual variable that directly or indirectly constrains these processes, usually through the availability of resources. In educational research, SES is often operationalized as *household income*, *parental education levels*, and *parental occupational prestige* after Hollingshead's four indicator model, which additionally included marital status (Hollingshead, 1975). *Free and reduced-priced lunch* status is another highly-utilized measure of SES. When operationalized with one of these indicators, the average relation between SES and academic achievement is between .26 and .30 (Sirin, 2005), with the size of the average relation tending to increase by grade level (Sirin, 2005). However, these indicators do not affect educational processes and outcomes in the same ways. For example, correlations between parental education and student achievement may reflect a combination of genetics and knowledge that parents pass on to their children (G.J. Duncan & Magnuson, 2003; Malanchini et al., 2019). By contrast, free and reduced priced lunch status is often taken to be an imperfect proxy for income and/or household volatility, with little or no causal effect on academic achievement (Domina et al., 2018).

Over the past two decades, research on the mechanism that link SES to achievement has increased rapidly due to contributions from multiple academic disciplines, including educational psychology, neuroscience, behavioral genetics (e.g., Amso & Lynn, 2017; Farah, 2017; Reardon, 2011; Seidler & Ritchie, 2018). However, our understanding of the mechanisms linking SES and academic achievement remains murky due to diverging methodological approaches and levels of explanation across studies (e.g., biomarker, individual, school, nation), and the many mechanisms through which SES seems to operate. Transactional theories of cognitive development (e.g., Malanchini et al., 2019; Tucker-Drob, 2013) provide a useful framework for understanding broad patterns in cognitive and academic development, especially when considered in conjunction with on-going research on SES-related differences in home and school environment (e.g., Amso & Lynn, 2017; Rosen et al., 2019).

Transactional Theories of Cognitive Development

Academic achievement and cognitive abilities, such as EF, are highly heritable phenotypes (Bouchard & McGue, 1981). It is thought that genetics can explain most (if not all) individual differences in EF by middle childhood or early adolescence (Engelhardt et al., 2015; N.P. Friedman et al., 2008). Similar patterns have been observed for academic performance (de Zeeuw et al., 2015), though heritability of academic achievement is higher than cognitive ability in elementary-aged children (Kovas et al., 2013), possibly due to schooling effects minimizing environmental differences that could contribute to academic learning. Though the precise nature of the relation between EF and academic achievement is still the subject of investigation, it is generally thought that EF plays a causal role in promoting academic achievement because they are closely related (e.g., Jacob & Parkinson, 2015a; Malanchini et al., 2019; Peng, Wang, & Namkung, 2018), as are academic achievement and general intelligence, a similar and possibly overlapping construct (Engelhardt et al., 2016; Friedman et al., 2006).

Behavioral geneticist often hold that the covariance between cognitive ability and academic achievement tends to be due genetic differences, while discrepancies tend to be due to environmental factors (Thompson et al., 1991). Because SES is a predictor of a broad array of environmental factors, it is an important variable to consider in studies of child development (Bradley & Corwyn, 2002; Briley & Tucker-Drob, 2014; Farah, 2017; Pepper & Nettle, 2017). As noted previously, the average correlation between SES and academic achievement is between .26 and .30 in the United States (Sirin, 2005). The average relation between any single SES indicator and individual EF is about .18. SES composites have a larger average correlation with EF composites of .31 (Lawson, Hook, & Farah, 2017), presumably due to a reduction of measurement error.

According to transactional models of cognitive development, which evolved primarily out twin studies, differences in SES act to facilitate or constrain learning experiences on the basis of genetically-influenced dispositions (Tucker-Drob et al., 2013). Noting that genetic influences on cognitive phenotypes tend to be maximized for older individuals and economically-advantaged individuals (e.g., Tucker-Drob & Bates, 2016), transactional accounts hold that children passively, evocatively, and actively interact with environments based on their genetics, and the types and frequencies of these interactions may be shaped by SES (Selzam et al., 2019). Passive interactions are those that parents intentionally or unintentionally create due to the genes they share with their child. An example might include the presence of books in the home due to a shared-genetic disposition to enjoy reading. Evocative processes arise when children elicit experiences based partially on genetics. An example might include a child who struggles with reading eliciting negative feedback from his or her parents, which in turn results in lower quality and/or less frequent practice opportunities (Tiberio et al., 2016). Active processes arise as children select or modify their environment based on genetic dispositions. An example might include a child seeking out reading opportunities despite the lack of books in the home. It is an open question as to whether the effect of specific genes and SES change over time (Tucker-Drob & Briley, 2014), but the possibility is consistent with the increasing correlations among SES, EF, and achievement from childhood into adulthood (Lawson et al., 2017a; Sirin, 2005), and the contributions of SES to academic achievement growth over and above contributions from intelligence (e.g., von Stumm, 2017).

Transactional models are useful for understanding how SES could relate to cognitive ability and academic achievement despite their high heritability over the lifespan, but at present, they have not been used to interpret previous research on *specific aspects* of the home and school environment that may explain SES-related differences in academic achievement (e.g., Amso & Lynn, 2017; Farah, 2017; Malanchini et al., 2019; Schibli, Wong, Hedayati, & D'Angiulli, 2017; Sirin, 2005). Though it is beyond the scope of this study to provide such a review, Rosen et al., (2019) recently proposed that cognitive stimulation—including parental involvement in learning, environmental complexity, and language quality and quantity—may serve as a parsimonious explanation of some of the SES-related differences in cognitive ability. For instance, there is evidence that parents from different SES backgrounds provide their children with cognitively stimulating behaviors to varying degrees, such as reading and exposure to words (e.g., Bradley & Corwyn, 2002; Daneri et al., 2019; Hango, 2007; Kiernan & Huerta, 2008; Pungello, Iruka, Dotterer, Mills-Koonce, & Reznick, 2009; Rosen et al., 2019). Levels of household chaos may also vary by SES and in turn shape cognitive development (e.g., Garrett-Peters, Mokrova, Vernon-Feagans, Willoughby, & Pan, 2016; Seidler & Ritchie, 2018). Though cognitive stimulation is probably not the only way SES influences cognitive development (Gearin et al., 2018), it is a useful explanation because it can explain the presence of the oft-observed SES-gradient in cognitive and academic measures. That is, individuals from higher-SES backgrounds tend to outperform even individuals from middle-SES backgrounds (e.g., Little, 2017). Explanations that focus only on deprivation and exposure to stresses or toxins may help explain variability in the ends of the normal distribution, but are generally not specified in sufficient detail to explain the often-observed SES-gradient.

The cognitive stimulation framework is also potentially useful for understanding how the school environment relates to academic development. SES-differences in achievement are present at school entry (Little, 2017), and SES-gaps in learning are evident even before then (Pungello et al., 2009). There is conflicting evidence about whether and how schools reduce or magnify these gaps. As noted above, several studies have reported that schools tend to equalize academic growth or even modestly shrink SES-related differences in cognitive ability and achievement (e.g., Aikens & Barbarin, 2008; Hughes et al., 2009; Kovas et al., 2013; Little, 2017a; P. L. Morgan et al., 2011; P. T. von Hippel et al., 2018), presumably because they provide children similar environments. However, modest gap reductions have also been reported in studies of elementary school students, and it is presently unclear if the gap trends that have been observed in elementary school students should be expected to hold in upper grades or for all students (Gearin et al., 2018). There is some evidence, for instance, that the compensatory effect of schools may decrease or even reverse over time (e.g., Kieffer, 2012; Langenkamp & Carbonaro, 2018; von Stumm, 2017). Furthermore, both students who do and do not receive free and reduced priced lunch have been observed to grow more quickly in low-poverty schools, suggesting that variation in school quality may contribute to the growth or reduction of achievement gaps (e.g., Kieffer, 2012; Langenkamp & Carbonaro, 2018). At present, the most reliable finding about SES-related school effects is probably one that originated with Coleman (1966), namely, that individual differences in achievement primarily reflect factors that occur outside of school.

Though out-of-school factors primarily drive achievement gaps, it has been argued that high-quality schooling has the potential to offset SES-related decrements in EF and academic achievement (e.g., Peng & Kievit, 2019; Ritchie & Tucker-Drob, 2018). For instance, Peng and Kievit (2019) have proposed that students from higher SES background have access to more frequent and higher quality learning opportunities, both within and outside of school. These opportunities may support the mutual development of cognitive ability and academic achievement as students must use their cognitive abilities when learning new academic skills. The acquisition of academic skills, meanwhile, often leads to additional learning opportunities. As evidence for this claim, the authors note that the positive effect of academic interventions tend to fade over time (Bailey et al., 2017) and Matthew effects are often apparent in educational research (e.g., Stanovich, 2009). It is therefore possible that school environments have the potential to influence developmental trajectories, but the benefits they confer tend to be overwhelmed in low SES contexts over time due to inconsistent access to high quality, personalized instruction.

The Need to Measure SES Comprehensively

One of the barriers to synthesizing research on SES and cognitive development is that there are challenges in measuring SES, and related challenges in generalizing about SES disparities. One overarching challenge is that SES is context-dependent (Rutkowski & Rutkowski, 2013). Contexts can differ both in terms of their levels of SES-disparities, as well as the capacity of their schools systems to address SES-disparities (Rutkowski & Rutkowski, 2013). That said, generalizations about SES can be made as long as researchers are mindful potential limitations in their measures and contextual differences (G.J. Duncan & Magnuson, 2003; P. von Hippel & Hamrock, 2019).

Another challenge is that researchers have tended to use only one two indicators of SES within a study, often without an explanation as to why a particular indicator was selected. This practice is understandable in burgeoning lines of research because SES measures often correlate highly with one another; and it is often desirable to minimize the number of statistical comparisons made within a study. However, it has proven a barrier to research synthesis because the practice obscures potential causal mechanisms (Farah, 2017; Gearin, 2017). The most common SES indicators are not expected to transmit their effects directly or in the same ways (G.J. Duncan & Magnuson, 2003; Farah, 2017; Sirin, 2005). For example, household income is a relatively volatile measure of SES, especially in houses with young children. It might be used to purchase access to environments that more conducive to cognitive development and learning. By contrast, parental education level (a) can only increase over time, (b) is slow to change at any point in the lifespan, and (c) presumably differs from household income in terms of heritability (e.g., Branigan et al., 2013). In light of such difference, it has been strongly recommended that researchers include multiple SES measures in their research when possible (G.J. Duncan & Magnuson, 2003; Farah, 2017).

The Present Study

In order to improve our understanding of how SES relates to cognitive development, the present study examined how seven common indicators of SES predict the co-development of EF and academic achievement in the Early Childhood Longitudinal Study Kindergarten 2011 dataset (ECLS-K: 2011), which tracks a large sample of American students as they moved from Kindergarten through Grade 4. Specifically, the study examined the association between SES (i.e., household income, parental education level, poverty level, adult food security status, parent occupation, free and reduced priced lunch status, and an SES composite) and the intercepts and slopes of EF and academic achievement as estimated by bivariate latent change score models with structured residuals (LCM-SRs) from a previous study (see previous chapter). LCM-SR's are an elaboration of growth models that partition between-subject variance from within-subject variance by regressing residuals (Curran et al., 2014). Like other types of LCMs, they can be easily adapted to examine the co-development of two constructs over time, such as working memory and reading achievement. Examining the relation between SES indicators and latent growth factors is useful because it addresses questions about when gaps in test performance begin and how they change over time for students from different SES backgrounds.

After examining how well various SES indicators predict the co-development of EF and achievement, the present study tested its unconditional growth models on subsamples of students below, at, or 200% above the poverty level. Testing the models on subsamples at different poverty levels makes it possible to evaluate the extent to which the models will generalize to different SES contexts. Poverty level was selected as the grouping variable because, unlike most other SES measures, there are clear qualitative differences in the levels. That is, being below, at, or above the poverty line provides meaningful information about income-to-needs ratio and purchasing power

(Lacour & Tissington, 2011) in a way that setting arbitrary cuts on measures like an SES composite would not. Prior research also suggested that there would be greater mean differences across poverty level groups than there were would have been for free and reduced priced lunch status groups (e.g., Cowan et al., 2012; Hair et al., 2015; Willoughby et al., 2019). Finally, poverty-level is one of the more malleable SES indicators, which makes it a useful object of study for the social sciences (G.J. Duncan & Magnuson, 2003).

Method

Data for this study came from the publicly-available ECLS-K:2011 dataset for grades K to 4 (N = 18,170), which is described in the previous chapter. Analyses for this study used the analytic sample (N = 5,890), as well as three subsamples of students: students who were below the poverty-level (N = 1,170), students who were at or above the poverty-level (N = 940), and students who were 200% above the poverty level (N = 2,280). The subsamples were similar in terms of male to female ratio. Students who were below the poverty level were 16.6% White, 15.7% Black, 58.4% Hispanic, 3.8% Asian, .6% Native Hawaiian/Pacific Islander, 2% American Indian, 2.8% multi-racial/non-Hispanic. Students at the poverty level were 34.4% White, 13.1 % Black, 39.3% Hispanic, 6.5% Asian, .6% Native Hawaiian/Pacific Islander, 2% American Indian, 3.9% multi-racial/non-Hispanic. Students 200% above the poverty level were 60.1% White, 5.7% Black, 16.8% Hispanic, 10.5% Asian, .4% Native Hawaiian/Pacific Islander, 1.1% American Indian, 5.4% multi-racial/non-Hispanic. There were small differences in the mean age at each time of assessment for each subsample (i.e., less than one month). Ages were such that differences in mean ages between measurement occasions tended to be higher for students in the high SES groups, suggesting that they may have received an additional week or less between most measurement occasions.

Measures

Measures of EF and academic achievement are described in the previous chapter. The SES measures were administered to parents via interview once per year beginning in the fall of Kindergarten. The measures were as follows:

Adult food security status. Food security status was estimated by having parents complete an 18-item questionnaire in the spring. Questions addressed food intake and experiences of food insecurity during the previous 12 months. NCES suggests that adult food security status is a more informative than child food security status because children are often protected from disrupted diets during food insecurity. Raw scores, which are an on ordinal scale, range from 0 to 10 and reflect the items concerning the adult's or household's food security.

Household income category. Household income was collected in the spring beginning in 2011. There were 18 levels, reflecting a detailed range of income. The lowest category was $5,000 and the highest category was greater than $200,000. Most levels increased by increments of $4,999. Income information was imputed by NCES if data were missing or not ascertained.

Poverty level. Household income information and poverty thresholds from the prior year's U.S. Census, which vary by household size, were used to calculate the poverty level variables. There were three levels: below the poverty threshold, at or above the threshold but less than 200% above, and 200% above the poverty threshold.

Parent education level. Parent education levels were assessed in the fall. There were eight levels ranging from "none" to "master's degree or higher." When used as a covariate, parent education level describes the education of the first parent to complete the interview. When used in composite variables, it reflects the education of one or two parents in the household.

Parent occupational prestige score. Information gathered about a parent's occupation was used to generate an occupational prestige score. Scores were derived using codes developed for the National Household Education Surveys Program. If an occupation could not be coded using this manual, the Standard Occupational Classification Manual—1980 (U.S. Department of Commerce, Office of Federal Statistical Policy and Planning, 1980) was used to identify the appropriate code. There were 22 levels ranging from "executive, administrative, and managerial" to "unemployed, retired, disabled, or unclassified worker." Inter-rater reliability checks were performed on manually-performed codes and a standardized adjudication process was used to resolve discrepant codes.

Free and reduced priced lunch status. The ECLS dataset contains several variables concerning free and reduced priced lunch status. For the present study, free and reduced priced lunch status was reported by the child's parent for consistency with the other SES variables. Information about lunch status was gathered during parent interviews and is intended to describe receipt of free and reduced priced lunch, not just eligibility. The variable was reverse-coded so that interpretation of levels would match the other SES variables.

SES composite. An SES composite was calculated using five components: Parent 1's education level, Parent 2's education level (where applicable), Parent 1's occupation prestige score, Parent 2's occupation prestige score (where applicable), and household income. To address missing data, NCES performed hot deck imputation on each component prior to creating the composite variable. Composite scores were *z*-transformed to create a continuous variable.

Analysis

The first step of the analysis was to examine descriptive statistics for the whole sample and the subsample. The second step of the analysis was to estimate bivariate growth models for the EF and academic achievement measures. This process is described in the previous chapter. For the sake of consistency, all the models used in the analyses for this chapter were the LCM-SRs *without cross-lagged residuals*, which were very small and inconsistently supported across models. The third step of the analysis consisted of adding each SES indicator independently to the bivariate growth models, along with student's age at the time of the first assessment. In the fourth step of the analysis, the unconditional bivariate growth models were re-run using the subsamples to test their robustness. As noted above, there were small mean differences in age at time of assessment for the different poverty level groups. Because it was unclear how much extra time between assessment occasions should warrant concern, age at time of first assessment was initially included as a covariate in all models. However, age was unrelated to the growth factors in the many of the working memory models and its inclusion prevented convergence for the attentional shifting models. Models were therefore re-run without age, which had the additional benefit of allowing an examination of the means and variances of the growth factors.

Results

Descriptive statistics are summarized in Table 12. A correlation matrix for the SES variables is presented in Table 13. Fit indices for the conditional bivariate growth models are presented in Table 14. All models exhibited good fit. Table 4 illustrates the correlations between the seven SES indicators and the growth factors in the bivariate latent growth models from Kindergarten to Grade 4. Results for the conditional models are as follows:

Working memory and mathematics achievement. SES indicators varied in terms of the number and size of their associations with EF and achievement latent growth factors. The SES composite associated with the most latent growth factors and often had the largest absolute associations. It was significantly related to initial status in working memory (r = .31, p < .001) and academic achievement (r = .39, p < .001), as well as growth in working memory (r = -.20, p < .001) and achievement (r = -.13, p = .003). The results imply that higher SES is associated with better test performance in the fall of Kindergarten, but slower growth thereafter. Similarly, parent education significantly associated with all of the growth factors in the model. It was significantly related to initial status in working memory (r = .28, p < .001) and academic achievement (r = .36, p < .001), as well as growth in working memory (r = -.18, p < .003) and achievement (r = -.13, p = .003). Household income and the derived poverty-level variable exhibited similar patterns of associations. They respectively associated with working memory and academic achievement in the low and mid .30’s. They were also associated with growth on working memory (r ~ .20), but not growth in academic achievement. Free and reduced priced lunch status performed about as well, predicting working memory (r = .28, p < .003) and achievement intercepts (r = .32, p < .003), and working memory slope (r = -.23, p < .001). Parent occupational prestige and adult food insecurity were not significantly related to the growth factors with one exception: adult food insecurity was related to academic achievement intercepts (r = -.12, p < .001), implying that being from a more food insecure food home was related to lower math scores in kindergarten, but not growth thereafter.

Working memory and reading achievement. Results for reading achievement were similar to those for mathematics, varying primarily in magnitude. The SES composite was significantly related to initial status in working memory (r = .31, p < .001) and academic achievement (r = .37, p < .001), as well as growth on those constructs, respectively (r = -.20, p < .001) and (r = -.14, p = .001). The results imply that higher SES is associated with better test performance in the fall of Kindergarten, but slower growth thereafter. Similarly, parent education significantly associated with all of the growth factors in the model. It was significantly related to initial status in working memory (r = .28, p < .001) and academic achievement (r = .34, p < .001), as well as growth (r = -.18, p < .003) and (r = -.13, p = .002) respectively. The results imply that higher parent education levels are associated with better test performance in the fall of Kindergarten, but slower growth thereafter. Household income and the derived poverty-level variable exhibited patterns in associations. They respectively predicted working memory and academic achievement in the low and mid .30’s. They also predicted growth on working memory (r ~ .20), but not growth in academic achievement.

Table 12

Weighted Descriptive Statistics for Measures of Socioeconomic Status in Kindergarten

Measure and Time	*N*	*M* (*SD*)	Skew/Kurtosis
Adult food security status	4,220	0.57 (2.07)	3.04
Household income category	4,390	10.98 (28.41)	-0.25
Poverty level	4,390	2.35 (.634)	-0.70
Parent education level	5,120	4.71 (3.72)	-0.59
Parent occupation prestige	4,190	7.61 (44.43)	-0.14
FRPL	5,890	0.66 (.22)	-0.69
SES composite	5,120	-0.03 (.55)	0.38

Note. FRPL = Free and reduced priced lunch status.

Table 13

Unweighted Correlations Between SES Variables Measured in Kindergarten

	Income category	Poverty level	Adult's food security	SES Composite	Parent education level	Occupational prestige
Income category						
Poverty level	.906*					
Adult's food security	-.348*	-.334*				
SES composite	.808*	.737*	-.294*			
Parent education level	.593*	.554*	-.214*	.833*		
Occupational prestige	.158*	.152*	-.057*	.110*	.600*	
FRPL (reverse coded)	.663*	.644*	-.289*	.511*	-.249*	-0.01

Note. FRPL = Free and reduced priced lunch status.

* = $p < .001$

Table 14

Fit Indices for Conditional Growth Models

Model	Description	*N*	χ^2 (df)	CFI	RMSEA	SRMR
	Numbers reversed and mathematics achievement K-4					
1	Poverty level in Grade K	3,760	422.06* (130)	.982	.024	.076
2	Household income in Grade K	3,760	432.08* (130)	.982	.025	.076
3	Parent education Grade K	4,430	426.90* (130)	.983	.023	.079
4	Parent occupational prestige Grade K	4,040	414.71* (130	.983	.023	.081
5	Adult food security Grade K	3,620	411.62* (130)	.982	.024	.085
6	Free or reduced-price lunch	5,010	419.33* (130)	.983	.021	.079
7	Household SES composite Grade K	4,430	437.23* (130)	.983	.023	.080
	Numbers reversed and reading achievement K-4					
8	Poverty level in Grade K	3,760	504.97* (130)	.977	.028	.076
9	Household income in Grade K	3,760	517.93* (130)	.977	.028	.076
10	Parent education Grade K	4,430	543.31* (130)	.976	.027	.078
11	Parent occupational prestige Grade K	4,050	502.48 * (130)	.977	.027	.082
12	Adult food security Grade K	3,620	508.54* (130)	.976	.028	.084
13	Free or reduced-prince lunch	5,010	520.65* (130)	.977	.024	.079
14	Household SES composite Grade K	4,430	552.41* (130)	.976	.027	.078
	Dimensional Card Sorting K-1 and Mathematics Achievement K-4					
15	Poverty level in Grade K	3,760	262.91* (71)	.983	.027	.043
16	Household income in Grade K	3,760	269.62* (71)	.983	.027	.043
17	Parent education Grade K	4,430	270.07* (71)	.984	.025	.041
18	Parent occupational prestige Grade K	4,040	244.88* (71)	.985	.025	.040
19	Adult food security Grade K	3,620	242.26* (71)	.984	.026	.042
20	Free or reduced-price lunch	5,010	255.33* (71)	.984	.023	.041
21	Household SES composite Grade K	4,430	277.64* (71)	.983	.026	.041
	Dimensional Card Sorting K-1 and Reading Achievement K-4					
22	Poverty level in Grade K	3,760	343.25* (71)	.976	.032	.057
23	Household income in Grade K	3,760	351.91* (71)	.975	.032	.057
24	Parent education Grade K	4,430	374.93* (71)	.975	.031	.056
25	Parent occupational prestige Grade K	4,040	327.824* (71)	.977	.030	.056
26	Adult food security Grade K	3,620	344.64* (71)	.975	.033	.058
27	Free or reduced-price lunch Grade K	5,010	345.75* (71)	.976	.028	.055
28	Household SES composite Grade K	4,427	381.17* (71)	.974	.031	.056

Table 15

Correlations Between SES Indicators Measured in Kindergarten and the Growth Factors for Kindergarten to Grade 4

Growth models

Model	Description	Executive Function Intercept	Executive Function Slope	Achievement Intercept	Achievement Slope
	Working memory and mathematics achievement K-4				
1	Poverty level in Grade K	**.30 (.03)**	**-.20 (.04)**	**.35 (.03)**	-.11 (.05)
2	Household income in Grade K	**.29 (.03)**	**-.18 (.04)**	**.36 (.03)**	-.10 (.05)
3	Parent education Grade K	**.28 (.03)**	**-.18 (.04)**[c]	**.36 (.03)**	**-.13 (.04)**[c]
4	Parent occupational prestige Grade K	.06 (.03)	-.01 (.04)	.09 (.03)	-.04 (.04)
5	Adult food insecurity Grade K	-.09 (.04)	.05 (.05)	**-.12 (.03)**	-.05 (.03)
6	Free or reduced-price lunch	**.28 (.03)**	**-.23 (.05)**	**.32 (.03)**	-.10 (.05)
7	Household SES composite Grade K	**.31 (.03)**	**-.20 (.04)**	**.39 (.02)**	**-.13 (.04)**[c]
	Working memory and reading achievement K-4				
8	Poverty level in Grade K	**.30 (.03)**	**-.20 (.04)**	**.34 (.03)**	-.12 (.05)
9	Household income in Grade K	**.29 (.03)**	**-.18 (.04)**	**.33 (.03)**	-.10 (.04)
10	Parent education Grade K	**.28 (.03)**	**-.18 (.04)**	**.34 (.03)**	**-.13 (.04)**[b]
11	Parent occupational prestige Grade K	.06 (.03)	-.01 (.04)	**.11 (.03)**	-.10 (.04)
12	Adult food insecurity Grade K	-.09 (.04)	.05 (.05)	**-.13 (.05)**	.03 (.04)
13	Free or reduced-price lunch	**.29 (.03)**	**-.24 (.05)**	**.29 (.03)**	-.04 (.05)
14	Household SES composite Grade K	**.31 (.03)**	**-.20 (.04)**	**.37 (.03)**	**-.14 (.04)**[a]
	Attentional shifting K-1 and mathematics achievement K-4				
15	Poverty level in Grade K	**.24 (.05)**	-.11 (.07)	**.35 (.03)**	-.11 (.05)
16	Household income in Grade K	**.23 (.04)**	-.10 (.07)	**.36 (.03)**	-.11 (.05)
17	Parent education Grade K	**.19 (.04)**	.03 (.06)	**.36 (.03)**	**-.13 (.04)**[c]
18	Parent occupational prestige Grade K	-.02 (.04)	.13 (.07)	**.08 (.03)**[b]	-.04 (.04)
19	Adult food insecurity Grade K	**-.17(.06)**[c]	.19 (.10)	**-.12 (.03)**	.05 (.05)

Continued next page

Table 15 (continued)

Model	Description	Executive Function Intercept	Executive Function Slope	Achievement Intercept	Achievement Slope
20	Free or reduced-price lunch	**.15 (.05)**[d]	.01 (.08)	**.32 (.03)**	-.10 (.05)
21	Household SES composite Grade K	**.22 (.04)**	-.05 (.06)	**.39 (.02)**	**-.14 (.04)**[b]
	Attentional shifting K-1 and reading achievement K-4				
22	Poverty level in Grade K	**.24 (.05)**	-.11 (.07)	**.34 (.03)**	-.12 (.05)
23	Household income in Grade K	**.23 (.04)**	-.10 (.07)	**.33 (.03)**	-.10 (.04)
24	Parent education Grade K	**.19 (.04)**	-.03 (.06)	**.34 (.03)**	**-.13 (.04)**[b]
25	Parent occupational prestige Grade K	-.02 (.04)	.13 (.07)	**.10 (.04)**[a]	-.09 (.04)
26	Adult food insecurity Grade K	**-.16 (.06)**[c]	.19 (.09)	**-.13 (.03)**	.03 (.04)
27	Free or reduced-price lunch	**.14 (.05)**[e]	.01 (.07)	**.29 (.03)**	-.04 (.05)
28	Household SES composite Grade K	**.22 (.04)**	-.05 (.06)	**.36 (.03)**	**-.14 (.04)** [a]

Note. Age in the Fall of Kindergarten was included as covariate. Free reduced priced lunch status was reverse-coded.
a = .001
b = .002
c = .003

Free and reduced priced lunch status performed about as well, predicting working memory ($r = .29$, $p < .003$) and achievement intercepts ($r = .29$, $p < .003$), and working memory slope ($r = -.24$, $p < .001$). Parent occupational prestige was associated with initial status in mathematics performance ($r = .08$, $p = .002$) but not growth. Adult food insecurity was negatively related to initial status in reading achievement ($r = -.13$, p < .001).

Attentional shifting and mathematics achievement. For attentional shifting, the SES composite exhibited the most associations. It was significantly related to initial status in attentional shifting ($r = .22$, $p < .001$) and academic achievement ($r = .39$, $p < .001$), as well as growth in achievement ($r = -.14$, $p < .002$), but not attentional shifting. Similarly, parent education significantly associated with most of the growth factors in the model. It was significantly related to initial status in attentional shifting ($r = .19$, $p < .001$) and academic achievement ($r = .36$, $p < .001$), as well as growth in achievement ($r = -.13$, $p < .003$) but not attentional shifting. Household income and the derived poverty-level variable exhibited similar patterns in associations. They respectively predicted attentional shifting ($r \sim .20$) and academic achievement ($r \sim .35$), but not growth on either construct. Free and reduced priced lunch status performed slightly worse, predicting attentional shifting ($r = .15$, $p < .001$) and achievement intercepts ($r = .32$, $p < .001$) only. Parent occupational prestige was associated with the reading intercept ($r = .10$, $p < .001$) but not growth. Adult food insecurity was negatively related to initial status in attentional shifting ($r = -.16$, p < .003) and mathematics achievement ($r = -.13$, $p < .001$).

Attentional shifting and reading achievement. Patterns in correlations were identical for reading achievement with only minor differences in the magnitudes of correlations. For attentional shifting, the SES composite exhibited the best predictive power. It was significantly related to initial status in attentional shifting ($r = .22$, $p = .001$) and academic achievement ($r = .39$, $p < .001$), as well as growth in achievement ($r = -.14$, $p < .002$), but not attentional shifting. Similarly, parent education significantly predicted most of the growth factors in the model. It was significantly related to initial status in working memory ($r = .19$, $p < .001$) and academic achievement ($r = .34$, $p < .001$), as well as growth in achievement ($r = -.13$, $p < .002$) but not attentional shifting. Household income and the derived poverty-level variable respectively related to attentional shifting ($r \sim .20$) and academic achievement ($r \sim .35$), but not growth on either construct. Free and reduced priced lunch status associated with attentional shifting ($r = .14$, $p < .001$) and achievement intercepts ($r = .29$, $p = .004$) only. Parent occupational prestige was associated with the reading intercept ($r = .11$, $p = .001$) but not growth. Adult food insecurity was negatively related to initial status in attentional shifting ($r = -.17$, $p < .003$) and mathematics achievement ($r = -.12$, $p < .001$).

Poverty-level subsamples

Unconditional bivariate models were also estimated for students from household with differing levels of poverty. Fit was good for all models. Covariance structures followed the same patterns as the whole sample in terms of direction (described in the previous chapter), but there were differences in terms of the number of significant parameters.

Working Memory and Mathematics Achievement. Overall, models had the same covariance structures and parameters were in the same direction as those of the whole sample, but there were exceptions for the low and medium SES groups. For

Table 16

Fit Indices for the Poverty Level Subsample Models

Model	Base Models	*N*	χ^2 (df)	CFI	RMSEA	SRMR
	Numbers Reversed with Mathematics					
	Below Poverty Line	1,170	178.40* (110)	.978	.023	.183
	At or Above Poverty Line	930	170.71* (110)	.984	.024	.145
	200% Above Poverty Line	2,260	380.35* (106)	.971	.034	.108
	Numbers Reversed with Reading					
	Below Poverty Line	1,170	200.52* (106)	.969	.028	.185
	At or Above Poverty Line	930	206.04* (106)	.971	.032	.143
	200% Above Poverty Line	2,260	366.27* (106)	.973	.033	.106
	Dimensional Card Sorting with Mathematics					
	Below Poverty Line	1,170	98.82* (62)	.984	.023	.063
	At or Above Poverty Line	930	133.35* (62)	.971	.035	.066
	200% Above Poverty Line	2,260	303.96* (59)	.966	.043	.085
	Dimensional Card Sorting with Reading					
	Below Poverty Line	1,170	152.68* (61)	.958	.036	.084
	At or Above Poverty Line	930	170.05* (61)	.956	.044	.099
	200% Above Poverty Line	2,260	298.95* (61)	.966	.042	.076

Table 17

Select Parameters for Bivariate Growth Models of Working Memory and Academic Achievement for Students Below, At and Above, and 200% Above the Poverty Line

	Mathematics			Reading		
Parameter	Below	At or Above	200% Above	Below	At or Above	200% Above
Working memory						
Mean intercept $\mu_{z\alpha}$	**425.54 (1.86)**	**435.49 (1.92)**	**442.31 (1.26)**	**425.49 (1.84)**	**435.43 (1.94)**	**442.20 (1.25)**
Mean slope $\mu_{z\beta}$	**65.32 (1.74)**	**61.90 (1.84)**	**57.32 (1.22)**	**65.36 (1.72)**	**61.96 (1.84)**	**57.47 (1.21)**
Intercept variance ψ_{33}	**444.26 (54.23)**	**526.03 (48.52)**	**407.70 (36.76)**	**472.38 (55.45)**	**539.15 (47.56)**	**407.83 (37.14)**
Slope variance ψ_{44}	**257.46 (54.23)**	**388.37 (82.25)**	**269.74 (46.63)**	**287.53 (68.87)**	**407.26 (84.66)**	**265.05 (45.80)**
Intercept slope covariance ψ_{21}	**-193.36 (54.94)**	**-352.31 (45.57)**	**11.18 (.86)**	**-223.47 (55.79)**	**-367.77 (46.31)**	**-235.59 (35.20)**
Residual variance $\sigma^2_{\varepsilon y}$	**390.34 (47.20)**	**382.75 (41.50)**	**508.92 (35.90)**	**381.15 (46.73)**	**366.06 (44.94)**	**498.03 (39.57)**
Achievement						
Mean intercept $\mu_{z\alpha}$	**-0.77 (.07)**	**-0.50 (.05)**	**-0.11 (.03)**	**-.78 (.05)**	**-0.54 (.04)**	**-0.18 (.04)**
Mean slope $\mu_{z\beta}$	**3.90 (.05)**	**3.87 (.04)**	**3.79 (.03)**	**3.42 (.05)**	**3.34 (.04)**	**3.28 (.03)**
Intercept variance ψ_{33}	**0.49 (.06)**	**0.41 (.04)**	**0.44 (.03)**	**0.45 (.05)**	**0.41 (.05)**	**0.48 (.03)**
Slope variance ψ_{44}	0.00	0.00	**0.15 (.02)**	**0.20 (.05)**	**0.15 (.04)**	**0.21 (.03)**
Intercept slope covariance ψ_{43}	0.00	0.00	**-0.12 (.02)**	**-0.18 (.05)**	**-0.14 (.04)**	**-0.22 (.03)**
Residual variance $\sigma^2_{\varepsilon z}$	**0.31 (.04)**	**0.29 (.05)**	**0.18 (.02)**	**0.21 (.04)**	**0.21 (.04)**	**0.23 (.02)**
Standardized Cross-construct covariances						
Intercept$_{wm}$ to intercept$_{achiev}$ ψ_{31}	**.80 (.06)**	**.83 (.04)**	**.84 (.03)**	**.65 (.06)**	**.69 (.04)**	**.76 (.04)**
Slope$_{wm}$ to slope$_{achiev}$ ψ_{42}	—	—	**.49 (.08)**	.26 (.17)	.17 (.14)	**.49 (.09)**
Intercept$_{wm}$ to Slope$_{achieve}$ ψ_{41}	—	—	**-.37 (.03)**	-.19 (.11)	-.26 (.11)	**-.40 (.07)**
Intercept$_{Achiev}$ to slope$_{wm}$ ψ_{32}	-.24 (.13)	**-.56 (.09)**	**-.60 (.07)**	-.27 (.12)	**-.44 (.09)**	**-.58 (.07)**
Within-person effect						
Contemporaneous $\sigma_{\varepsilon zy}$	0.36 (.16)	**0.51 (.12)**	**0.38 (.07)**	0.24 (.12)	**0.35[b] (.11)**	**0.19 (.06)**
WM autoregression ρ_{yy}, $\rho_{\varepsilon yy}$	0.08 (.03)	**0.12 (.04)** [b]	**0.13 (.02)**	0.08 (.04)	**0.12 (.04)**	**0.14 (.02)**
Achievement autoregression ρ_{zz}, $\rho_{\varepsilon zz}$	**0.31 (.04)**	**0.33 (.04)**	**0.23 (.02)**	**0.34 (.05)**	**0.32 (.04)**	**0.28 (.02)**

Table 18

Select Parameters for Bivariate Growth Models of Attentional Shifting and Academic Achievement for Students Below, At and Above, and 200% Above the Poverty Line

Parameter	Mathematics Below	Mathematics At or Above	Mathematics 200% Above	Reading Below	Reading At or Above	Reading 200% Above
Attentional Shifting						
Mean intercept $\mu_{z\alpha}$	**13.44 (.29)**	**14.44 (.19)**	**14.74 (.12)**	**13.99 (.21)**	**14.69 (.17)**	**14.96 (.09)**
Mean slope $\mu_{z\beta}$	**2.46 (.27)**	**1.65 (.20)**	**1.88 (.13)**	**.68 (.06)**	**0.50 (.06)**	**.58 (.03)**
Intercept variance ψ_{33}	**2.18 (.74)**[c]	**1.84 (.44)**	**1.30 (.29)**	**2.18 (.74)**	**1.83 (.46)**	**1.29 (.29)**
Slope variance ψ_{44}	0.00	0.00	0.00	0.00	0.00	0.00
Intercept slope covariance ψ_{21}	—	—	—	0.00	0.00	0.00
Achievement						
Mean intercept $\mu_{z\alpha}$	**-0.77 (.07)**	**-0.51 (.05)**	**-0.12 (.03)**	**-0.78 (.05)**	**-0.54 (.04)**	**-0.18 (.04)**
Mean slope $\mu_{z\beta}$	**3.91 (.05)**	**3.88 (.04)**	**3.78 (.03)**	**3.43 (.05)**	**3.34 (.04)**	**3.28 (.03)**
Intercept variance ψ_{33}	**0.49 (.05)**	**0.41 (.04)**	**0.44 (.03)**	**0.44 (.05)**	**0.40 (.05)**	**0.48 (.03)**
Slope variance ψ_{44}	0.00	0.00	**0.15 (.02)**	**0.20 (.05)**	**0.14 (.04)**[a]	**0.21 (.03)**
Intercept slope covariance ψ_{43}	—	—	**-0.12 (.02)**	**-0.17 (.05)**	**-0.12 (.02)**	**-0.22 (.03)**
Residual variance $\sigma^2_{\varepsilon z}$	**0.34 (.04)**	**0.29 (.05)**	**0.18 (.02)**	**0.21 (.04)**	**0.21 (.03)**	**0.22 (.02)**
Standardized Cross-construct covariances						
$\text{Intercept}_{\text{atn}}$ to $\text{intercept}_{\text{achiev}}$ ψ_{31}	**.67 (.05)**	**.74 (.05)**	**.64 (.04)**	**.57 (.08)**	**.48 (.09)**	**.51 (.04)**
$\text{Slope}_{\text{attn}}$ to $\text{slope}_{\text{achiev}}$ ψ_{42}	—	—	—	—	—	—
$\text{Intercept}_{\text{attn}}$ to $\text{Slope}_{\text{achieve}}$ ψ_{41}	—	—	**-.27 (.08)**	-.21 (.13)	**-.55 (.10)**	**-.20 (.06)**[a]
$\text{Intercept}_{\text{Achiev}}$ to $\text{slope}_{\text{attn}}$ ψ_{32}	—	—	—	—	—	—
Within-person effect						
Contemporaneous $\sigma_{\varepsilon zy}$	—	—	—	—	—	—
AS autoregression ρ_{yy}, $\rho_{\varepsilon yy}$	—	—	—	—	—	—
Achievement autoregression ρ_{zz}, $\rho_{\varepsilon zz}$	**.31 (.04)**	**.33 (.04)**	**.23 (.02)**	**.34 (.05)**	**.33 (.05)**	**.28 (.03)**

mathematics achievement, the latent slope variances were not significant for low and medium SES groups. Consequently, these parameters were fixed to zero and their covariances were not estimated, implying that there is no association between initial status and growth of working memory growth and growth in mathematics achievement. Furthermore, the association between initial achievement and working memory growth was not significant. In terms of within person effects, neither the contemporaneous association between working memory and achievement nor the effect of prior working memory performance was significant for the low SES sample. All other parameters were significant and in the expected direction across groups (i.e., the associations were positive).

Working memory and reading achievement. Results for working memory and reading achievement were similar to those for working memory and mathematics achievement. Although latent slopes were significant for reading achievement in the univariate models, none of the cross-construct parameters involving the slope of reading achievement were significant in the low and middle SES models. Furthermore, the association between initial achievement and working memory growth was not significant. In terms of within person effects, neither the contemporaneous association between working memory and achievement nor the effect of prior working memory performance was significant for the low SES sample. All other parameters were significant and in the expected direction across groups.

Attentional shifting and mathematics achievement. Overall, results for attentional shifting and mathematics achievement models were similar to those from the whole sample in terms of the directions of associations and within-person effects, but there were differences in covariance structures. In addition to the mathematics achievement latent slope variances not being significant for the low and middle SES groups, the latent variance of the attentional shifting slope was not significant for any SES group. Consequently, cross-construct covariances involving these parameters were not estimated. Initial status in attentional shifting was associated with initial status in achievement for all SES groups. Additionally, there was a significant negative relation between initial status in attentional shifting and growth in mathematics achievement for students 200% above the poverty line, $r = -.27$, $p < .001$. All other parameters were significant and in the expected direction based on findings with the whole sample.

Attentional shifting and reading achievement. Results for the attentional shifting and reading achievement models were similar to those involving mathematics achievement. Parameters involving the latent slope of attentional shifting were not estimated. The association between initial status in attentional shifting and growth in reading achievement was not significant for students below the poverty line, but it was for students at and above the poverty line, $r = -.55$, $p < .001$, and students 200% above the poverty line, $r = -.20$, $p = .001$. All other parameters were significant and in the expected direction based on findings with the whole sample.

Discussion

This study examined seven indicators of SES to evaluate their associations with cognitive and academic growth in elementary school students. It found that indicators were not uniform in their associations with the growth factors, suggesting that choice of SES measure can have important consequences for researchers and social systems seeking to understand how SES relates to cognitive and academic development.

Furthermore, it found that whenever SES was related to growth factors, the relations were such that lower SES was associated with lower initial performance but faster growth thereafter. Similar findings have been reported in research previously, but the pattern warrants more attention from researchers and the general public. Finally, the study found evidence that growth trajectories were not uniform across students from different SES backgrounds, underscoring the need for future research on the causes and characteristics of SES-achievement gaps over time.

Patterns in SES Associations

This study found that patterns in the association between SES and cognitive and academic growth factors differed across different SES indicators. In terms of total number of associations, the SES composite performed the best, correlating with all of the growth factors in each model, except for the attentional shifting slope, which no indicator predicted. It also had the largest absolute correlations with the growth factors. Although not tested directly, the patterns in correlations across indicators suggest that the more numerous and larger associations for the composite may owe to unique variance contributions from parental education because parent education was the only other indicator that associated with academic achievement slopes. Following the composite and parental education, poverty-level and household income exhibited the most associations with growth factors. Interestingly, the magnitude of poverty-level's associations tended to be slightly larger than parental education. It also tended to have larger associations with intercepts but not slopes compared to free and reduced priced lunch status. It is unclear why this is the case, but it was recently suggested that while free and reduced priced lunch status may be an imperfect measure of household income, it seems to capture household volatility to a degree that other SES markers do not (Domina et al., 2018). Parent occupational prestige and adult food insecurity, meanwhile, had the fewest number of associations and they were the smallest in magnitude.

Given the pattern in findings, a few conclusions can be drawn. First, most SES indicators have unique strengths and weaknesses (G.J. Duncan & Magnuson, 2003). These strengths and weaknesses should be considered before selecting an SES measure for research or decision-making in educational and social program. SES composites will likely be the most useful indicator for predicting between student differences related to SES, but as composites, they are not readily interpretable and do not suggest specific malleable factors for intervention. Similarly, parental education was related to academic achievement growth where most other indicators were not. However, parental education is a difficult target for intervention, especially because the mechanisms that drive its association with cognitive and academic ability and growth are uncertain. Poverty level and free and reduced priced lunch status were generally associated with initial performance in cognitive ability and academic achievement, but only growth in working memory. On the other hand, these measures (a) are some of the easiest to obtain, (b) describe malleable factors, and (c) are relatively easy to interpret. Thus, they have unique benefits despite the lack of associations with some growth factors. Meanwhile, the present study does not suggest any unique affordances offered by parental occupation level or adult food insecurity as these two measures only associated with intercepts, and to a lesser extent than the other SES indicators.

A second conclusion that can be drawn is that lower SES tends to predict lower initial performance but also faster growth. This is not an unprecedented finding, but it is one that deserves closer scrutiny for two reasons. First, there seems to be a popular perception that schools serving economically disadvantaged youth, and urban schools in particular, are failing to adequately serve their students (National Center on Education Statistics, 1996). It is also sometimes claimed that SES disparities in achievement imply that the American educational system is “broken.” Findings that SES predicts faster growth complicate this narrative because they imply that schools have a positive effect at reducing SES-disparities, even if it is small and gaps do not close before graduation (Reardon, 2011b). It is important to acknowledge this dynamic because social and education policies should be based on an understanding of what works and why. If schools have and (have always had; Reardon, 2011b), a small positive effect on closing SES-gaps, then it might be concluded that they continue to “work”, but expectations about how schools should influence SES gap or the consequences thereof may need to change.

That said, it is unclear from the present study whether the faster growth rates for students from low-SES backgrounds should simply be attributed to school or instructional quality. It is not uncommon in studies of academic growth to find that students with lower initial abilities grow initially grow faster than their more able peers. For instance, studies of early literacy acquisition often find that the lowest performing students growth faster than their peers after school entry (e.g., Fien et al., 2010), probably because they are receiving formal instruction for the first time. These early growth trajectories are not necessarily predictive of later growth trajectories (e.g., Langenkamp & Carbonaro, 2018; Shanley, 2016) and the relation between initial status and growth can depend on many factors, including the student’s characteristics (e.g., P. L. Morgan et al., 2009, 2019) and the academic subject (e.g., Jordan et al., 2009). As mentioned in the introduction, the average association between SES and achievement tends to increase with age, as does the heritability of cognitive ability and achievement. Given these seemingly contradictory patterns, future research should investigate (a) when and why there are initial gap reductions, (b) whether and how more vigorous growth can be sustained.

Growth Rates by Poverty Level

An additional reason to pay closer attention to growth trajectories for students from different SES backgrounds is that patterns in growth trajectories seem to differ for students from different SES groups. The previous chapter estimated LCM-SRs using an analytic sample that contained students from all SES-backgrounds. The present chapter tested these models on students below, at or above, and 200% above the poverty level. Results suggested that there may be important differences in the covariance structures and within-person effects for students at different levels of poverty. For students 200% above the poverty line, all parameters were significant and in the same directions implied by whole sample analyses. This was not the case for the other two groups, where there was likely to be a correlation between initial status and growth within or across constructs, and within person effects were less likely to be significant.

It has been argued that elementary schools may be more conducive to economically-advantaged students insofar as they create environments where their cognitive and academic abilities can reinforce each other (Peng & Kievit, 2019). Results from the present study lend partial support for this claim. Cross-construct covariances and within-person contemporaneous effects were more likely to be significant for the middle and upper SES group. Furthermore, cross-construct slopes only covaried for the upper SES group. However, contemporaneous effects involving working memory were larger for the middle SES group; and there was not a straightforward pattern in the magnitude of associations for the attentional shifting measure. That is, correlations did not simply increase or decrease with poverty-level. Further research is required to test Peng and Kievit (2019)'s hypothesis, especially research that can disentangle between and within-person effects.

CHAPTER IV: CONCLUSION

The past decade has witnessed heightened interest in EF as educationally-relevant construct. There has been an increased in research on school-based EF interventions (Diamond, 2013; Jacob & Parkinson, 2015) and social policies that may contribute to EF development at home, prior to school-entry (Teacher's College Newsroom, 2018). Charitable organizations have also increased their efforts to study and intervene on EF in school (Chan Zuckerberg Initiative, 2018). The purpose of this dissertation was to promote a better understanding of the co-development of EF and academic achievement, especially among children from low-SES backgrounds, in order to promote better research and intervention efforts.

The first chapter reported the results of an analysis in which LCM was used to examine the developmental trajectories of EF and academic achievement in a large sample of students as they progressed from Kindergarten to Grade 4. It also examined the co-development of EF and achievement, and developmental trajectories for students with low and high initial working memory. Consistent with prior research (Peng, Barnes, et al., 2018b; Peng et al., 2016), it found that higher initial status on the EF measures was, on average, associated with higher initial status on the achievement measures. It also found that faster growth on the EF measures was, on average, associated with faster growth on the achievement measures, except for attentional shifting in Grades 2-4; and that higher initial working memory and achievement was associated with slower growth on both the EF and achievement measures. For within-person associations, the finding of primary interest was that, after accounting for (a) the covariance between working memory and academic achievement at each time point and (b) prior test performance, there was only a small negative within-person association between fall of Kindergarten working memory and spring academic achievement. However, different patterns emerged when subsamples of students were examined. Among students with low working memory in the fall of Kindergarten, working memory was significantly associated with subsequent achievement for certain intervals in Kindergarten and Grade 1. Among students with high working memory, higher achievement was associated with subsequent working memory in Grade 1. These results lend support for claims regarding the potentiality for EF to serve as a bottleneck for low achieving students, and the potentiality that formal instruction may improve EF in the early years.

The second chapter investigated the association between SES and the co-development of executive function and academic achievement. Specifically, it examined how seven common indicators of SES associated with executive function and academic achievement growth factors. Though lower SES was generally associated with lower initial status and faster growth in both constructs, the indicators varied in terms of their predictive power. The SES composite and parental education level associated with the most growth factors, followed by household income, poverty level, and free and reduced priced lunch status. The results are important because administrative data on a student's data are often difficult to access, and when they are accessible, they typically only describe a student's free and reduced priced lunch status. Such data do not fully capture the variance related to student growth in EF or achievement, so researchers should be mindful of this limitation. The study also tested co-developmental models of executive function and academic achievement on students from households with differing poverty levels. It found that covariance structures and within-person effects differed according to student poverty-level, but covariance patterns varied across measure and group.

Future Directions

The analyses reported here support several research directions for the field of education and developmental psychology. First, they highlight the need for research on the longitudinal validity of early EF measures (and as a corollary, research on the structure of early EF). They also highlight the need for more attention to the role that individual differences play in the association between EF and achievement. The analyses from Chapters 1 and 2 both imply that student background characteristics, such as initial cognitive ability and household SES, may determine when and how EF affects learning and achievement and vice versa. Future studies should aim to provide a fuller picture of their longitudinal associations between EF and achievement by considering issues such as (a) whether the observed within-person differences are related to differences in instruction and (b) whether the growth patterns observed in elementary school remain stable in older students.

In addition to the basic research questions described above, it would be worthwhile to promote greater engagement with EF research in educator preparation programs and translational research. The field of education's renewed interest in EF has evoked a range of responses from the educational research community. Some have lamented the revitalized interest in the cognitive measures because the field of education is still grappling with special education policies whereby students are identified as having disabilities only if there is a severe discrepancy between their IQ and academic achievement (Burns, 2016; Burns et al., 2016). It is feared by some that attention to EF may come at the expense of more proximal behavioral measures, and ultimately, do more harm than good. On the other hand, there has been increased interest in understanding how EF fits into the Simple View of Reading (Cirino et al., 2019; Kim, 2017; Spencer et al., 2020), a theoretical framework that has been particularly influential in the realm of public policy (Castles et al., 2018).

A possibility that has not been discussed by proponents or detractors of EF research in peer-reviewed research is that EF research may be important for drawing attention to scientific research in the field of education general. Educator preparation programs typically do not require any formal training in the psychology of attention and memory, which are fundamental to reading and learning. Over the past decade, there has been increased advocacy for reforming educator preparation programs so that they better address scientific research on literacy acquisition (Drake et al., 2018; Moats, 2009). In fact, eleven states have changed their laws in the past five years so that preservice teachers must now receive more training in the science of reading. Extending these reform efforts so that address psychological research in attention and memory would be a worthwhile endeavor. Most educators are not reading instructors per se, so limiting reform efforts to promoting scientific research on reading may not result in widespread and sustainable change to educator preparation programs that is desired. Broadening reform efforts to promote a more thorough grounding in psychology may pave the way for more enduring change because all educators would benefit from a deeper understanding of the learning process.

APPENDIX

Appendix Table 1

Weighted Descriptive Statistics for Kindergarten through Grade 4 (Two-Level)

Measure and Time	*N*	*M* (*SD*)	Skew/Kurtosis	ICC	Design Effects
Numbers reversed					
Grade K fall	4,970	434.47 (30.16)	0.32	.24	3.94
Grade K spring	5,510	451.10 (29.62)	-0.37	.23	3.84
Grade 1 fall	5,020	459.38 (27.12)	-0.68	.21	3.59
Grade 1 spring	5,150	471.16 (24.36)	-0.77	.21	3.55
Grade 2 fall	4,530	475.57 (22.86)	-0.94	.18	3.25
Grade 2 spring	4,890	482.00 (21.77)	-0.88	.21	3.63
Grade 3 spring	4,660	490.96 (20.60)	-0.68	.22	3.69
Grade 4 spring	5,510	497.77 (20.05)	-0.23	.18	3.15
Dimensional card sorting					
Grade K fall	4,970	14.24 (3.22)	-1.63	.14	2.73
Grade K spring	5,510	15.32 (2.53)	-2.02	.11	2.29
Grade 1 fall	5,020	15.80 (2.28)	-2.19	.09	2.10
Grade 1 spring	5,150	16.18 (2.13)	-2.16	.11	2.37
Grade 2 fall	4,510	6.46 (1.37)	-1.44	.20	3.40
Grade 2 spring	4,880	7.00 (1.17)	-1.61	.24	3.88
Grade 3 spring	4,650	7.27 1.21)	-3.73	.17	3.04
Grade 4 spring	4,470	7.71 (.90)	-1.52	.21	3.52
Mathematics achievement					
Grade K fall	4,970	-0.40 (.87)	-0.41	.31	4.75
Grade K spring	5,510	0.49 (.73)	-0.77	.28	4.46
Grade 1 fall	5,020	0.99 (.82)	0.10	.29	4.57
Grade 1 spring	5,150	1.71 (.80)	-0.18	.28	4.44
Grade 2 fall	4,530	1.96 (.79)	-0.92	.31	4.78
Grade 2 spring	4,890	2.51 (.77)	-1.40	.33	5.07
Grade 3 fall	4,660	3.11 (.71)	-0.49	.28	4.41
Grade 4 spring	4,510	3.47 (.71)	-0.76	.29	4.60
Reading achievement					
Grade K fall	4,990	-0.42 (.84)	0.32	.30	4.71
Grade K spring	5,520	0.52 (.73)	-0.38	.27	4.34
Grade 1 fall	5,020	0.95 (.77)	0.16	.28	4.49
Grade 1 spring	5,160	1.67 (.73)	-0.39	.31	4.78
Grade 2 fall	4,530	1.89 (.66)	-0.23	.30	4.67
Grade 2 spring	4,890	2.27 (.63)	-0.37	.30	4.67
Grade 3 spring	4,660	2.67 (.62)	-0.06	.28	4.49
Grade 4 spring	4,510	2.93 (.59)	-0.55	.28	4.44

Note. Means for Numbers Reversed, Reading Achievement, and Mathematics Achievement are weighted with W8CF8P_80. Dimensional Card Sorting is weighted with W4CF4P_20 in grades K-1 and W8CF8P_80 in 2-4. Students were clustered in 438 classes for Numbers Reversed, Mathematics Achievement, and Dimensional Card Sorting Grade K-1, 439 classrooms for Reading Achievement, and 400 classrooms for Dimensional Card Sorting Grade 2-4. Sample sizes rounded to the nearest 10 per National Center on Education Statistics convention. ICCs and design effects were calculated using fall of kindergarten cluster sizes.

Appendix Table 2

Fit Indices for Unconditional Multilevel Growth Models with Fixed Time Scores

Model	Description	*N*	χ^2 (df)	CFI	RMSEA	SRMR
	Unrestricted No Growth Only					
1	Numbers Reversed	5,820	1735.027* (61)	.732	.069	.071
2	Dimensional Card Sorting K-1	5,800	292.801* (13)	.668	.061	.030
3	Dimensional Card Sorting 2-4	5,020	334.140* (13)	.546	.070	.095
4	Mathematics Achievement	5,820	3959.845* (61)	.801	.105	.059
5	Reading Achievement	5,820	5081.214* (61)	.728	.119	.099
	Unrestricted with Linear Growth Factor					
6	Numbers Reversed	5,820	523.997* (56)	.925	.038	.040
7	Dimensional Card Sorting K-1	5,800	46.979* (8)	.954	.029	.013
8	Dimensional Card Sorting 2-4	5,020	28.152* (8)	.972	.022	.014
9	Mathematics Achievement	5,820	1,326.007* (56)	.935	.062	.042
10	Reading Achievement	5,820	2,462.923* (56)	.870	.086	.056
	Unrestricted with Quadratic Growth Factor					
11	Numbers Reversed	5,820	150.390* (49)	.984	.017	.024
12	Dimensional Card Sorting K-1	5,800	9.347* (1)	.990	.038	.000
13	Dimensional Card Sorting 2-4	5,020	7.002* (1)	.992	.035	.000
14	Mathematics Achievement	5,820	513.224* (49)	.976	.040	.031
15	Reading Achievement	5,820	781.212* (49)	.960	.051	.038
	Unrestricted with Quadratic Growth Factor and First Order Structured Residuals					
16	Numbers Reversed	5,820	137.635* (45)	.988	.021	.018
17	Dimensional Card Sorting K-1	—	—	—	—	—
18	Dimensional Card Sorting 2-4	—	—	—	—	—
19	Mathematics Achievement	5,820	372.684* (45)	.983	.035	.031
20	Reading Achievement	5,820	655.768* (45)	.967	.048	.033
	Final Univariate Models					
16	Numbers Reversed	5,820	202.037* (54)	.976	.022	.029
17	Dimensional Card Sorting K-1	5,800	53.294* (10)	.949	.027	.014
18	Dimensional Card Sorting 2-4	5,020	33.555* (10)	.967	.022	.014
19	Mathematics Achievement	5,820	483.668* (52)	.978	.038	.033
20	Reading Achievement	5,820	901.736* (50)	.954	.054	.048

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