

Examining the relations between executive function, math, and literacy during the transition to kindergarten: A multi-analytic approach

Sara A. Schmitt^a, G. John Geldhof^b, David J. Purpura^a,
Robert Duncan^b, and Megan M. McClelland^b

Published: March, 2017

Grant support: IES Grants R305A100566 (PI: McClelland)

Citation: Schmitt, S. A., Geldhof, G. J., Purpura, D. J., Duncan, R. J., & McClelland, M. M. (2017). Examining the relations between executive function, math, and literacy during the transition to kindergarten: A multi-analytic approach. *Journal of Educational Psychology*, 109, 1120-1140. doi: 10.1037/edu0000193

Author Note

^aHuman Development and Family Studies, Purdue University, 1202 W. State Street, West Lafayette, IN 47907.

^bHuman Development & Family Sciences, Oregon State University, 245 Hallie E. Ford Center for Healthy Children & Families, Corvallis, OR 97331.

This study was supported by a grant from the U.S. Department of Education Institute for Education Sciences (grant #R305A100566).

Correspondence concerning this article should be addressed to Sara A. Schmitt, Purdue University, West Lafayette, IN, 47907. E-mail: saraschmitt@purdue.edu.

Abstract

The present study explored the bidirectional and longitudinal associations between executive function (EF) and early academic skills (math and literacy) across four waves of measurement during the transition from preschool to kindergarten using two complementary analytical approaches: cross-lagged panel modeling and latent growth curve modeling (LGM).

Participants included 424 children (49% female). On average, children were approximately 4.5 years old at the beginning of the study ($M = 4.69$, $SD = .30$) and 55% were enrolled in Head Start. Cross-lagged panel models indicated bidirectional relations between EF and math over preschool, which became directional in kindergarten with only EF predicting math. Moreover, there was a bidirectional relation between math and literacy that emerged in kindergarten.

Similarly, LGM revealed correlated growth between EF and math as well as math and literacy, but not EF and literacy. Exploring the patterns of relations across the waves of the panel model in conjunction with the patterns of relations between intercepts and slopes in the LGCMs led to a more nuanced understanding of the relations between EF and academic skills across preschool and kindergarten. Implications for future research on instruction and intervention development are discussed.

Key words: Executive function, mathematics, literacy, preschool, kindergarten

Examining the relations between executive function, math, and literacy during the transition to kindergarten: A multi-analytic approach

Over the last decade, there has been increased focus on children's executive function (EF)—specifically on its development and how it relates to other school readiness domains. One reason for this surge of interest is that EF in early childhood has been connected to a range of critical developmental outcomes, including physical health, social-emotional well-being, and occupational attainment in adulthood (Moffitt et al., 2011). Of particular interest are the significant and direct relations found between early EF and academic achievement. Findings from a number of studies indicate that individual differences in EF measured in early childhood predict concurrent and long-term math and literacy achievement (Duckworth, Tsukayama, & May, 2010; Fuhs, Nesbitt, Farran, & Dong, 2014; McClelland, Acock, Piccinin, Rhea, & Stallings, 2013; Monette, Bigras, & Guay, 2011) as well as growth in children's higher-level reasoning strategies (Richland & Burchinal, 2013).

Although the predictive link between EF and early achievement is established, it is less clear whether early academic skills also predict the development of EF. Recent evidence indicates that there may be a bidirectional association between EF and academic skills, particularly for math (Fuhs et al., 2014; Welsh, Nix, Blair, Bierman, & Nelson, 2010). However, these studies were limited to just three time points over the course of the preschool and kindergarten years and by the analytic approach employed (i.e., only panel models were used). Further, it is unclear whether growth trajectories in EF are related to growth trajectories in other domains (e.g., math). The overarching goal of the current study was therefore to examine the longitudinal relations between EF and academic skills across four waves of measurement during the transition from preschool to kindergarten. We had two specific aims. First, we investigated

the bidirectional relations between EF and academic skills (math and literacy) through a longitudinal panel model that tested whether relative standing on the domains at each time point was related to changes in relative standing on the other domains. Second, we examined relations between growth in EF, math, and literacy using latent growth curve models that tested whether the rate of absolute change across all time points on the domains was correlated. The two models provide unique information by identifying when early skills are most related to subsequent skill development (i.e., panel models), and to what extent children's overall growth on skills during this developmental period are related (i.e., latent growth curve models).

Importance of Executive Function for Academic Achievement

EF emerges early in life and develops across the life span; however, structural changes in the prefrontal cortex between ages two and five allow for dramatic increases in EF skills during early childhood (Zelazo & Ulrich, 2011). Evidence suggests that EF involves three related, yet distinct, cognitive processes (Miyake, Friedman, Emerson, Witzki, & Howerter, 2000): working memory (holding information in mind while processing other information; Gathercole, Pickering, Knight, & Stegmann, 2004), inhibitory control (overriding a dominant response; Dowsett & Livesey, 2000), and cognitive flexibility or attention shifting (maintaining focus and flexibly adapting to changing goals; Rueda, Posner, & Rothbart, 2005). When children enter kindergarten, they must adapt to new, more formal, and structured educational contexts that may require greater EF to navigate, compared to the less formal and structured educational environments experienced earlier.

The transition from preschool to kindergarten is not only an important developmental period for EF, it is also a time when early academic skills develop rapidly. Similar to EF, a substantial body of research highlights the importance of the preschool years for the

development of early literacy (e.g., National Early Literacy Panel, 2008; Whitehurst & Lonigan, 1998) and math skills (e.g., Ginsberg, Klein, & Starkey, 1998; National Mathematics Advisory Panel, 2008), and it is well known that early academic skills are precursors to later academic success (e.g., La Paro & Pianta, 2000; NICHD ECCRN, 2005; Stevenson & Newman, 1986). Furthermore, evidence supports an association between early math and reading (Duncan et al., 2007; Jordan, Kaplan, Oláh, & Locuniak, 2006; LeFevre et al., 2010; Purpura, Hume, Sims, & Lonigan, 2011). These two academic domains are related over time and children who demonstrate difficulties in one area are at elevated risk for having difficulties in the other (Barberisi, Katusic, Colligan, Weaver, & Jacobsen, 2005). Theory and research suggest that aspects of literacy may be foundational for math development. Children may need to draw upon vocabulary skills in order to learn number words and complete math tasks that are inherently language based (LeFevre et al., 2010; Purpura et al., 2011). Although EF, early math, and emergent literacy appear to develop during the same time frame, some scholars argue that EF is foundational for academic achievement (Blair & Raver, 2015; McClelland, et al., 2007; Raver et al., 2011). Furthermore, children's EF is related to both their own and their peers' acquisition of academic skills (Skibbe, Phillips, Day, Brophy-Herb, & Connor, 2012). For example, Skibbe and colleagues (2012) found that children demonstrated greater gains in literacy skills during the academic year when they were part of classrooms where their classmates had higher levels of EF.

Theoretical and empirical perspectives support the connection between EF and math and literacy skills. In order for children to take advantage of learning opportunities in classroom contexts, they must be able to pay attention, persist on challenging tasks, and avoid distractions (Blair & Raver, 2015; McClelland, Geldhof, Cameron, & Wanless, 2015). Specifically, strong

EF may be critical for aspects of early math development such as cardinality or formal addition, which require children to flexibly shift attention from procedural to more conceptual problem elements and inhibit previously learned rules. Similarly, EF may be needed for growth in emergent literacy skills, such as phonological awareness, because children must have the ability to hold letter sounds in mind and switch between combining and separating sounds and words. Studies suggest there is a predictive relation between EF and math and literacy achievement in diverse samples of young children, even after controlling for relevant socio-demographic factors (e.g., maternal education, child IQ) and initial achievement scores (Bull, Espy, & Wiebe, 2008; Duncan et al., 2007; McClelland, Acock, & Morrison, 2006). Findings from a recent study demonstrate a long-term relation between EF and achievement, such that children who were rated higher on aspects of EF (e.g., attention and persistence) during preschool were more likely to complete college (McClelland et al., 2013). Even among children with academic difficulties (i.e. those who experienced grade retention), EF appears to play a role in subsequent math and reading growth. For example, Chen, Hughes, and Kwok (2013) found that, among children who had been held back a grade, those who exhibited patterns of more rapid academic growth displayed higher EF skills.

Although prior evidence suggests EF is associated with both math and literacy in early childhood, the concurrent and predictive relation between EF and math seems to be stronger than the relation between EF and literacy in young children (Blair & Razza, 2007; Blair, Ursache, Greenberg, Vernon-Feagans, & the Family Life Project Investigators, 2015; Cameron Ponitz et al., 2009; Schmitt, Pratt, & McClelland, 2014). Furthermore, EF skills may mediate the development of math skills across the early elementary years, but not the development of literacy skills (Hassinger-Das, Jordan, Glutting, Irwin, & Dyson, 2014). Several interpretations

explaining these differential associations have been introduced in recent literature. For example, one interpretation is that math content and activities place more cognitive demands on children than does literacy content. Math skills, therefore, may require stronger EF skills to acquire (Bull, Espy, & Wiebe, 2008; Clark et al., 2010; Espy et al., 2004; Willoughby, Blair, Wirth, & Greenberg, 2012). Evidence from the neuroscience literature also indicates an overlap between the brain regions that support EF and math development (Klingberg, 2006), suggesting that growth in EF may strongly facilitate growth in math while having a weaker influence on the development of literacy. A second interpretation is that this relation results from instructional content (or lack thereof) provided in early childhood classrooms (Fuhs et al., 2014). Preschool teachers spend significantly more time engaged in direct literacy instruction than in math instruction (Hofer, Farran, & Cummings, 2013), suggesting that children may need to seek out their own independent math activities which may be influenced by their EF skills. For example, children who have stronger levels of EF may choose more complex and difficult math activities during free play (or may be directed to by teachers and parents) because they may be more cognitively ready to do so. A third interpretation is that EF provides a foundation for the development of reasoning abilities or fluid mental capacities (e.g., problem solving), which are typically required to do well on many math assessments (Blair et al., 2015). In contrast, many literacy assessments are more knowledge-based, making stronger demands on crystallized mental abilities (e.g., vocabulary) and fewer demands on EF and fluid mental abilities.

Bidirectional Relations Between EF and Academic Skills

Although EF is considered by some to be foundational for the development of academic skills, recent analyses have investigated these relations by exploring the bidirectionality between EF and achievement (Fuhs et al., 2014; Welsh et al., 2010). Indeed, early academic skills may be

important for the development of EF, just as EF is important for the development of early academic skills. Although the ability to pay attention, remember complex rules, and persist on challenging tasks likely helps children perform better academically (Blair et al., 2007, Blair & Raver, 2015), strong academic skills may also contribute to children's ability to sustain attention, remember a series of rules, and inhibit incorrect responses on complex tasks (Fuhs et al., 2014). Engaging in a complex math activity, for example, requires children to identify the quantities of multiple sets, retain those quantities in memory, and compare them.

Recent empirical evidence has suggested that there may be a bidirectional relation between direct assessments of EF and academic skills. In one study assessing developmental associations between EF and academic skills during the prekindergarten year, EF at the beginning of the year predicted gains in math and literacy; however, math at the beginning of prekindergarten also predicted gains in EF (Welsh et al., 2010). In a second study, Fuhs and colleagues (2014) found reciprocal associations between EF and math. These associations were maintained across preschool, and, although EF continued to predict math through kindergarten, the predictive relation of math on EF dissipated between the end of preschool and end of kindergarten. However, it was not clear when during this year the predictive association of math on EF faded. Results from Fuhs and colleagues' (2014) study also indicated a reciprocal relation between EF and oral comprehension skills across the prekindergarten year, but not for other literacy skills. These findings provide initial evidence for a bidirectional relation between EF and early achievement; however, the analyses utilized in these studies were limited to three time points (fall and spring of preschool and spring of kindergarten). The addition of a fourth time point at the beginning of kindergarten is needed to understand these relations more thoroughly; significant changes in children's experiences and in the development of EF and academic skills

may occur between the spring of preschool and the spring of kindergarten. Further, the addition of a fourth time point allows us to determine when early EF, math, and literacy interventions may be most beneficial and likely to facilitate cross-domain growth. Identifying more specific and precise times at which these relations may change could have applied implications as children enter and move through kindergarten. Moreover, the relations between these variables at different ages remain unclear.

Correlated Growth between EF and Academic Skills

In addition to a need for more research on the bidirectional relations between EF and academic skills, there is a dearth in extant literature exploring whether the rates of change in these domains are correlated during the transition to kindergarten. Understanding whether growth in one domain is related to growth in another has theoretical as well as practical implications for instruction and intervention. From a theoretical standpoint, exploring correlated growth across domains will help us understand the potential that improvements in one domain lead to improvements in another domain or that other individual or environmental factors may be influencing EF math, and literacy development similarly over time (Floyd et al., 2010; Willoughby, Kupersmidt, & Voegler-Lee, 2012), rather than earlier skills in and of themselves. Some have suggested that the relation between EF and math may be attributable to other factors such as IQ (Floyd et al., 2010), but there is also evidence showing that EF is separate from IQ (e.g., Blair, 2006). From a practical standpoint, if improvements in EF are associated with improvements in math, instruction or intervention efforts focused on EF may also have a beneficial effect on children's math development. Likewise, instruction or intervention efforts focused on math or literacy could have beneficial effects on children's EF development. For example, engaging in math activities may not only support the development of math concepts,

but doing so may also allow children to practice EF skills (e.g., attending to details, remembering instructions). Similarly, retaining details of a story in memory while simultaneously attending to new developments in the plotline in order to comprehend the broader story also may provide children an opportunity to practice EF skills.

To our knowledge, no studies to date have examined dual trajectory latent growth curves between EF and academic skills. In one related study, fixed effects models were used to explore whether intra-individual change on measures of EF predicted intra-individual change in math, literacy, and vocabulary during the transition to kindergarten. Results indicated that growth in EF on some, but not all, of the measures predicted growth in math, and that growth on one measure of inhibitory control was related to vocabulary development (McClelland et al., 2014). The current study extends these analyses by using latent growth curve modeling (LGCM). Although using fixed effects models can be informative, this type of analysis only explores relations between intra-individual changes over time between the domains. In the current study, we attempted to more accurately measure children's trajectories using LGCM, which estimates associations across domains on random intercepts and linear and quadratic slopes. Further, LGCM is able to estimate the associations between the EF, math, and literacy slopes, conditional on differences in their intercepts. However, the LGCM is not able to determine whether one domain contributes to or is causally related to development in another, or whether other factors simultaneously influence multiple domains of development (e.g., high quality early math instruction). Once correlated growth is established, follow-up studies would be needed to further elucidate the relations between cross-domain growth trajectories.

Multi-Analytic Approach

Previous work exploring longitudinal relations between EF and early academic skills has typically taken a single-analysis approach, and this approach has primarily been panel models (e.g., path analysis). Although findings from single-analysis studies have been useful, they provide limited information on the development of these important skills. As Greene and colleagues noted more than two decades ago, "all methods have inherent biases and limitations, so use of only one method to assess a given phenomenon will inevitably yield biased and limited results" (Greene, Caracelli, & Graham, 1989, p.256; see also Campbell & Fiske, 1959; Symonds & Gorard, 2010). Thus, we took a multi-analytic approach to address our overarching research goal: examining the longitudinal associations between EF and achievement. We first implemented a cross-lagged panel model using a latent EF factor to determine how children's relative standing on measures of EF, math, and literacy was related over time. That is, stability and cross-lagged effects in cross-lagged panel models determine the stability of participants' relative standing on a variable without regard for whether the sample (or individual participants) actually exhibited gains in absolute magnitude. High stability indicates that participants who scored higher than the sample mean at one time point tend to score higher on the sample mean at the previous time point, regardless of whether that sample mean increased, decreased, or remained the same (see also Wu, Selig, & Little, 2013).

Previous work examining the bidirectional associations between EF and academic skills using cross-lagged panel models (e.g., Fuhs et al., 2014) has relied on factor scores rather than modeling latent associations directly. The use of factor scores as dependent variables is known to produce biased regression slopes and standard errors (Muthén, 2011; Skrondal & Laake, 2001). The extent that previous findings are biased by a reliance on factor scores therefore remains unclear, and we overcome this limitation by modeling EF directly as a latent factor.

We also addressed our research goal using a series of latent growth curve models (LGCMs) that examined absolute changes (i.e., sample- and individual-level growth) in EF, math, and literacy. By examining absolute changes, the LGCMs allowed us to paint a more complete picture of how EF, math, and literacy co-develop by demonstrating to what extent growth in one domain is related to growth in another domain during the same time frame. Thus, the panel models allowed us to examine the bidirectional relations between EF and achievement and whether relative standing on one domain predicts relative standing on another domain at the subsequent time point, and the LGCMs allowed us to examine changes in absolute magnitude and relations between growth trajectories across all four time points (Wu, Selig, & Little, 2013).

The Present Study

The goal of the present study was to clarify and expand upon prior work (e.g., Fuhs et al., 2014; McClelland et al., 2007) that has examined the longitudinal relations between EF, math and literacy across the transition to kindergarten (preschool-kindergarten). More specifically, we aimed to paint a broader picture of how EF, math and literacy are associated over time. Based on recent theoretical and empirical evidence indicating that EF and math may be tightly coupled constructs and reciprocally related (Fuhs et al., 2014; McClelland et al., 2015), we hypothesized that EF would significantly predict math in preschool and kindergarten, and also that math would predict EF. Further, we expected that EF and math growth trajectories would be correlated, although previous research on associations between intra-individual change between the two domains is mixed (McClelland et al., 2014; Willoughby, Kupersmidt et al., 2012). Previous research has shown inconsistent links between EF and literacy (Blair & Razza, 2007; Cameron Ponitz et al., 2009; Schmitt, Pratt, & McClelland, 2014), non-significant bidirectional associations (Fuhs et al., 2014), and non-significant associations for intra-individual change

models (McClelland et al., 2014). We therefore did not expect that this same reciprocal association would emerge for EF and literacy, nor did we expect the EF and literacy growth trajectories to be correlated. We also hypothesized a bidirectional relation as well as correlated growth between math and literacy due to the noted strong relation between early math and literacy skills over the preschool and kindergarten years (Duncan et al., 2007; Jordan et al., 2006; LeFevre et al., 2010; Purpura et al., 2011).

Findings from this study will contribute to the existing literature in multiple ways. In contrast to other studies, we have four data points (fall and spring of preschool and kindergarten), which will allow us to explore changes in the relations as well as growth trajectories between these skills during the school year and at critical junctures throughout the transition from preschool to kindergarten at a more fine-grained level. This could have important practical implications for children as they enter and progress through kindergarten. Other studies examining bidirectional associations between EF and early achievement (e.g., Fuhs et al., 2014) were limited to just one data point in kindergarten (end of the year). This additional time point is important in extending previous work because it allows us to better identify at which point between the end of preschool and end of kindergarten the relations between EF and math may change. That is, modeling change in relations across four waves of data collection will allow a better understanding of whether change occurs primarily during the school year (i.e., between Times 1 and 2 and between Times 3 and 4), or if the change is relatively constant across time. In addition, we modeled latent associations directly rather than relying on factor scores that may produce biased results. Finally, no studies to date have examined whether growth trajectories of EF, math, and literacy are correlated using LGCM. Our multi-analytic approach also allows us to examine the same overarching research question using two types of analyses, allowing us to

better distill a single story from multiple models that acknowledge diverse ways development can manifest while reducing methodological biases. Results from the present study will further our understanding of the complexity of the relations between EF, math, and literacy, which could have theoretical implications as well as implications for the design and timing of instruction and intervention efforts in preschool and early elementary school.

Method

Participants and Procedure

Children and families ($N = 435$) were recruited from 38 classrooms in 17 preschools in a small city in the Pacific Northwest to participate in a federally funded study focused on refining and evaluating the Head-Toes-Knees-Shoulders task, a direct assessment of EF, as a screening tool for children ages 4-5. As part of this study, several measures of EF as well as a math and literacy assessment were collected at 4 data points from 2011 to 2014. There was no intervention included as part of the larger study that would influence the interpretation of our results. To recruit schools, the principal investigator contacted preschool directors via telephone, e-mail and via individual meetings to invite preschools to be a part of the study. Preschools were selected using a convenience sampling approach (i.e., preschools that were accessible and willing to participate in the study). Children were excluded if they were younger than 4 years old ($n = 5$) or older than 5.5 years old ($n = 1$) in the fall of preschool. Additionally, children were excluded if they did not participate in the study in the fall of preschool ($n = 5$). The remaining 424 eligible children were included in the sample in the current study.

Parents signed a written informed consent statement to allow their child to participate in the study that was approved by the university Institutional Review Board. Children gave verbal assent prior to participating in direct assessments. After consenting to the study, children were

assessed in two to three sessions (lasting 10 to 15 minutes each) during the fall and spring of their preschool and kindergarten years (4 waves total). At each wave of data collection, families received a \$20 gift card for their participation. In the fall of preschool, 55% of the children were enrolled in Head Start and 15% were primarily Spanish speakers (all Spanish speakers were enrolled in Head Start). Teachers identified which children in their classrooms were Spanish-speaking and should receive the assessments in Spanish. We chose this method for identifying Spanish speakers because teachers have the most experience with children in their classroom context and to avoid over-testing children by administering assessments in both languages. Parent demographic questionnaires were collected during the first wave of the study (in Spanish when applicable; $n = 372$, 88% response rate). The sample was predominantly reported as White (63%), followed by Latino/Hispanic (19%), multiracial (13%), Asian/Pacific Islander (3%), and other ethnicities (2%). Self-reported parent (87% maternal) education ranged from 0 to 30 years, with an average of approximately two years in college ($M = 14.40$, $SD = 3.68$). Children enrolled in Head Start had parents with significantly lower reported years of education ($M = 11.58$, $SD = 3.06$) than the parents of children not enrolled in Head Start ($M = 17.34$, $SD = 3.14$; $t(351) = 17.48$, $p < .001$). Among children enrolled in Head Start, the primarily Spanish speaking children had parents with significantly lower reported years of education ($M = 9.08$, $SD = 3.12$) than their English-speaking peers ($M = 12.59$, $SD = 2.38$; $t(178) = 8.17$, $p < .001$).

Measures

At each wave of the study, children were assessed on executive function (EF), literacy, and math skills. EF was assessed with four measures: the Head-Toes-Knees-Shoulders (HTKS) task, a Card Sort task, the Auditory Working Memory subtest from the Woodcock-Johnson III Tests of Cognitive Abilities, and the Simon Says task. Literacy skills were assessed with the

Letter-Word Identification subtest from the Woodcock-Johnson III Tests of Achievement Abilities. Math skills were assessed with the Applied Problems subtest from the Woodcock-Johnson III Tests of Achievement Abilities.

Head-Toes-Knees-Shoulders (HTKS). The HTKS was used to assess children's cognitive flexibility, working memory, and inhibitory control through gross motor responses (McClelland & Cameron, 2012; McClelland et al., 2014). In previous research, the measure has been significantly related to measures of cognitive flexibility, working memory, and inhibitory control (see McClelland et al., 2014). There are two parallel forms of the HTKS, which only differ for part one of the assessment (McClelland et al., 2014). The measure includes three sections of ten items each, with the task becoming progressively harder. In part one, children were instructed to touch their toes (knees in the parallel form) when told to "touch your head (shoulders in the parallel form)" and vice versa. In parts two and three, rules were changed and added, increasing the complexity of the task. Possible scores range from 0 to 60, with a total of 30 test items receiving scores of 0 (incorrect), 1 (self-correct), or 2 (correct). Previous research indicates high inter-rater agreement ($\kappa > .90$) and evidence supports convergent and predictive validity of this measure when assessing children's EF in culturally diverse samples and in different languages (McClelland et al., 2007; McClelland et al., 2014; Suchodoletz et al., 2013; Wanless, McClelland, Acock, Chen, et al., 2011; Wanless, McClelland, Tominey, & Acock, 2011). In the current sample, this measure demonstrated strong internal consistency across all waves (Cronbach's α : wave 1 = .96, wave 2 = .96, wave 3 = .96, wave 4 = .95).

Card Sort task. Children's cognitive flexibility was assessed using a Card Sort task similar to the traditional Dimensional Change Card Sort measure (Blackwell, Cepeda, & Munakata, 2009; Frye, Zelazo, & Palfai, 1995; Zelazo, 2006). Administration procedures were

similar to those described by Hongwanishkul, Happaney, Lee, and Zelazo (2005). The Card Sorting task consisted of up to 24 items, with each sorting trial having 6 items. During this task, children were asked to sort colored picture cards of a dog, fish, or bird on the basis of three dimensions: color, shape, and size. Four sorting boxes with target cards (either a dog, fish, bird, or frog) affixed on them were placed directly in front of children. The frog target card was meant to be a distractor, and thus, there were no picture cards with frogs on them. The same target and test cards were used for all participants. Children were given one practice trial prior to testing trials. During all test trials, children were given a test card (that had the same picture on it as one of the target cards) and asked the question, “Where does this one go?” and they were to place the card in one of the boxes. No feedback was given. For the first six items (pre-switch trial), children were to sort on the basis of shape (e.g., the dog cards go in the sorting box with the dog card affixed). For the second six items (post-switch trial), children were told they were going to play a new game and would now sort on the basis of color. For the third six items (post-switch trial), children were told they were going to play a new game and would now sort on the basis of size. If children scored five or more points on the third section, a fourth set of items were administered which consisted of a new rule: when the card had a black border on it, children were to sort on the basis of size. When the card did not have a black border, children were to sort on the basis of color. All items were weighted equally (including pre-switch trial items). Children were given a score of 0 for an incorrect response and 1 for a correct response, with scores ranging from 0 to 24. This assessment demonstrated strong internal consistency in the current sample across all waves for all sections (Cronbach’s α : wave 1 = .95, wave 2 = .93, wave 3 = .91, wave 4 = .88).

Auditory Working Memory. The Auditory Working Memory subtest from the Woodcock-Johnson III Tests of Cognitive Abilities (Woodcock, McGrew, & Mather, 2001b) or the Bateria III Woodcock- Muñoz (Muñoz-Sandoval, Woodcock, McGrew, & Mather, 2005b) was used to assess children's working memory. The task required children to repeat back to the experimenter things and numbers in a specific order. That is, children had to hold information in mind and then reproduce it in a different order. This standardized task demonstrates strong internal consistency for English-speaking and Spanish-speaking preschool children (Mather & Woodcock, 2001a). In the current sample, internal consistency was good across all waves for the full sample (Cronbach's α : wave 1 = .87, wave 2 = .89, wave 3 = .85, wave 4 = .82), and for the English-speaking children only (Cronbach's α : wave 1 = .89, wave 2 = .88, wave 3 = .86, wave 4 = .81) and the Spanish-speaking children only (Cronbach's α : wave 1 = .92, wave 2 = .83, wave 3 = .85, wave 4 = .91).

Simon Says task. The Simon Says task was used to assess inhibitory control (Carlson, 2005; Strommen, 1973). The Simon Says task has been identified in previous research as an advanced anti-imitation task and a measure of inhibitory control in that it requires children to inhibit a prepotent response (i.e., do all requested actions) in favor of a different response (i.e., only do the action if experimenter says "Simon Says;" Carlson, 2005). Specifically, children were asked to perform an action only if the experimenter said, "Simon says," but to remain still otherwise. Of the 10 total trials, five trials required inhibitory control. These trials were scored and children were given a proportion score of the number correct (items requiring inhibitory control). In previous studies, this measure has been significantly correlated with other assessments of inhibitory control (McClelland et al., 2014). Internal consistency for this

assessment was good across all waves (Cronbach's α : wave 1 = .87, wave 2 = .89, wave 3 = .85, wave 4 = .82).

Reliability of EF. Using the factor loadings presented below and discussed later, we computed composite reliability (ω ; McDonald, 1970, 1999; Raykov, 1997; Werts, Linn, & Jöreskog, 1974) for each EF construct. ω is identical to Cronbach's (1951) coefficient α , except that it relaxes the assumption of essential tau equivalence (i.e., an assumption that all items have equal factor loadings onto the latent construct)¹. Reliability for the EF factors was weak but acceptable and increased across the four waves of the present study ($\omega = .69, .74, .74, .78$, for Waves 1 through 4, respectively).

Measures of Academic Achievement. Children's literacy and math skills were assessed using the Woodcock Johnson Psycho-Educational Battery-III Tests of Achievement (WJ-III; Woodcock, McGrew, & Mather, 2001a) in English or the Bateria III Woodcock-Muñoz (Muñoz-Sandoval, Woodcock, McGrew, & Mather, 2005a) in Spanish. In a study using a large and diverse sample of 2000 children, cross-language equating procedures were employed using item-response theory (IRT) methods. Results suggested that the WJ-III and the Woodcock-Muñoz assess the same competencies and can be combined appropriately for use in cross-language studies (Woodcock & Muñoz-Sandoval, 1993). Woodcock-Johnson W-scores were used because they utilize Rasch-based measurement models to create equal-interval scale characteristics, with the W-score centered at 500 as the approximate average performance of a 10-year-old (Mather & Woodcock, 2001).

¹ Willoughby, Pek, & Blair (2013), have advocated for the use of maximal reliability—the reliability of an optimally-weighted composite—when examining latent EF factors. However, recent simulation evidence has drawn the usefulness of maximal reliability into question (Geldhof, Preacher, & Zyphur, 2014). We therefore do not include estimates of maximal reliability in the present study.

Letter-Word Identification. Children's literacy skills were measured using the Letter-Word Identification subtest of the WJ-III (Woodcock et al., 2001a) or the Bateria III Woodcock-Muñoz (Muñoz-Sandoval et al., 2005a). This test measures letter identification and word-reading skills through expressive and receptive items and had strong internal consistency for both the English-speaking (Cronbach's α : wave 1 = .92, wave 2 = .92, wave 3 = .94, wave 4 = .94) and Spanish-speaking children (Cronbach's α : wave 1 = .83, wave 2 = .80, wave 3 = .83, wave 4 = .90) in the present sample. Although these two subtests have been deemed comparable in rigorous cross-language validation studies in terms of content and difficulty (Woodcock & Mather, 1993), they could not be appropriately combined to provide full-sample reliabilities because children receive different items to ensure cultural relevance.

Applied Problems. Children's math skills were measured using the Applied Problems subtest of the WJ-III (Woodcock et al., 2001a) or the Bateria III Woodcock-Muñoz (Muñoz-Sandoval et al., 2005a). This measure assesses children's early mathematical operations (e.g., counting, addition, and subtraction) through practical problems and had good internal consistency for the full sample (Cronbach's α : wave 1 = .86, wave 2 = .87, wave 3 = .85, wave 4 = .83), for English-speaking children only (Cronbach's α : wave 1 = .80, wave 2 = .81, wave 3 = .79, wave 4 = .81), and for Spanish-speaking children only (Cronbach's α : wave 1 = .86, wave 2 = .82, wave 3 = .82, wave 4 = .80).

Analytic Approach

We examined longitudinal relations between EF and two academic domains: math and literacy. As described above, we explored these relations using two separate sets of analyses (i.e., cross-lagged panel models and latent growth curve models) to obtain a more complete understanding of our data than could be provided by either analysis alone. Although we had

specific hypotheses for our research questions, we did not favor one analytic approach over the other when interpreting the models that were used to answer our research questions. Instead, we chose two analytic models because each model provides a unique perspective on the data at hand and to our overarching research question. Treating each model as equally informative allows for a fuller understanding of the developmental processes impacting EF and academic achievement.

Participating children were nested in classrooms at each wave, and we computed ICCs for all target variables (i.e., EF indicators as well as math and literacy scores). The models for these ICCs specified wave-specific clustering, such that ICCs for Wave 1 variables used Wave 1 classrooms as the clustering units, ICCs for the Wave 2 variables used Wave 2 classrooms as the clustering units, et cetera. We anticipated that between-classroom differences would be strongly related to socio-demographic factors, and we supplemented our examination of ICCs with computation of conditional ICCs. To obtain conditional ICCs, we first regressed all EF and academic achievement variables on participant age (at Time 1), Head Start Status, and ELL status in a single-level regression model and stored the residuals from these models (i.e., residual centering, Lance, 1988). We then fit a saturated two-level path analysis (i.e., freely estimating all item variances and covariances at both levels) for each wave of data and obtained conditional ICCs for the EF and academic achievement variables.

As Table 1 shows, all variables exhibited substantial variability at the between-classroom level (i.e., all ICCs > .05), but this variance was largely accounted for by the demographic covariates. Only kindergarten literacy retained a substantial amount of between-classroom variance. Appropriately modeling the longitudinal observations as nested in children and also cross-classified in wave-specific classrooms would complicate our results and detract from model interpretability. Given that controlling for the covariates using single-level regression

largely accounted for between-classroom variation in the measures, we present single-level models that control for the same covariates included when computing conditional ICCs. The caveat, therefore, is that the standard errors for paths involving kindergarten literacy may be slightly biased.

Data Screening. Both sets of analyses used robust maximum likelihood estimation (MLR in Mplus) to deal with non-normality and missing data (Muthén & Muthén, 1998-2015). Skewness ranges for the four EF tasks and achievement measures were -1.23 to 1.97 at Wave 1, -1.20 to 0.83 at Wave 2, -1.85 to 1.02 at Wave 3, and -2.37 to 0.74 at Wave 4. Kurtosis ranges were 1.29 to 5.87 at Wave 1, 1.72 to 6.16 at Wave 2, 1.44 to 7.07 at Wave 3, and 1.63 to 8.58 at Wave 4. For children participating in the study at any given wave (i.e., missing data not due to children leaving the study in between waves of data collection), there was less than 6% missing data on direct assessments and no missing data on age, gender, Head Start status, or language status (see Table 2 for the number of observations for every variable). Once missing data due to attrition was factored in (i.e., children leaving the longitudinal study and resulting in a loss of data at later waves), the range of missing data was 0-30.66% for individual measures (average missingness was 15.34%). Two variables had 30.66% missing data at wave four (i.e., the Simon Says task and Auditory Working Memory; 294 observations out of the original sample size of 424). Because most missing data occurred due to participant attrition, we created binary variables (0 = did not leave study, 1 = did leave study) to test whether any of our covariates were related to attrition throughout the study. None of our covariates were related to attrition that occurred within the school years (i.e., Wave 1 to Wave 2 and Wave 3 to Wave 4). For attrition between Waves 2 and 3 (i.e., the transition from prekindergarten to kindergarten), we found that Head Start status ($b = 0.72, p = .005$) and parent education ($b = -0.08, p = .015$) were

significantly related to attrition when running bivariate logistic regression models. In other words, children in Head Start and children of parents with fewer years of education were more likely to leave the study between the spring of prekindergarten and fall of kindergarten. However, when both predictors were used to predict attrition, neither was significant, suggesting substantial shared variance in their relation to attrition (i.e., reduction in size of coefficient and increases in standard errors). Thus, all models included Head Start status (as opposed to parent education, which had substantial missing data), along with child age and language status as time-invariant covariates.

Cross-lagged panel model. We used a cross-lagged panel model to examine whether changes in relative standing on each construct (EF, math, literacy) were related over time. The cross-lagged panel models specifically tested whether children whose EF, math, and literacy scores were higher (or lower) than their peers at earlier waves were also higher (or lower) than their peers at subsequent times of measurement (i.e., a test of stability). After controlling for the stability of relative standing, these analyses also allowed us to test whether relative standing on one variable at earlier waves predicted *changes in relative standing* (not changes in absolute magnitude) on a different variable at subsequent waves. For each cross-lagged effect (e.g., EF predicting changes in math), we simultaneously examined the reciprocal relation (e.g., math predicting changes in EF) as a test of bidirectionality.

We first specified a longitudinal Confirmatory Factor Analysis (CFA), controlling all indicators for participants' age at the beginning of the study, ELL status, and Head Start enrollment status. This approach to controlling for covariates allows minor differences between indicators and the covariates to not impact overall model fit (see also Geldhof, Pornprasertmanit, Schoemann, & Little, 2013). The initial CFA allowed us to examine the structure of EF because,

although there is strong evidence in younger children that EF is best described as a unitary construct (Hughes, Ensor, Wilson, & Graham, 2010; Wiebe, Espy, & Charak, 2008), there is also evidence that it becomes more differentiated over time (Huizinga, Dolan, & van der Molen, 2007; Lehto, Juujarvi, Kooistra, & Pulkkinen, 2003). Good fit for a CFA that specified a single EF factor per time point would support the underlying assumption of our analyses—that EF is reasonably unidimensional as it was measured in this sample.

We scaled all latent variables in the initial CFA by fixing latent means of zero and latent variances to one. We modeled math and literacy as single-indicator factors by freely estimating the factor loading for each indicator onto its respective construct and additionally fixing the indicators' residual variances to zero. To account for correlated residuals over time, we estimated residual covariances within each indicator of EF (e.g., all HTKS indicators were allowed to covary, independent of their relations implied by the stability of EF as a latent construct). Figure B.1 in the Technical Appendix provides a partial path diagram that illustrates the EF component of this model.

We established measurement invariance of the EF construct across waves using the change in CFI criterion suggested by Cheung and Rensvold (CFI decreases by $< .01$; 2002). Modeling invariance requires equating factor loadings (weak invariance) and intercepts (strong invariance), allowing for differences at the latent level (i.e., latent variances and means, respectively; see Little, 1997 for a discussion). Thus, latent variances for EF in Times 2 through 4 were freely estimated in the weak invariance model, and latent means for EF in Times 2 through 4 were additionally freed in the strong invariance model. These tests ensured that the qualitative meaning of EF remained stable across the four waves of data collection rather than EF being strongly indicated by one measure in earlier waves and strongly indicated by a different

measure in later waves. Invariance could not be tested for math or literacy because those factors had only one indicator per time point (e.g., equating factor loadings for math over time would result in three additional degrees of freedom that would then be lost by freely estimating the latent variances for math at Times 2 through 4, resulting in no change in model fit).

After establishing measurement invariance, we specified a longitudinal Structural Equation Model (SEM) that included single-lag stability regressions (e.g., EF at Time 1 predicting EF at Time 2) and single-lag cross-construct regressions (e.g., EF at Time 1 predicting math at Time 2). We freely estimated all within-wave covariances (e.g., EF at Time 1 covaried with math and literacy at Time 1). The cross-lagged panel model assumes no longitudinal covariances except those specified by the longitudinal regression coefficients, and we tested this assumption by first estimating all covariances between constructs separated by more than one lag (e.g., EF and Time 1 covaried with math at Times 3 and 4). The latent variable covariance matrix was therefore completely saturated, and our initial SEM model had identical fit to our strong-invariance CFA model. We then tested the assumption of no longitudinal covariance by removing all covariances between constructs separated by more than one lag and performing a likelihood ratio test.

Latent Growth Curve Models (LGCM). To examine whether rates of change in EF, math, and literacy were correlated in our data, we estimated the associations between the growth parameters for each construct in a three-trajectory latent growth curve model. Based on the assumption that growth in the target variables, especially EF (Zelazo et al., 2013), may be nonlinear, we specified quadratic growth curves for all target constructs. The model then examined how initial standing (i.e., the random intercepts) and the rates of change and acceleration (i.e., the random linear and quadratic slopes) were correlated. The LGCM treated EF

as a latent factor, meaning the growth model for that construct was technically a curve-of-factors model (McArdle, 1988; see also Hancock, Kuo, & Lawrence, 2001). We imposed the same invariance constraints from the panel model on the EF factor in the growth model, although factors in the growth model were identified by constraining the factor loading of HTKS to one and fixing the intercepts for all HTKS indicators to zero. Latent intercepts for EF were also fixed to zero to identify the growth component of the model (see also Figure 1 in Hancock et al., 2001). Due to model complexity, and to acknowledge that the covariates were between-persons variables, we controlled for all covariates at the level of the growth parameters. Figure B.2 in the Technical Appendix provides a partial path diagram of the EF component of this model.

For the sake of comparability to our panel models, we used wave in the study as loadings for these models (i.e., loadings for the linear slope were 0, 1, 2, and 3, for Waves 1, 2, 3, and 4, respectively). This approach allowed us to model each wave of data as a discrete time point rather than taking the more traditional approach of modeling each observation of each child as occurring at the child's unique age at the assessment. Given participants' relatively narrow age range, very few children in later waves were younger than children measured in earlier waves. That is, child ages did not substantially overlap across waves.

Results

Descriptive statistics are presented in Table 2. Overall, and as expected, children improved at each wave of the study on EF tasks, math, and literacy.

Panel Models

The initial CFA fit the data well (fit for all panel models is presented in Table 3) and had statistically significant factor loadings for all indicators of EF (all $ps < .001$). Modification indices did not indicate areas of localized misfit. An initial test of weak (i.e., loading) invariance

substantially decreased model fit ($\Delta CFI = -.02$), with modification indices suggesting that the relation between EF and the Card Sort total score changed across waves and that the relation between Working Memory and EF was significantly different at wave 4 than in the other waves. Freely estimating the Card Sort factor loading for waves 1 and 2 and the Working Memory factor loading in wave 4 resulted in a model that supported partial weak invariance ($\Delta CFI = -.005$; $\Delta BIC = -3.65$). Equating the intercepts across waves in this model further supported partial strong factorial invariance ($\Delta CFI = -.003$; $\Delta BIC = -28.75$). Table 4 presents factor loadings and intercepts from the strong invariance model and highlights which parameters were freely estimated versus equated across time. This model shows that HTKS was a relatively strong indicator of EF across waves, Working Memory was a stronger indicator of EF in wave 4 (relative to other waves), and the Card Sort was an especially strong indicator of EF at wave 1. Latent variances and correlations from this model are presented in Table 5, with actual (rather than latent) means and variances provided for the math and literacy scores.

We next specified a cross-lagged panel SEM and tested the assumption of no longitudinal covariances above and beyond those specified by the lag-1 structural regressions. A likelihood ratio test comparing models that did versus did not allow longitudinal covariances between EF, math, and literacy measures separated by two or more lags (e.g., EF at Time 1 and math at Time 3) supported this assumption ($\Delta \chi^2 (df = 27) = 30.70, p = .28$; $\Delta BIC = -130.28$). The structural component of this final model is illustrated in Figure 1. This path diagram omits nonsignificant regression estimates and within-wave covariances. These additional details are provided in Figure B.3 and Table B.1 of the Technical Appendix.

Results suggest that (a) relative standing on all variables was stable (i.e., all autoregressive paths were statistically significant at $p < .001$), with EF displaying especially high

stability (β s ranged from .75 to .86); (b) that changes in relative standing on EF and literacy were essentially unrelated across waves (i.e., low cross-lagged regression coefficients); (c) that EF and math were mutually influential in preschool and this relation shifted in kindergarten, such that only EF predicted math; and (d) that math and literacy were not consistently related across time.

Latent Growth Curve Models

The initial three-trajectory model indicated a non-positive-definite latent covariance matrix caused by collinearity between the EF intercept and quadratic slope and by non-significant residual variances for the linear slope for literacy and the quadratic slope for math. These nonsignificant residual variances suggest an overfitted model. We therefore eliminated the collinearity by regressing the quadratic slope for EF on the intercept for EF and constraining the residual variance of the quadratic slope to zero. We also fixed the nonsignificant residual variances to zero. These constraints did not significantly reduce model fit ($\Delta \chi^2$ (df = 23) = 29.68, $p = .16$; Δ BIC = -107.65) and the resulting model fit the data well (χ^2 (df = 277) = 574.57, $p < .001$; RMSEA = .05 [.05, .06]; CFI = .95; TLI = .93). An examination of the modification indices did not reveal areas of extreme local misfit. Table 6 contains the estimated means and variances for the latent growth parameters from this model and clarifies which growth parameters were estimated in which ways (i.e., fixed versus random variances). All growth parameters with freely estimated variances were regressed on the covariates and allowed to covary among themselves. Partial correlations among these parameters are presented in Table 7. Fixed growth parameters were regressed on the control variables (i.e., age, Head Start status, and ELL status) but did not have freely estimated variances and did not covary with any other growth parameter. The correlations in Table 7 highlight strong associations among the intercepts and between the intercept and slope parameters. Average growth trajectories are plotted in Figure 2.

To better understand how the constructs at Wave 1 (estimated as the intercepts) may have impacted the results of the LGCMs, we took the additional step of regressing all three random slopes on all three random intercepts. This final model allowed us to examine how absolute changes in each variable were correlated after controlling for initial standing on each (i.e., all three random intercepts). As shown in Table 8, the residual random slope for math was significantly correlated with both other slopes, although the correlation between the EF and literacy slopes was not statistically significant. Thus, after children's initial standing was accounted for in the LGCM, the results suggested growth in EF and math were associated during this developmental period.

Discussion

The overarching aim of the current study was to examine the longitudinal relations between EF, math, and literacy across four waves of measurement spanning preschool and kindergarten. We employed a multi-analytic approach, first using a cross-lagged panel model to test the extent to which relative standing on EF, math, and literacy were related across time. We then used LGCMs to test whether growth in our constructs were associated. As expected, results generally demonstrated significant reciprocal relations and correlated growth between EF and math as well as math and literacy, but not between EF and literacy. Notably, results from our panel models indicated that these significant relations may change over time. For example, EF predicted math but math did not predict EF during the kindergarten school year. These findings contribute to the current literature by demonstrating a bidirectional association and correlated growth between EF, a more domain-general set of cognitive processes, and math, a domain-specific skill. These results have implications for research on curriculum development and

intervention design. Further, this study adds to the theoretical discourse surrounding the development of EF and academic skills in early childhood.

Bidirectional Relations Between EF, Math, and Literacy: Cross-Lagged Panel Models

Consistent with previous research (Blair & Razza, 2007; Bull et al., 2008; Bull, Johnston, & Roy, 1999; McClelland et al., 2007), our panel models suggested that EF is a significant predictor of math in preschool and kindergarten. These findings provide support for the notion that EF may be foundational for the development of important early math skills. In addition, and also consistent with a recent study (Fuhs et al., 2014), these results demonstrated reciprocal associations between EF and math during preschool and as children transition into kindergarten (i.e., from the spring of preschool to the fall of kindergarten). These findings suggest that EF may not only be important for the development of math, but that math may also be important for the development of EF during this time. Thus, it is possible that math skills are foundational for growth in EF. Essentially, the ability to pay attention, remember complex rules, and persist on challenging tasks may help children perform better on math tasks (McClelland et al., 2007) and, conversely, strong math skills (e.g., solving complicated math problems) may contribute to children's ability to sustain attention, remember a series of rules, and inhibit incorrect responses on complex EF tasks (Fuhs et al., 2014).

With the addition of a fourth time point at the beginning of kindergarten (in comparison to prior research), we were able to extend the existing literature and identify at which point during preschool and kindergarten relations between EF and math may change. Findings revealed that although math and EF were reciprocally related during preschool and during the transition to kindergarten, this bidirectional relation faded during the kindergarten year. Specifically, during the kindergarten year (between Waves 3 and 4), EF in the fall remained a

significant predictor of math in the spring, but not vice versa. Changes in the relations between EF and math may be due to factors associated with preschool and/or kindergarten instruction. In kindergarten, children are charged with more challenging math tasks and they may need to call upon EF skills to resist the natural inclination to either give up and abandon a task or use a less efficient previously learned rule (Bull et al., 1999). In contrast, mathematics instruction in preschool is often limited in complexity and focused around a narrow range of activities (e.g., counting; Ginsburg, Lee, & Boyd, 2008). It may be the case that, in preschool—where limited mathematics instruction is provided—children who have higher levels of math skills are engaged in instructional activities that provide the opportunity for them to develop higher EF skills and, in turn, those children with higher levels of EF are better able to acquire the limited mathematics instructional information that is provided. These instructional differences may explain why the bidirectional relationship ($EF \leftrightarrow \text{math}$) emerges during preschool and fades during kindergarten, when children begin experiencing more uniform and frequent math instruction during kindergarten.

Taken together, these findings have potential implications for the development and evaluation of instructional strategies and interventions that are designed to improve either EF or math. In preschool, it may be more beneficial for children if teachers target both EF and math simultaneously, whereas in kindergarten, focusing instructional efforts on EF as a foundational skill set may be more important. Additionally, these findings suggest that children who enter kindergarten with low levels of EF may be at risk for academic difficulties and in need of extra instructional supports or intervention. Critically, the causal nature of such instructional strategies need to be evaluated experimentally.

In contrast to math, the panel model indicated that relative standing on EF and literacy were essentially unrelated across waves. These findings are not surprising given inconsistent links between EF and literacy in previous studies (Blair & Razza, 2007; Blair et al., 2015; Cameron Ponitz et al., 2009; Schmitt et al., 2014) and non-significant bidirectional associations in recent work (Fuhs et al., 2014). Several speculations as to why associations are stronger for EF and math than EF and literacy have been introduced in recent literature. For example, some argue that math content and activity place more cognitive demands on children and, thus, require stronger EF skills to master (Bull, Espy, & Wiebe, 2008; Clark et al., 2010; Espy et al., 2004; Willoughby, Blair, Wirth, & Greenberg, 2012). A second explanation is that EF is a foundational skill set that supports growth in reasoning abilities (Richland & Burchinal, 2013). Higher-order reasoning skills are necessary to succeed on math tasks that require children to solve complex story or word problems (e.g., “Katie had three balls. One of them rolled away. Now how many does she have?”; Blair et al., 2015). In contrast, literacy tasks typically assess children’s knowledge, making fewer demands on reasoning abilities and EF. Others argue that differences in academic focus in early childhood classrooms could play a role in explaining differences in the development of math versus literacy (Cameron Ponitz et al., 2009). Extant research suggests that preschool teachers spend more time engaged in literacy instruction compared to math instruction (Layzer, Goodsen, & Moss, 1993; Skibbe, Hindman, Connor, Housey, & Morrison, 2013). Children may, therefore, have to engage in math activities (e.g., patterning during free play) spontaneously and independently during the school day, which may require higher levels of EF. Similarly, parents report engaging in significantly more literacy activities at home than math activities (Cannon & Ginsburg, 2008; Skwarchuk, Sowinski, & LeFevre, 2014). Parents who believe their children are more academically ready may engage their children in more

cognitively demanding math activities at home (DeFlorio & Beliakoff, 2014). The greater consistency of literacy activities at home and school may contribute to its overall distinction from growth in EF.

Another aspect of our research question was to investigate bidirectional relations between math and literacy skills across the preschool and kindergarten years. Somewhat contrary to our expectations, these relations were weaker in preschool and became bidirectional during the kindergarten year. These differences in the findings compared to expectations also are likely due to instructional practices. In contrast to the divergence of the relation between math and EF, there may be a convergence in the relation between math and literacy as instruction in both domains becomes more parallel in quantity. In preschool, children are generally exposed to more literacy instruction compared to math instruction. In contrast, in kindergarten, math and literacy instruction become more uniform and consistent, and all children are typically exposed to the same quantity of instruction for both academic domains. This parallel exposure likely allows children to draw on concepts learned from the instruction in the other domain (e.g., being able to read a word problem allows children to complete the math task) and thus, the relation between math and literacy may be strengthened.

Correlated Growth Between EF, Math, and Literacy: Latent Growth Curve Models

To further investigate the longitudinal associations between EF, math, and literacy, we employed a second analytic approach: Latent Growth Curve Models. Consistent with prior evidence (e.g., McClelland et al., 2007), these models indicated that the latent intercepts (a proxy for where children started) for EF, math, and literacy were all significantly correlated, suggesting that performance relative to peers was consistent across measures. Also, consistent with prior research (McClelland et al., 2007; Schmitt et al., 2014), initial levels of EF and math were more

highly correlated than EF and literacy. However, whether the coupling of the three variables is a result of unidirectional causality, bidirectional causality, or the result of unmeasured third variables is not clear.

In terms of cross-domain relations in growth, the final LGCM indicated that, after controlling for initial standing on each construct (i.e., all latent intercepts), the latent EF and math slopes were positively correlated. In contrast, results revealed a non-significant relation between growth in EF and literacy. This finding is in line with prior studies demonstrating that the longitudinal association between EF and math is more robust than EF and literacy (Blair et al., 2015; Cameron Ponitz et al., 2009). This finding also supports our earlier assertion that engaging in math activities may be a context in which children are able to expand their EF and that domain-specific differences in instruction during the preschool and kindergarten years may account for these differential patterns of growth. For example, over the last two decades, there has been a strong emphasis on early literacy instruction in both preschool and kindergarten. Indeed, previous research indicates a strong schooling effect for children's literacy development (Burrage et al., 2008; Christian, Bachman, & Morrison, 2001). Due to this emphasis on literacy instruction, children may not need to call upon their EF as much when engaging in literacy activities, and thus, improvement in EF would be less likely to be related to improvement in literacy during this time frame. Finally, the latent math and literacy slopes were significantly related, providing additional evidence that early math and literacy skills co-develop over the preschool and kindergarten years (Duncan et al., 2007; Jordan et al., 2006; LeFevre et al., 2010; Purpura et al., 2011).

Conclusions from the Integration of Both Analytic Approaches

Results from the two analytic approaches provide a similar story with regard to our overarching research question. Both the panel model and the LGCM suggested positive correlations between initial levels of EF, math, and literacy. Thus, and consistent with previous research (McClelland et al., 2007; Schmitt et al., 2014), there is strong evidence that these three constructs are tightly coupled by the time children enter preschool. However, both sets of results also suggest that EF and math are consistently related over time, whereas the association between EF and literacy is weak. Taken together, the LGCM and panel model therefore suggest that some early factor (math or an outside variable) likely helps explain the correlation between EF and literacy. The development of EF and literacy seem to be driven by separate processes during the transition to kindergarten, however.

Limitations and Future Directions

Although this study extends existing literature on the relations between EF and early academic skills, there are also several limitations. First, we utilized several measures of EF in our study but only one measure each for math (Applied Problems) and literacy (Letter-Word Identification). These subtests measure specific components of math (e.g., counting, calculation) and literacy (e.g., decoding, word-reading) and may therefore not represent comprehensive growth in these broader academic domains. It will be important for future studies to include additional measures of early academic skills to further our understanding of how complex skills like math and literacy develop. For instance, other research has shown that the relations between EF and math differ based on the distinct subcomponents of math that were measured (Lan, Legare, Cameron Ponitz, & Morrison, 2011; Purpura & Ganley, 2014). A comparison of more targeted relations was not possible in the current study due to our use of only one measure each for math and literacy. Moreover, utilizing multiple measures of math in future studies will help

elucidate the extent to which EF actually differentially predicts components of math at different ages. Indeed, as the Applied Problems subtest becomes more challenging, demands on EF become stronger. Changes in the relations between EF and math at different ages may not necessarily mean EF is a better or worse predictor of math, but that changes in these relations are related to the mathematics concepts targeted within specific assessment measures.

Second, as noted above, the quantity of instruction may have varied across time for specific domains (particularly for math), and these differences may have altered the relations between domains. For example, more time spent engaging in math instruction may affect the development of math, which, in turn, could change the relations between math and EF or between math and literacy. In the current study, math and literacy instructional practices, activities in schools and at home, or active learning in these domains were not assessed. Moreover, other contextual factors as well as individual child characteristics not measured in this study, such as parenting practices, early language abilities, or motor development, may be contributing to growth in EF and academic skills (McClelland et al., 2015). Further research that includes contextual factors and additional child characteristics may enhance our understanding of the linked development across these domains.

Third, recent research suggests that cross-lagged panel models can produce biased estimates due to unmodeled trait-like stability (e.g., Hamaker, Kuiper, & Grasman, 2015). Although the present analyses used a likelihood ratio test to show no evidence of additional trait-like stability (i.e., by constraining the correlations between factors separated by more than one lag to be zero), it will be critical for future research to explore alternative model specifications when investigating EF and academic outcomes over time. Future studies should also test for

mediating effects (e.g., via panel models), as our findings suggest that EF may partially mediate the relation between math in preschool and math in kindergarten.

Fourth, it is important to note that there was attrition across the four waves of data, particularly as children were transitioning from preschool to kindergarten (between Times 2 and 3). Although we accounted for missing data by using robust maximum likelihood and included Head Start status in all of our models (which predicted missingness between these waves), different patterns of reciprocal relations in preschool and kindergarten may be due to attrition.

Finally, although our sample was diverse in terms of socioeconomic status, it was less ethnically diverse. We relied on a convenience sample for the present analyses, and future research is needed to replicate our findings with more representative and ethnically diverse samples to determine whether or not the findings generalize to other populations.

Conclusions

Findings from this study have potential implications for instruction and intervention development that need to be investigated in a more targeted manner. It may be important to consider the EF demands on mathematical instruction at these ages. The relation between EF and math may be something that can be capitalized on through instruction. Integrating the domains at a very targeted level (e.g., that includes appropriate individual scaffolding) may be a useful mechanism for enhancing success across domains. Further, intervention efforts focused on EF (or math) may also have a beneficial effect on children's math (or EF) development. Although our analyses preclude causality, the bidirectional associations, as well as correlated growth trajectories, between EF and math suggests that interventions and programs that contain both EF *and* academic training, particularly in math, may be a potential avenue for affecting change

during the transition to kindergarten. Future research examining causal connections between these domains at a more nuanced level is needed.

Findings from this study also suggest that, without intervention, children's relative standing on EF, math, and literacy assessments are fairly stable over time. This finding has implications for future theoretical work examining the development of these constructs. More research is needed to identify predictors of these skills prior to and during preschool at the biological, familial, and socioeconomic levels.

In sum, the current study replicates and extends current literature exploring EF, math, and literacy. Unlike previous work, we used a multi-analytic approach and found converging evidence for the longitudinal relations between EF and math and weaker relations between EF and literacy. These findings expand upon what was found in the study conducted by Fuhs and colleagues (2014). With the addition of a fourth time point at the beginning of kindergarten, we were able to contribute to current research by improving the specificity of the relations between EF and academic skills by identifying at which points the relations change during the transition to kindergarten at a more fine-grained level. Changes in these relations may be due to factors within the preschool and kindergarten classrooms, such as instructional methods and alignment to children's needs, or due to the constructs being assessed at those ages. This change in relation is important for the development of instructional strategies and interventions that aim to improve either EF or math. In preschool, it may be more efficacious to target both EF and math simultaneously, whereas in kindergarten, targeting EF as a foundational skill set may be more important. Alternatively, there may be differential relations between aspects of EF and mathematics where EF is only related to certain mathematics skills (Lan et al., 2011; Purpura, Schmitt, Ganley, 2017; Purpura & Ganley, 2014) that affect this relation. These differential

relations may need to be accounted for in intervention and curricular development. Nonetheless, findings from both sets of analyses suggest that fostering the development of EF and early math skills during the transition to kindergarten may be a potentially important avenue for promoting school readiness and fostering academic success that needs to be investigated more thoroughly.

References

- Acock, A. C. (2012). What to do about missing values. In H. Cooper, P. M. Camic, D. L. Long, A. T. Panter, D. Rindskopf & K. J. Sher (Eds.), *Data analysis and research publication. APA handbook of research methods in psychology, Vol. 3.* (Vol. 3, pp. 27-50). Washington, DC: American Psychological Association.
- Barberisi, M. J., Katusic, S. K., Colligan, R. C., Weaver, A. L., & Jacobsen, S. J. (2005). Math learning disorder: Incidence in a population-based birth cohort, 1976–1982, Rochester, Minn. *Ambulatory Pediatrics, 5*, 281–289.
- Bierman, K. L., Nix, R. L., Greenberg, M. T., Blair, C., & Domitrovich, C. E. (2008). Executive functions and school readiness intervention: Impact, moderation, and mediation in the Head Start REDI program. *Development and Psychopathology, 20*, 821–843.
doi:10.1017/S0954579408000394
- Blackwell, K. A., Cepeda, N. J., & Munakata, Y. (2009). When simple things are meaningful: working memory strength predicts children’s cognitive flexibility. *Journal of Experimental Child Psychology, 103*, 241–249. doi:10.1016/j.jecp.2009.01.002
- Blair C. 2006. How similar are fluid cognition and general intelligence? A developmental neuroscience perspective on fluid cognition as an aspect of human cognitive ability. *Behavioral and Brain Sciences, 29*, 109–25.
- Blair, C., & Raver, C. C. (2015). School readiness and self-regulation: A developmental psychobiological approach. *Annual Review of Psychology, 66*, 711–731. doi: 10.1146/annurev-psych-010814-015221
- Blair, C., & Razza, R. (2007). Relating effortful control, executive function, and false belief understanding to emerging math and literacy ability in kindergarten. *Child Development,*

78, 647–663. doi:10.1111/j.1467-8624.2007.01019.x

- Blair, C., Ursache, A., Greenberg, M., & Vernon-Feagans, L., & the Family Life Project Investigators (2015). Multiple aspects of self-regulation uniquely predict mathematics but not letter–word knowledge in the early elementary grades. *Developmental Psychology*, *51*, 459–472. doi: 10.1037/a0038813
- Bowles, R. P., McClelland, M. M., Cameron, C., Acock, A. C., Montroy, J. J., & Duncan, R. (2015). *A Rasch analysis of the Head-Toes-Knees-Shoulders (HTKS) measure of behavioral self-regulation*. Manuscript under review.
- Bull, R., Espy, K. A., & Wiebe, S. A. (2008). Short-term memory, working memory, and executive functioning in preschoolers: Longitudinal predictors of mathematical achievement at age 7 years. *Developmental Neuropsychology*, *33*, 205–228. doi:10.1080/87565640801982312
- Bull, R., Johnston, R. S., & Roy, J. A. (1999). Exploring the roles of the visual-spatial sketch pad and central executive in children’s arithmetical skills: Views from cognition and developmental neuropsychology. *Developmental Neuropsychology*, *15*, 421–442.
- Burrage, M. S., Cameron Ponitz, C., McCready, E. A., Shah, P., Sims, B. C., Jewkes, A. B., & Morrison, F. J. (2008). Age- and schooling-related effects on executive functions in young children: A natural experiment. *Child Neuropsychology*, *14*, 510–524. doi: [10.1080/09297040701756917](https://doi.org/10.1080/09297040701756917)
- Cameron Ponitz, C., McClelland, M. M., Matthews, S. S., & Morrison, F. J. (2009). A structured observation of behavioral self-regulation and its contribution to kindergarten outcomes. *Developmental Psychology*, *45*, 605–619. doi:10.1037/a0015365

- Campbell, D. T., & Fiske, D. W. (1959). Convergent and discriminant validation by the multitrait-multimethod matrix. *Psychological Bulletin*, *56*, 81–105.
- Cannon, J., & Ginsburg, H. P. (2008). ‘Doing the math’: Maternal beliefs about early mathematics versus language learning. *Early Education and Development*, *19*, 238–260. doi:[10.1080/10409280801963913](https://doi.org/10.1080/10409280801963913)
- Carlson, S. M. (2005). Developmentally sensitive measures of executive function in preschool children. *Developmental Neuropsychology*, *28*(2), 595-616. doi: [10.1207/s15326942dn2802_3](https://doi.org/10.1207/s15326942dn2802_3)
- Chen, Q., Hughes, J. N., & Kwok, O. (2013). Differential growth trajectories for achievement among children retained in first grade: A growth mixture model. *The Elementary School Journal*, *114*, 327–353. doi:[10.1086/674054](https://doi.org/10.1086/674054)
- Christian, K., Bachman, H. J., & Morrison, F. J. (2001). Schooling and cognitive development. In *Environmental effects on cognitive cognitive abilities* (pp. 287–335). Mahwah, NJ: Lawrence Erlbaum Associates.
- Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*, *16*, 297-334.
- Clark, C. A. C., Pritchard, V. E., & Woodward, L. J. (2010). Preschool executive functioning abilities predict early mathematics achievement. *Developmental Psychology*, *46*, 1176–1191. doi:[10.1037/a0019672](https://doi.org/10.1037/a0019672)
- Dowsett, S. M., & Livesey, D. J. (2000). The development of inhibitory control in preschool children: Effects of “executive skills” training. *Developmental Psychobiology*, *36*, 161–174. doi:[10.1002/\(SICI\)1098-2302\(200003\)36:2](https://doi.org/10.1002/(SICI)1098-2302(200003)36:2)

- Duckworth, A. L., Tsukayama, E., & May, H. (2010). Establishing causality using longitudinal hierarchical linear modeling: An illustration predicting achievement from self-control. *Social Psychology and Personality Science, 1*, 311–317. doi:10.1177/1948550609359707
- Duncan, G. J., Dowsett, C. J., Claessens, A., Magnuson, K., Huston, A. C., Klebanov, P. et al. (2007). School readiness and later achievement. *Developmental Psychology, 43*, 1428–1446. doi:10.1037/0012-1649.43.6.1428
- Engel, M., Claessens, A., & Finch, M. A. (2013). Teaching students what they already know? The (mis)alignment between mathematical instructional content and student knowledge in kindergarten. *Educational Evaluation and Policy Analysis, 35*, 157–178. doi:10.3102/0162373712461850
- Espy, K. A., McDiarmid, M. M., Cwik, M. F., Stalets, M. M., Hamby, A., & Senn, T. E. (2004). The contribution of executive functions to emergent mathematic skills in preschool children. *Developmental Neuropsychology, 26*, 465–486. doi:10.1207/s15326942dn2601_6
- Frye, D., Zelazo, P. D., & Palfai, T. (1995). Theory of mind and rule-based reasoning. *Cognitive Development, 10*, 483 – 527. doi: 10.1016/0885-2014(95)90024-1
- Fuhs, M. W., Nesbitt, K. T., Farran, D. C., & Dong, N. (2014). Longitudinal associations between executive functioning and academic skills across content areas. *Developmental Psychology, 50*, 1698–1709. <http://dx.doi.org/10.1037/a0036633>
- Gathercole, S. E., Pickering, S. J., Knight, C., & Stegmann, Z. (2004). Working memory skills and educational attainment: Evidence from national curriculum assessments at 7 and 14 years of age. *Applied Cognitive Psychology, 18*, 1–16. doi: 10.1002/acp.934

- Geldhof, G. J., Preacher, K. J., & Zyphur, M. (2014). Reliability estimation in a multilevel confirmatory factor analysis framework. *Psychological Methods, 19*, 72-91.
- Ginsburg, H. P., Lee, J. S., & Boyd, J. S. (2008). Mathematics education for young children: What it is and how to promote it. *Social Policy Report—Giving Child and Youth Development Knowledge Away, 22*, 1–24.
- Greene, J. C., Caracelli, V. J., & Graham, W. F. (1989). Toward a conceptual framework for mixed-method evaluation designs. *Educational Evaluation and Policy Analysis, 11*, 255–274.
- Hancock, G. R., Kuo, W., & Lawrence, F. R. (2001). An illustration of second-order growth models. *Structural Equation Modeling, 8*, 470-489.
- Hassinger-Das, B., Jordan, N. C., Glutting, J., Irwin, C., & Dyson, N. (2014). Domain-general mediators of the relation between kindergarten number sense and first-grade mathematics achievement. *Journal of Experimental Child Psychology, 118*, 78-92.
doi:[10.1016/j.jecp.2013.09.008](https://doi.org/10.1016/j.jecp.2013.09.008)
- Hongwanishkul, D., Happaney, K. R., Lee, W. S. C., & Zelazo, P. D. (2005). Assessment of hot and cool executive function in young children: Age-related changes and individual differences. *Developmental Neuropsychology, 28*, 617–644.
doi:[10.1207/s15326942dn2802_4](https://doi.org/10.1207/s15326942dn2802_4)
- Hughes, C., Ensor, R., Wilson, A., & Graham, A. (2010). Tracking executive function across the transition to school: A latent variable approach. *Developmental Neuropsychology, 35*, 20–36. doi:[10.1080/87565640903325691](https://doi.org/10.1080/87565640903325691)

- Huizinga, M., Dolan, C. V., & van der Molen, M. W. (2007). Age-related change in executive function: Developmental trends and a latent variable analysis. *Neuropsychologia, 44*, 2017–2036. doi:[10.1016/j.neuropsychologia.2006.01.010](https://doi.org/10.1016/j.neuropsychologia.2006.01.010)
- La Paro, K. M., & Pianta, R. C. (2000). Predicting children's competence in the early school years. A meta-analytic review. *Review of Educational Research, 70*, 443–484. doi:[10.3102/00346543070004443](https://doi.org/10.3102/00346543070004443).
- Lan, X., Legare, C. H., Cameron Ponitz, C., Su, L., & Morrison, F. J. (2011). Investigating the links between the subcomponents of executive function and academic achievement: A cross-cultural analysis of Chinese and American preschoolers. *Journal of Experimental Child Psychology, 108*, 677-692.
- Layzer, J. L., Goodsen, B. D., & Moss, M. (1993). *Life in preschool: Observational study of early childhood programs for disadvantaged four-year-olds* (Vol. 1). Cambridge, MA: Abt. Associates.
- LeFevre, J., Fast, L., Skwarchuk, S., Smith-Chant, B. L., Bisanz, J., Kamawar, D., & Penner-Wilger, M. (2010). Pathways to mathematics: Longitudinal predictors of performance. *Child Development, 81*, 1753–1767. doi:[10.1111/j.1467-8624.2010.01508.x](https://doi.org/10.1111/j.1467-8624.2010.01508.x)
- Lehto, J. E., Juuhaarvi, P., Kooistra, L., & Pulkkinen, L. (2003). Dimensions of executive function: Evidence from children. *The British Journal of Developmental Psychology, 21*, 59–80. doi:[10.1348/026151003321164627](https://doi.org/10.1348/026151003321164627)
- Little, T. D. (1997). Mean and covariance structures (MACS) analyses of cross-cultural data: Practical and theoretical issues. *Multivariate Behavioral Research, 32*, 53-76. doi:[10.1207/s15327906mbr3201_3](https://doi.org/10.1207/s15327906mbr3201_3)
- McArdle, J. J. (1988). Dynamic but structural equation modeling of repeated measures data. In

- Handbook of multivariate experimental psychology* (pp. 561-614). Springer US.
- McClelland, M. M., Acock, A. C., & Morrison, F. J. (2006). The impact of kindergarten learning-related skills on academic trajectories at the end of elementary school. *Early Childhood Research Quarterly, 21*, 471–490. doi:10.1016/j.ecresq.2006.09.003
- McClelland, M. M., Acock, A. C., Piccinin, A., Rhea, S. A., & Stallings, M. C. (2013). Relations between preschool attention span-persistence and age 25 educational outcomes. *Early Childhood Research Quarterly, 28*, 314–324. doi:[10.1016/j.ecresq.2012.07.008](https://doi.org/10.1016/j.ecresq.2012.07.008)
- McClelland, M. M., & Cameron, C. E. (2012). Self-Regulation in early childhood: Improving conceptual clarity and developing ecologically valid measures. *Child Development Perspectives, 6*, 136–142. doi: 10.1111/j.1750-8606.2011.00191.x
- McClelland, M. M., Cameron, C. E., Duncan, R., Bowles, R. P., Acock, A. C., Miao, A...Pratt, M. E. (2014). Predictors of early growth in academic achievement: The Head-Toes-Knees-Shoulders task. *Frontiers in Psychology, 5*. doi: 10.3389/fpsyg.2014.00599
- McClelland, M. M., Cameron, C. E., Wanless, S. B., & Murray, A. (2007). Executive function, behavioral self-regulation, and social-emotional competence: Links to school readiness. In O. N. Saracho & B. Spodek (Eds.), *Contemporary perspectives on social learning in early childhood education* (pp. 83–107). Charlotte, NC: Information Age.
- McClelland, M. M., Cameron, C. E., Connor, C. M., Farris, C. L., Jewkes, A. M., & Morrison, F. J. (2007). Links between behavioral regulation and preschoolers' literacy, vocabulary, and math skills. *Developmental Psychology, 43*, 947–959. doi:10.1037/0012-1649.43.4.947
- McClelland, M. M., Geldof, J., Cameron, C. E., & Wanless, S. B. (in press). Development and self-regulation. In Overton, W. F. & Molenaar, P. C. M. (Eds.). *Theory and Method*.

Volume 1 of the Handbook of child psychology and developmental science. (7th ed.),

Editor-in-Chief: Richard M. Lerner. Hoboken, NJ: Wiley.

McDonald, R. P. (1970). The theoretical foundations of principal factor analysis, canonical factor analysis and alpha factor analysis. *British Journal of Mathematical Psychology*, *23*, 1-21.

McDonald, R. P. (1999). *Test theory: A unified treatment*. Mahwah, NJ: Erlbaum.

McGrew, K. S., & Woodcock, R. W. (2001). *Technical Manual. Woodcock-Johnson III*. Itasca, IL: Riverside Publishing.

Miyake, A. U., Friedman, N. P., Emerson, M. J., Witzki, A. H., & Howerter, A. (2000). The unity and diversity of executive functions and their contributions to complex 'frontal lobe' tasks: A latent variable analysis. *Cognitive Psychology*, *41*, 49–100.
doi:10.1006/cogp.1999.0734

Moffitt, T. E., Arseneault, L., Belsky, D., Dickson, N., Hancox, R. J., Harrington, H. et al. (2011). A gradient of childhood self-control predicts health, wealth, and public safety. *Proceedings of the National Academy of Sciences*, *108*, 2693–2698.
doi:10.1073/pnas.1010076108

Muñoz-Sandoval, A. F., Woodcock, R. W., McGrew, K. S., & Mather, N. (2005a). *Bateria III Woodcock- Muñoz: Pruebas de aprovechamiento*. Itasca, IL: Riverside Publishing.

Muñoz-Sandoval, A. F., Woodcock, R. W., McGrew, K. S., & Mather, N. (2005b). *Bateria III Woodcock-Muñoz: Pruebas de habilidades cognitivas*. Itasca, IL: Riverside Publishing.

Muthén, L. K. (2010, April 25). Convergence [Msg. 21]. Message posted to

<http://www.statmodel.com/discussion/messages/12/17.html?1438886834>

Muthén, B. O. (2011, May 19). Factor scores as dependent variables [Msg. 2]. Message posted to

<http://www.statmodel.com/discussion/messages/9/7397.html?1359828921>

Muthén, L. K., & Muthén, B. O. (1998-2015). *Mplus User's Guide. Seventh Edition*. Los Angeles, CA: Muthén & Muthén.

National Early Literacy Panel (2008). *Report of the National Early Literacy Panel: Developing Early Literacy*. Washington, DC: U.S. Department of Health and Human Services.

National Mathematics Advisory Panel (2008). *Foundations for Success: The Final Report of the National Mathematics Advisory Panel*, U.S. Department of Education: Washington, DC.

Purpura, D. J., & Ganley, C. (2014). Working memory and language: Skill-specific or domain general relations to mathematics? *Journal of Experimental Child Psychology, 122*, 104-121. doi:[10.1016/j.jecp.2013.12.009](https://doi.org/10.1016/j.jecp.2013.12.009)

Purpura, D. J., Hume, L., Sims, D., & Lonigan, C. J. (2011). Early literacy and early numeracy: The value of including early literacy skills in the prediction of numeracy development. *Journal of Experimental Child Psychology, 110*, 647–658. doi:[10.1016/j.jecp.2011.07.004](https://doi.org/10.1016/j.jecp.2011.07.004)

Purpura, D. J., Schmitt, S. A., Ganley, C. M. (2017). Foundations of mathematics and literacy: The role of executive functioning components. *Journal of Experimental Child Psychology, 153*, 15-34. doi:[10.1016/j.jecp.2016.08.010](https://doi.org/10.1016/j.jecp.2016.08.010)

Raykov, T. (1997). Estimation of composite reliability for congeneric measures. *Applied Psychological Measurement, 21*, 173-184.

Richland, L. E., & Burchinal, M. R. (2013). Early executive function predicts reasoning development. *Psychological Science, 24*, 87–92. doi:[10.1177/0956797612450883](https://doi.org/10.1177/0956797612450883)

Rueda, M. R., Posner, M. I., & Rothbart, M. K. (2005). The development of executive

- attention: Contributions to the emergence of self-regulation. *Developmental Neuropsychology*, 28, 573–594. doi: 10.1207/s15326942dn2802_2
- Schmitt, S. A., McClelland, M. M., Tominey, S., & Acock, A. C. (2015). Strengthening school readiness for Head Start children: An evaluation of a self-regulation intervention. *Early Childhood Research Quarterly*, 30, 20-31. [doi:10.1016/j.ecresq.2014.08.001](https://doi.org/10.1016/j.ecresq.2014.08.001)
- Schmitt, S. A., Pratt, M., & McClelland, M. M. (2014). Examining the validity of behavioral self-regulation tools in predicting preschoolers' academic achievement. *Early Education and Development*, 25, 641–660. doi:[10.1080/10409289.2014.850397](https://doi.org/10.1080/10409289.2014.850397)
- Skibbe, L. E., Hindman, A., Connor, C. M., Housey, M., & Morrison, F. J. (2013). Relative contributions of pre-kindergarten and kindergarten to children's literacy and mathematics skills. *Early Education and Development*, 24, 687–703. doi:
[10.1080/10409289.2012.712888](https://doi.org/10.1080/10409289.2012.712888)
- Skibbe, L. E., Phillips, B. M., Day, S. L., Brophy-Herb, H. E., & Connor, C. M. (2012). Children's early literacy growth in relation to classmates' self-regulation. *Journal of Educational Psychology*, 104, 541–553. doi:[10.1037/a0029153](https://doi.org/10.1037/a0029153)
- Skrondal, A., & Lakke, P. (2001). Regression among factor scores. *Psychometrika*, 66, 563–576.
- Skwarchuk, S. L., Sowinski, C., & LeFevre, J. A. (2014). Formal and informal home learning activities in relation to children's early numeracy and literacy skills: The development of a home numeracy model. *Journal of Experimental Child Psychology*, 121, 63–84. doi:[10.1016/j.jecp.2013.11.006](https://doi.org/10.1016/j.jecp.2013.11.006)
- Stevenson, H. W., & Newman, R. S. (1986). Long-term prediction of achievement and attitudes in mathematics and reading. *Child Development*, 57, 646–659. doi:[10.2307/1130343](https://doi.org/10.2307/1130343)

- Strommen, E. A. (1973). Verbal self-regulation in a children's game: Impulsive errors on "simon says". *Child Development*, 849-853. doi: 10.2307/1127737
- Symonds, J. E., & Gorard, S. (2010). Death of mixed methods? Or the rebirth of research as a craft. *Evaluation & Research in Education*, 23, 121-136.
- Welsh, J. A., Nix, R. L., Blair, C., Bierman, K. L., & Nelson, K. E. (2010). The development of cognitive skills and gains in academic school readiness for children from low-income families. *Journal of Educational Psychology*, 102, 43-53. doi:10.1037/a0016738
- Werts, C. E., Linn, R. L., & Jöreskog, K. G. (1974). Intraclass reliability estimates: Testing structural assumptions. *Educational and Psychological Measurement*, 34, 25-33.
- Whitehurst, G. J., & Lonigan, C. J. (1998). Child development and emergent literacy. *Child Development*, 69, 848-872.
- Wiebe, S. A., Espy, K. A., & Charak, D. (2008). Using confirmatory factor analysis to understand executive control in preschool children: I. Latent structure. *Developmental Psychology*, 44, 575-587. doi:10.1037/0012-1649.44.2.575
- Willoughby, M. T., Blair, C. B., Wirth, R. J., & Greenberg, M. (2012). The measurement of executive function at age 5: Psychometric properties and relationship to academic achievement. *Psychological Assessment*, 24, 226-239. doi:10.1037/a0025361
- Willoughby, M. T., Kupersmidt, J. B., & Voegler-Lee, M. E. (2012). Is preschool executive function causally related to academic achievement? *Child Neuropsychology*, 18, 79-91. doi:10.1080/09297049.2011.578572
- Willoughby, M. T., Pek, J., & Blair, C. B. (2013). Measuring executive function in early childhood: A focus on maximal reliability and deviation of short forms. *Psychological Assessment*, 664-670.

Woodcock, R. W., McGrew, K. S., & Mather, N. (2001a). *Woodcock-Johnson III Tests of Achievement*. Itasca, IL: Riverside Publishing Company.

Woodcock, R. W., McGrew, K. S., & Mather, N. (2001b). *Woodcock-Johnson III Tests of Cognitive Abilities*. Itasca, IL: Riverside Publishing.

Woodcock, R. W., & Muñoz-Sandoval, A. F. (1993). An IRT approach to cross-language test equating and interpretation. *European Journal of Psychological Measurement, 32*, 233–241.

Wu, W., Selig, J. P., & Little, T. D. (2013). Longitudinal models. In T. D. Little (Ed.), *Oxford Handbook of Quantitative Methods*. New York, NY: OUP.

Zelazo, P. D. (2006). The Dimensional Change Card Sort (DCCS): A method for assessing executive function in children. *Nature Protocols, 1*, 297–301.

Zelazo, P. D., Anderson, J. E., Richler, J., Wallner - Allen, K., Beaumont, J. L., & Weintraub, S. (2013). National Institutes of Health Toolbox Cognition Battery (NIH Toolbox CB): Validation for children between 3 and 15 years: II. NIH Toolbox Cognition Battery (CB): Measuring executive function and attention. *Monographs of the Society for Research in Child Development, 78*(4), 16-33. doi: 10.1111/mono.12032

Zelazo, P. D., & Ulrich, M. (2011). Executive function in typical and atypical development. In U. Goswami (Ed.), *The Wiley-Blackwell handbook of childhood cognitive development* (2nd edition, pp. 574–603). Hoboken, NJ: Wiley-Blackwell.

Table 1

ICCs for all items by wave-specific cluster

Construct Indicator	UNCONDITIONAL				CONDITIONAL			
	W1	W2	W3	W4	W1	W2	W3	W4
EF								
Working memory	.09	.12	.14	.12	.04	.00	.01	.06
Simon says	.06	.09	.10	.11	.02	.02	.03	.06
HTKS	.12	.19	.13	.10	.06	.03	.02	.02
Card sort	.11	.11	.13	.07	.03	.00	.01	.02
Literacy	.21	.21	.17	.12	.05	.02	.14	.15
Math	.19	.17	.19	.19	.01	.04	.05	.03

Note. Conditional ICCs control for age (at Time 1), Head Start status, and ELL Status.

Table 2

Descriptive Statistics for all study variables

	Prekindergarten (Year 1)				Kindergarten (Year 2)			
	Fall (wave 1)		Spring (wave 2)		Fall (wave 3)		Spring (wave 4)	
	<i>N</i>	<i>M (SD)</i>	<i>N</i>	<i>M (SD)</i>	<i>N</i>	<i>M (SD)</i>	<i>N</i>	<i>M (SD)</i>
Age	424	4.70 (0.30)	394	5.15 (0.30)	308	5.67 (0.30)	299	6.17 (0.29)
Percent male	424	51%	394	51%	308	50%	299	51%
Percent Head Start	424	55%	394	54%	308	51% ^h	299	51% ^h
Percent ELL ^a	424	15%	394	15%	308	15%	299	14%
Parent education	353	14.40 (4.23)	336	14.34 (4.26)	275	14.60 (4.45)	269	14.67 (4.46)
HTKS ^b	403	17.41 (17.20)	391	25.15 (18.28)	303	33.17 (17.74)	296	39.22 (16.00)
Card sort	409	13.64 (6.67)	389	16.49 (5.92)	307	18.60 (4.88)	295	19.78 (3.88)
Working memory ^c	400	450.30 (14.80)	385	456.17 (17.97)	303	464.60 (19.21)	294	473.18 (19.90)
Simon says	408	0.14 (0.28)	387	0.29 (0.38)	307	0.45 (0.39)	294	0.54 (0.38)
Math ^d	401	410.17 (23.30)	391	419.83 (23.11)	305	431.02 (20.71)	295	442.09 (19.29)
Literacy ^e	408	335.65 (26.59)	390	349.33 (26.80)	305	366.00 (29.14)	295	400.24 (35.21)

^aEnglish language learner; ^bHead-Toes-Knees-Shoulders task; ^cAuditory Working Memory subtest from the Woodcock-Johnson III Tests of Cognitive Abilities; ^dApplied Problems subtest from the Woodcock-Johnson III Tests of Achievement; ^eLetter-Word Identification subtest from the Woodcock-Johnson III Tests of Achievement.

Table 3

Fit for Panel Models

	χ^2 ^a	df	RMSEA	90% C.I. (RMSEA)	CFI	TLI	BIC
Initial	284.72	170	0.04	[.03, .05]	0.979	0.96	30786.98
Weak Invariance	387.09	179	0.05	[.05, .06]	0.962	0.93	30831.28
Partial Weak Invariance	319.45	176	0.04	[.04, .05]	0.974	0.95	30783.33
Strong Invariance and Initial SEM ^b	343.63	185	0.05	[.04, .05]	0.971	0.95	30754.58

^aModels were estimated using robust maximum likelihood; χ^2 statistics cannot be directly compared.

^bFit for these models was identical because the latent covariance structure of the initial SEM was saturated.

Table 4

Factor Loadings and Intercepts from the Strong Invariance CFA Model

Construct Indicator	Standardized Loading (SE) ^a	Raw-Metric Loading (SE) ^a	Raw-Metric Intercepts (SE)
Time 1 EF			
Working memory	.34* (.04)	0.51 (.06)	45.37 (.10)
Simon says	.45* (.04)	0.67 (.07)	0.90 (.10)
HTKS	.45* (.06)	0.49 (.06)	1.36 (.08)
Card sort	.59* (.04)	1.30 (.09)	5.04 (.15)
Time 2 EF			
Working memory	.40* (.03)	<i>equated (T1)</i>	<i>equated (T1)</i>
Simon says	.49* (.03)	<i>equated (T1)</i>	<i>equated (T1)</i>
HTKS	.58* (.04)	<i>equated (T1)</i>	<i>equated (T1)</i>
Card sort	.55* (.05)	0.76 (.09)	<i>equated (T1)</i>
Time 3 EF			
Working memory	.41* (.03)	<i>equated (T1)</i>	<i>equated (T1)</i>
Simon says	.52* (.04)	<i>equated (T1)</i>	<i>equated (T1)</i>
HTKS	.63* (.04)	<i>equated (T1)</i>	<i>equated (T1)</i>
Card sort	.52* (.05)	0.54 (.07)	<i>equated (T1)</i>
Time 4 EF			
Working memory	.54* (.04)	0.72 (.09)	<i>equated (T1)</i>
Simon says	.54* (.04)	<i>equated (T1)</i>	<i>equated (T1)</i>
HTKS	.66* (.04)	<i>equated (T1)</i>	<i>equated (T1)</i>
Card sort	.59* (.04)	<i>equated (T3)</i>	<i>equated (T1)</i>

Note. Indicators were divided by constants to make their variances more homogenous, expediting model convergence (e.g., Muthén, 2010). For more information, see Online Technical Appendix A.

^aLoadings are somewhat attenuated because covariates were controlled at the item level.

* $p < .001$.

Table 5

Means, Variances and Correlations for Strong Invariance Model

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	Mean
1. EF1	1.00												0.00
2. Math1	.65*	4.03											41.71
3. Literacy1	.44*	.39*	5.45										34.77
4. EF2	.91*	.71*	.43*	1.97									1.50
5. Math2	.68*	.74*	.40*	.74*	3.72								42.71
6. Literacy2	.36*	.41*	.77*	.40*	.41*	5.66							36.16
7. EF3	.85*	.70*	.40*	.92*	.78*	.34*	2.36						2.63
8. Math3	.59*	.67*	.41*	.66*	.79*	.40*	.77*	3.14					43.67
9. Literacy3	.36*	.37*	.70*	.40*	.35*	.80*	.36*	.41*	7.02				37.60
10. EF4	.71*	.64*	.32*	.83*	.69*	.32*	.92*	.71*	.34*	2.18			3.24
11. Math4	.60*	.62*	.41*	.67*	.70*	.41*	.71*	.75*	.41*	.69*	2.79		44.74
12. Literacy4	.43*	.42*	.60*	.46*	.45*	.65*	.43*	.50*	.78*	.43*	.48*	10.69	41.02

Note. Variances on diagonal, correlations below diagonal. Actual (as opposed to latent) means and variances provided for Math and Literacy. Indicators were divided by constants to make their variances more homogenous, thus expediting model convergence (e.g., Muthén, 2010). For more information, see Online Technical Appendix A.

* $p < .001$.

Table 6

Estimated Growth Parameter Conditional Means and Variances

Parameter	Mean (SE)	Variance (SE)
Executive function†		
Intercept	1.299 (.07)***	0.28 (.05)***
Linear	0.91 (.07)***	0.05 (.02)*
Quadratic	-0.13 (.02)***	0.00 (FIXED)
Literacy		
Intercept	34.86 (.18)***	4.26 (.49)***
Linear	0.60 (.17)***	0.00 (FIXED)
Quadratic	0.48 (.05)***	0.05 (.01)***
Math		
Intercept	41.72 (.14)***	3.18 (.51)***
Linear	0.97 (.12)***	0.10 (.03)**
Quadratic	0.01 (.04)	0.00 (FIXED)

Note. Indicators were divided by constant values to create more homogenous indicator variances. Values in this table therefore provide meaningful information about the shape of each growth trajectory but do not describe scores in their raw metric.

†Calculated as the estimated intercept (.02) plus the conditional mean of the EF Intercept (1.299) multiplied by the regression coefficient regressing the EF Quadratic slope in the EF Intercept (-.12).

* $p < .05$; ** $p < .01$; *** $p < .001$.

Table 7

Partial Correlations Between Growth Parameters

	1.	2.	3.	4.	5.	6.
1. EF – Intercept:	1.00					
2. EF – Linear:	.82***	1.00				
3. Literacy – Intercept:	.48***	.38**	1.00			
4. Literacy – Quadratic:	.20**	.31**	.08	1.00		
5. Math – Intercept:	.81***	.82***	.49***	.25*	1.00	
6. Math – Linear:	-.40**	-.17	-.14	.12	-.53***	1.00

Note. The raw-metric regression of the EF quadratic slope on the EF intercept was $-.12$ ($p < .01$). A parallel model that relied on numerical integration provided a standardized coefficient of $-.91$. * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 8

Correlations Between Slopes, Conditional on Intercepts and Covariates

	1.	2.	3.
1. EF – Linear:	1.00		
2. Literacy – Quadratic:	.21	1.00	
3. Math – Linear:	.63**	.32**	1.00

* $p < .05$; ** $p < .01$; *** $p < .001$.

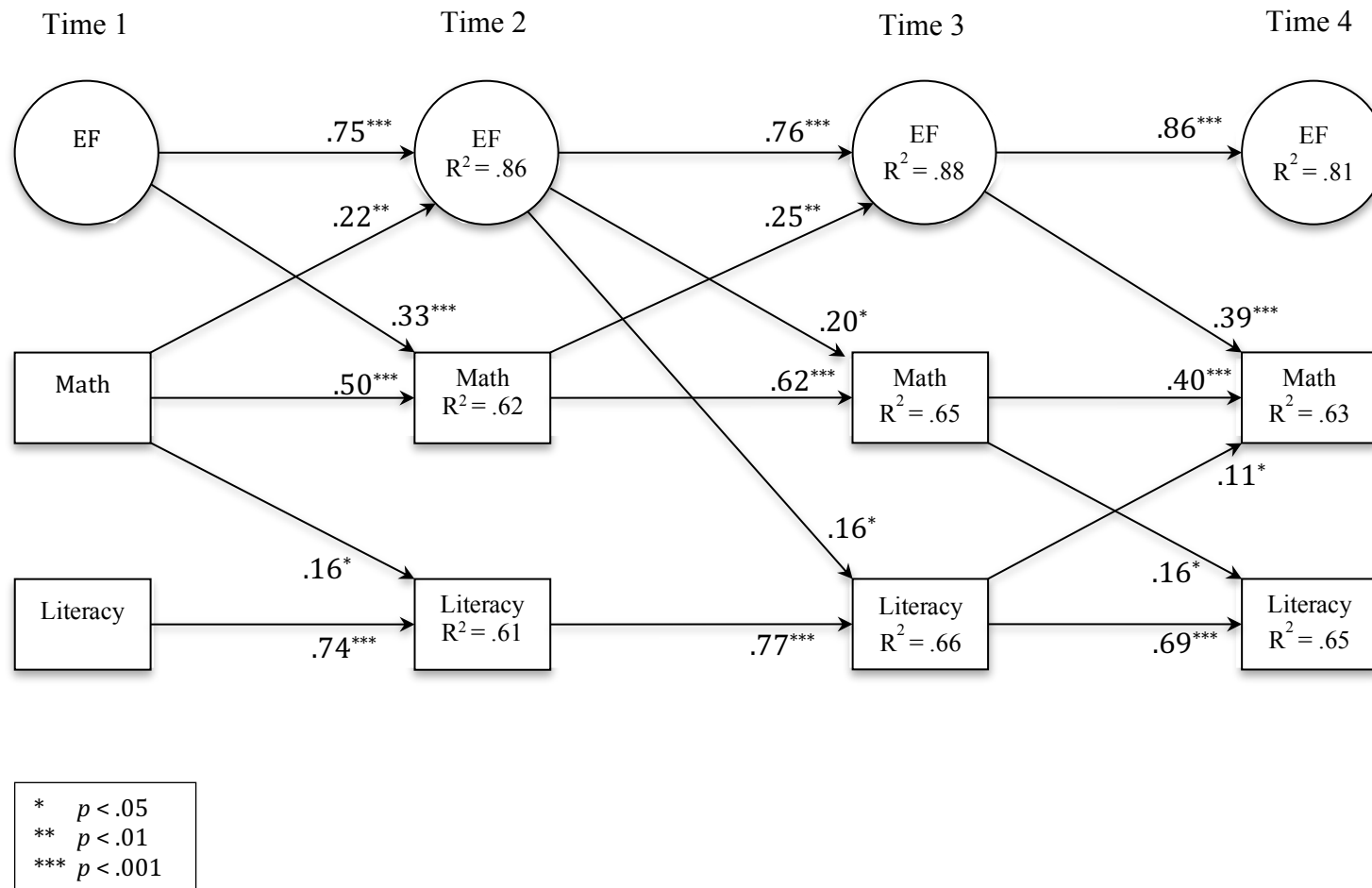


Figure 1. Path diagram for our final structural model (standardized coefficients). Within-wave covariances and nonsignificant regression paths not shown). Time 1 = fall of preschool; Time 2 = spring of preschool; Time 3 = fall of kindergarten; Time 4 = spring of kindergarten.

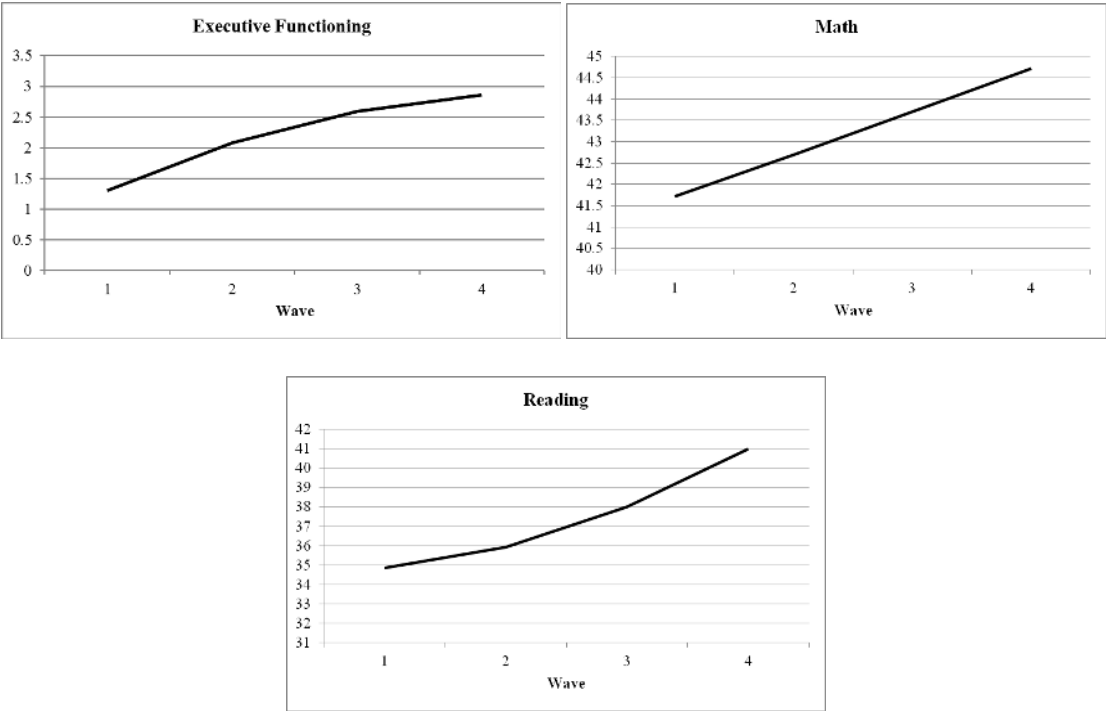


Figure 2. Average growth trajectories from the LGCM. Math and literacy scores were rescaled from original values.

Technical Appendix

Technical Appendix A: SAS Code for Dividing Items by Constants

```

DATA use; SET use;
  /*DIVIDE HTKS SUMS BY 15*/
  htk1 = sum (of htkss1_1 htkss2_1 htkss3_1)/15;
  htk2 = sum (of htkss1_2 htkss2_2 htkss3_2)/15;
  htk3 = sum (of htkss1_3 htkss2_3 htkss3_3)/15;
  htk4 = sum (of htkss1_4 htkss2_4 htkss3_4)/15;

  /*DIVIDE DCCS SUMS BY 3*/
  dccs1 = sum (of dccss1_1 dccss2_1 dccss3_1 dccss4_1)/3;
  dccs2 = sum (of dccss1_2 dccss2_2 dccss3_2 dccss4_2)/3;
  dccs3 = sum (of dccss1_3 dccss2_3 dccss3_3 dccss4_3)/3;
  dccs4 = sum (of dccss1_4 dccss2_4 dccss3_4 dccss4_4)/3;

  /*DIVIDE ALL WJ SCORES BY 10*/
  wjapw_1 = wjapw_1/10;
  wjapw_2 = wjapw_2/10;
  wjapw_3 = wjapw_3/10;
  wjapw_4 = wjapw_4/10;
  wjlww_1 = wjlww_1/10;
  wjlww_2 = wjlww_2/10;
  wjlww_3 = wjlww_3/10;
  wjlww_4 = wjlww_4/10;
  wjpvw_1 = wjpvw_1/10;
  wjpvw_2 = wjpvw_2/10;
  wjpvw_3 = wjpvw_3/10;
  wjpvw_4 = wjpvw_4/10;
  wjwmw_1 = wjwmw_1/10;
  wjwmw_2 = wjwmw_2/10;
  wjwmw_3 = wjwmw_3/10;
  wjwmw_4 = wjwmw_4/10;

  /*RECENTER AGE AT 4.5 YRS*/
  ageyrs_1 = ageyrs_1-4.5;
  ageyrs_2 = ageyrs_2-4.5;
  ageyrs_3 = ageyrs_3-4.5;
  ageyrs_4 = ageyrs_4-4.5;

  /*DROP INDIVIDUAL ITEMS, ANALYSIS AT COMPOSITE LEVEL ONLY*/
  drop htkss1_1 htkss1_2 htkss1_3 htkss1_4
        htkss2_1 htkss2_2 htkss2_3 htkss2_4
        htkss3_1 htkss3_2 htkss3_3 htkss3_4
        dccss1_1 dccss2_1 dccss3_1 dccss4_1
        dccss1_2 dccss2_2 dccss3_2 dccss4_2
        dccss1_3 dccss2_3 dccss3_3 dccss4_3
        dccss1_4 dccss2_4 dccss3_4 dccss4_4
        hstart_2 cspan_2 cspan_3 cspan_1
  ;
RUN;

```

Technical Appendix B: Additional Tables and Figures

Table B.1
Residual Correlations from Final SEM Model

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1. EF1	1.00											
2. Math1	.66***	4.01										
3. Literacy1	.45***	.40***	5.46									
4. EF2	<i>na</i>	<i>na</i>	<i>na</i>	.28								
5. Math2	<i>na</i>	<i>na</i>	<i>na</i>	.25*	1.43							
6. Literacy2	<i>na</i>	<i>na</i>	<i>na</i>	.11	.10	2.20						
7. EF3	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	.29					
8. Math3	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	.43**	1.11				
9. Literacy3	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	.05	.16**	2.43			
10. EF4	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	.40		
11. Math4	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	.13	1.01	
12. Literacy4	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>	.06	.06	3.76

Note. *na* = not estimated. Variances and residual variances on diagonal, correlations below diagonal. Squared factor loadings (therefore representing item variances) provided for Math and Literacy. Indicators were divided by constants to make their variances more homogenous, thus expediting model convergence (e.g., Muthén, 2010).

For correlations: * $p < .05$; ** $p < .01$; *** $p < .001$;

Table B.2
Comparison of BIC for final panel model and growth curve. (N = 424)

Panel Model:	30624.303
Growth Curve:	30435.914

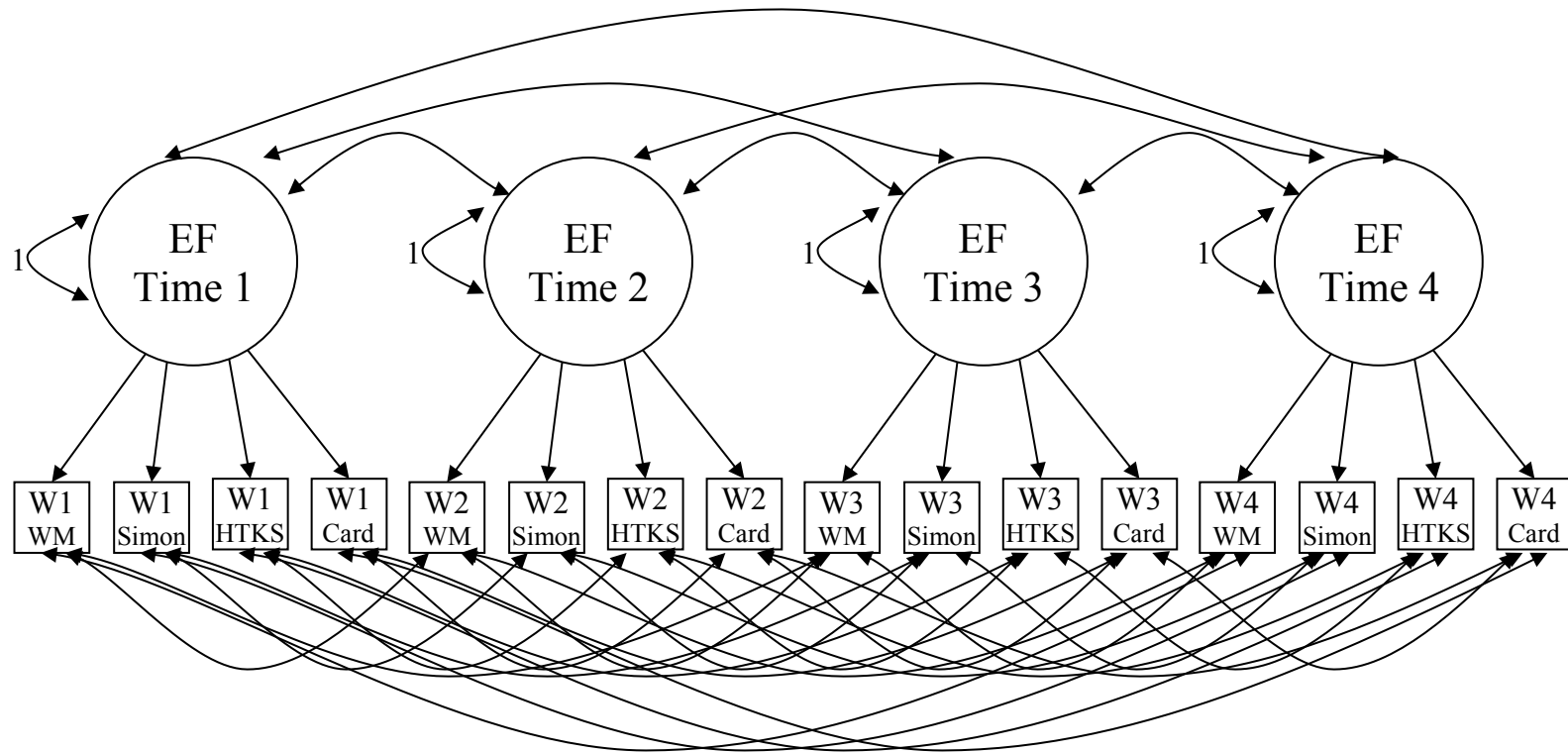


Figure B.1. Path diagram representing the EF component of the initial CFA. Mean structure and indicator residuals are omitted from the diagram, but all indicator residuals and intercepts were freely estimated. All latent means were fixed to zero. All indicators were controlled for covariates (not shown).

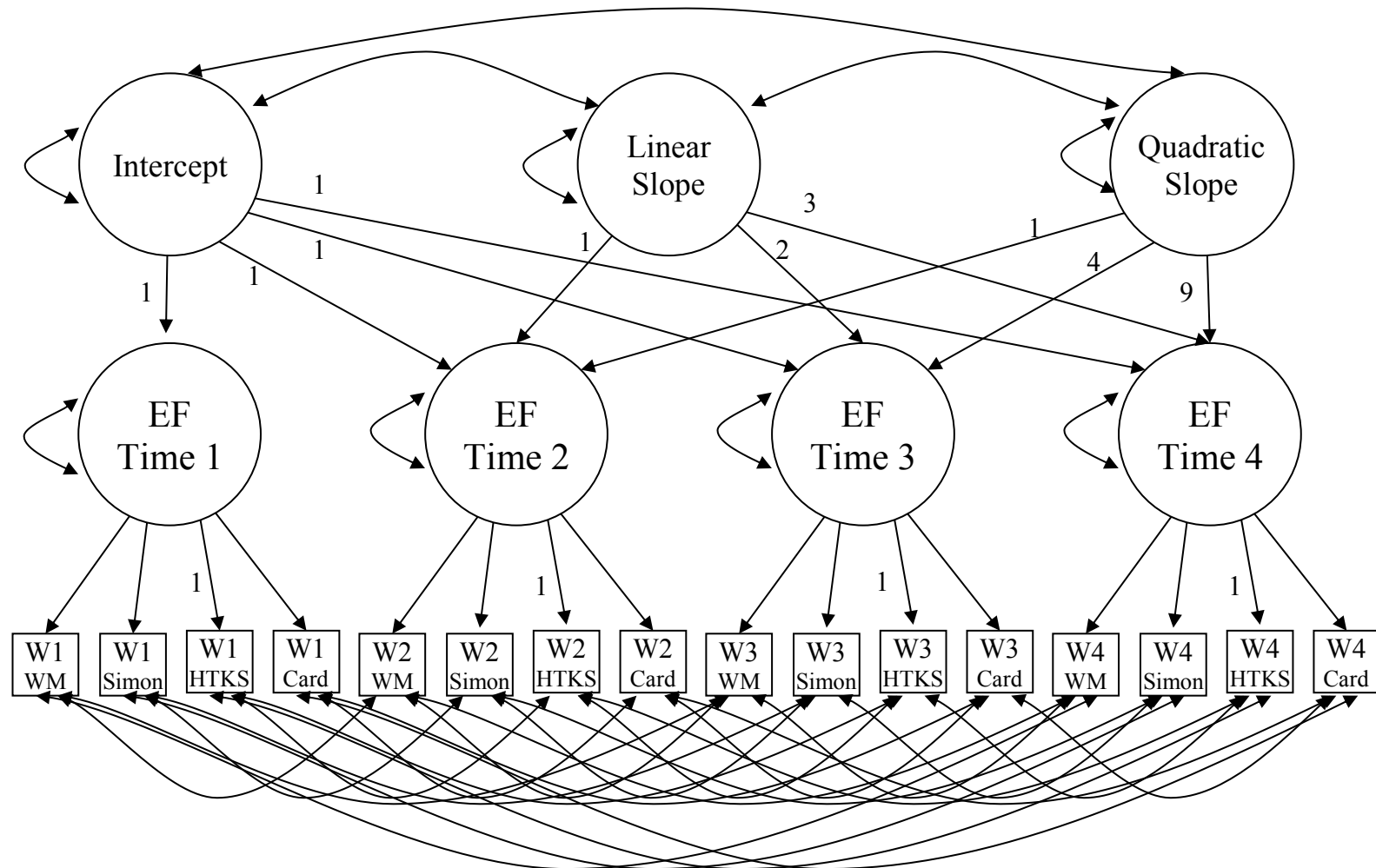


Figure B.2. Path diagram representing the EF component of the initial LGCM. Mean structure and indicator residuals are omitted from the diagram, but all indicator residuals were freely estimated, with factor loadings and indicator intercepts estimated but equated across time. HTKS served as a marker variable, with its loading fixed to 1.00 and intercept fixed to 0.00. All latent means for EF were fixed to zero and means for all growth parameters (intercept and two slopes) were freely estimated. All growth parameters were controlled for covariates (not shown).

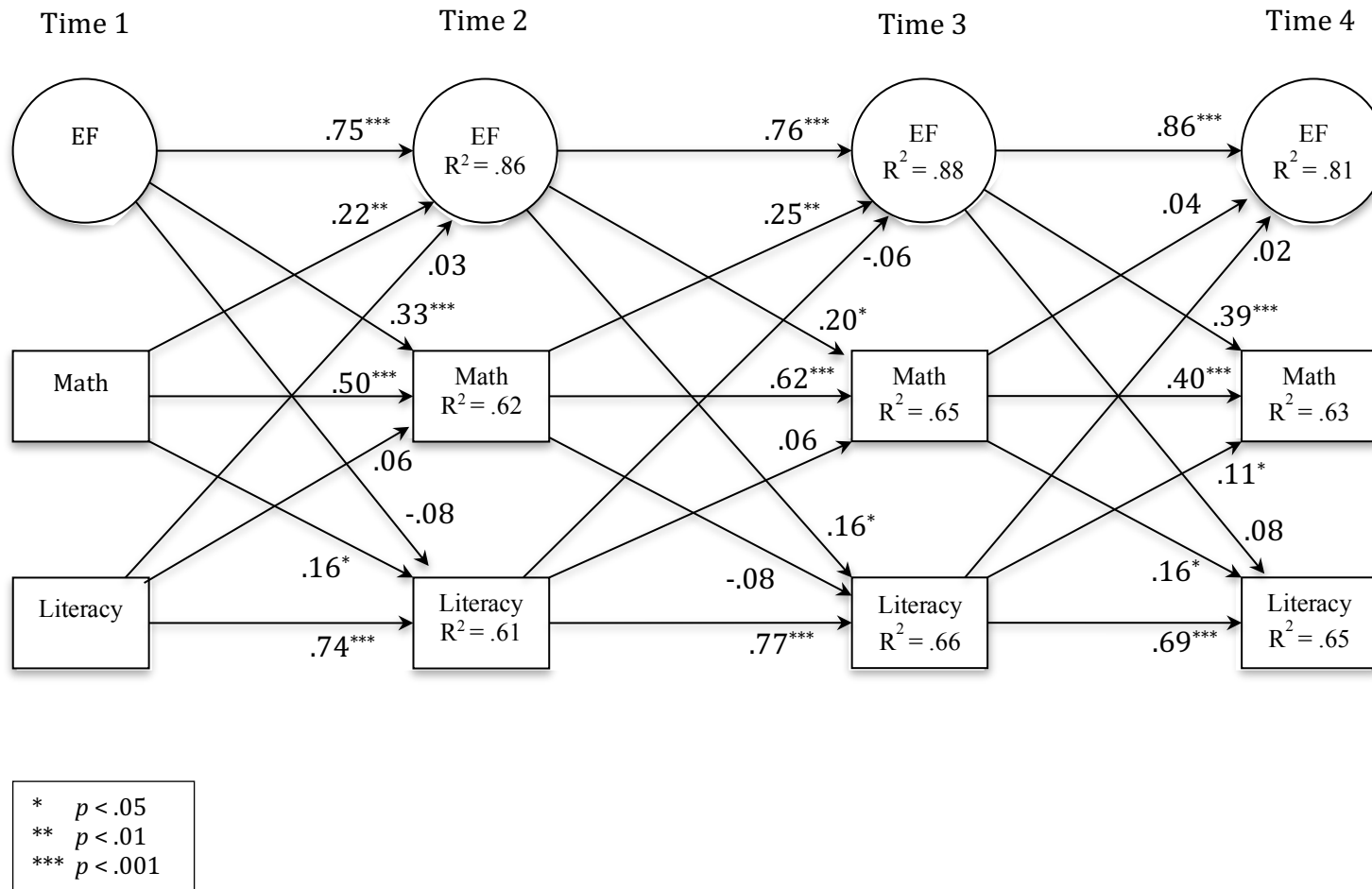


Figure B.3. Path diagram for the final structural model (standardized coefficients). Variances, residual variances, and within-wave covariances provided in Table B.1. Time 1 = fall of preschool; Time 2 = spring of preschool; Time 3 = fall of kindergarten; Time 4 = spring of kindergarten.