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THE RELATIVE IMPORTANCE OF SIX CLASSES OF SCHOOL-READINESS VARIABLES WITH ACADEMIC ACHIEVEMENT IN ELEMENTARY- SCHOOL STUDENTS: A GROWTH ANALYSIS OF THE ECLS-K:2011

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Dissertation Abstract

THE RELATIVE IMPORTANCE OF SIX CLASSES OF SCHOOL-READINESS VARIABLES WITH ACADEMIC ACHIEVEMENT IN ELEMENTARY-SCHOOL STUDENTS: A GROWTH ANALYSIS OF THE ECLS-K:2011

School readiness is a multi-variable construct that includes six classes of variables: (a) cognitive knowledge and skills, (b) social and emotional skills, (c) physical skills and health, (d) family structure and home environment, (e) access to community resources, and (e) early school experiences. The problem with school readiness is that the six classes have been studied *separately but never together*, which raises the question, what variables make children the *most ready* to succeed academically in school? Answering this question may help to address the achievement gap because differences in students' academic achievement can be linked to differences in school readiness.

This study examined the relationships between 13 school-readiness variables that were organized into six classes with students' academic achievement and growth as represented by students' reading and mathematics assessment scores over 5 years of elementary school (fall kindergarten through spring fourth grade). This study was a secondary analysis of the longitudinal data set ECLS-K:2011, a national probability sample of more than 18,000 U.S. elementary-school students, using hierarchical linear growth modeling (HLM growth modeling). Results indicated that of the six classes of variables the three with the strongest relationship to academic achievement in fall kindergarten were student's cognitive knowledge and skills, social and emotional skills, and family structure and home environment. Within these three classes, the variables with the strongest influence on reading and mathematics academic achievement in fall kindergarten as well as on academic growth in elementary school in order of importance were kindergarten teachers' ratings of students' general academic knowledge, students' working memory ability, students' socioeconomic status (SES), students' cognitive flexibility, and teachers' ratings of students' behavior.

The academic starting points as measured by reading and mathematics assessment scores in fall kindergarten and the growth rates for each variable as measured by reading and mathematics assessment points in the spring semesters of grades first through fourth are provided in this study. Implications for future research include examining the relationships between students' general academic knowledge, SES, and working memory. Implications for future practice include providing more feedback to early-childhood educators and elementary school teachers in the form of classroom observations to help them improve their teaching practice. By improving their teaching practice, early-childhood teachers can help their young students achieve greater academic success and preparedness to start elementary school, which in turn can help alleviate the school-readiness gap and ultimately the achievement gap.

This dissertation, written under the direction of the candidate's dissertation committee and approved by the members of the committee, has been presented to and accepted by the Faculty of the School of Education in partial fulfillment of the requirements for the degree of Doctor of Education. The content and research methodologies presented in this work represent the work of the candidate alone.

Kimberly Ehret Kalkbrenner May 3, 2019
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CHAPTER 1

STATEMENT OF THE PROBLEM

The achievement gap—the term used to label the large standardized test score differences between various racial, socioeconomic status, and ethnicity groups—is a long-standing issue in education that produces many complicated and negative consequences for students at the bottom test-score percentiles including reduced educational attainment, income disparities, reduced employment opportunities, and a higher likelihood of adult criminality (Kirk & Sampson, 2011; Mashburn & Pianta, 2006; Reardon, 2011; Sadowski, 2006). If we take a step back from the achievement gap it becomes obvious that children beginning elementary school are part of a *school-readiness gap* which is understood as the differences in academic and social skills among children entering kindergarten (Sadowski, 2006). Little research exists on understanding how a multitude of school-readiness variables influence students' academic starting points in kindergarten and their subsequent academic achievement in elementary school. Understanding how different variables contribute to school-readiness and academic achievement can address the achievement gap with explanations based on research. This was the main goal of this study.

The school-readiness gap is not a new educational trend. The importance of school readiness, especially for students from low-income backgrounds, was formally acknowledged in the mid-1960s by the United States federal government with the establishment of Head Start (Winter & Kelley, 2008). Head Start, the end result of research that highlighted the importance of school readiness, was designed to be a free, public, early-intervention program for children from low-income families who were at risk for developmental delays (Winter & Kelley, 2008). In the years following, similar preschool programs (e.g., High/Scope, Bank Street, Bereiter Engelmann, and many other state-funded preschool programs) were designed to address the school-readiness gaps among preschool students (Winter & Kelly, 2008). Although funding for Head Start has been inconsistent, many studies have found that Head Start students have better academic outcomes than their peers who did not participate in early-education intervention programs (Brown, 1985; Wortham, 1992).

Even though research pointed to improvements in school readiness that Head Start graduates were making, gains were not sufficient to address the ever-growing school-readiness gap among preschool students (Brown, 1985). In 1990, the National Education Goals Panel (NEGP), founded by President George H. W. Bush and 50 state governors, declared school readiness its number one goal for early-childhood education in America (Mashburn & Pianta, 2006). And, in 1991, approximately one-third of U.S. children entering school were not prepared to achieve academic success (Boyer, 1991).

Even though acknowledgement of the need for early-childhood education to prepare children for school was established decades ago, children's lack of school readiness is a problem that continues in the twenty-first century. For example, in 1999, 34% of incoming kindergarteners were not proficient in letter naming, and 2018 data from the Illinois State Board of Education reported that three out of four kindergarteners in Illinois were not ready to start school (Burke, 2018; West, Denton, & Germino-Hausken, 2000). Additionally, more than ever, Head Start is under tight scrutiny to improve facilities, provide better teacher training and evaluation, and hire high-quality teachers in an effort to improve their student's long-term academic performance

(DeParle, 2019). Even though the No Child Left Behind Act (NCLB) replaced the NEGP in 2002, education stakeholders continue to work to understand how different factors contribute to school readiness and how to best prepare children for formal schooling (Mashburn & Pianta, 2006). The unchanging need to improve school readiness shows that not enough has been done to understand it and how to help children become more "school ready."

The emphasis on school readiness by the U.S. government throughout and beyond the 20th century has been warranted, given that research suggests that the relationship between school readiness and student success is irrefutable. For example, a child's school readiness is correlated positively with future academic and social success in school (Duncan et al., 2007). Also, children who are "ready" for school when they start kindergarten tend to score higher on academic assessments, are more socially and emotionally competent throughout elementary school, and have an easier time acquiring additional academic skills, which in turn allows them to continue to achieve academic success throughout their educational careers (Britto, 2012; Duncan & Murnane, 2011; Hair, Halle, Terry-Humen, Lavelle, & Calkins, 2006). Many state politicians recognize that preparing children to succeed in school ultimately benefits economies and the work force decades later, and consequently, many preschool programs are being funded at the local level (Pérez-Peña & Rich, 2014).

Along with the positive academic and social results of school readiness, formal schooling beginning at kindergarten is more academic and rigorous than ever before, especially with the introduction of the Common Core Standards. This has raised the interest of educational practitioners, organizations, and researchers in understanding school readiness, especially because children who begin school unprepared to meet its academic requirements are more likely to struggle academically (Cannon, Jacknowitz, & Karoly, 2012; Linder, Ramey, & Zambak, 2013). Because of the extensive implications of school readiness, it is not considered a child or family issue, but an issue that society must resolve (Winter & Kelley, 2008).

Educational organizations and government agencies were prompted to advocate for building school-readiness skills in all children following the outpouring of studies and reports that demonstrated the benefits of school readiness (Winter & Kelley, 2008). Even though there is a general consensus that school readiness is vital, agencies and organizations define school readiness in various ways. For example, in 1995, the NEGP defined five dimensions of school readiness: (a) physical well-being and motor development, (b) social and emotional development, (c) approaches toward learning, (d) language development, and (e) cognition and general knowledge (Kagan, Moore, & Bredenkamp, 1995). In 2009, in another attempt at definition, the National Association for the Education of Young Children (NAEYC) broadened school readiness as a construct that extended beyond children's basic academic knowledge. For NAEYC (2009), school readiness also includes social skills, emotional readiness, physical readiness, positive attitudes toward learning, a supportive family and home environment, early school and learning experiences, and access to community resources. Further developing and defining school readiness, the *School Readiness Conceptual Framework* by the United Nations Children's Fund (UNICEF; Britto, 2012) and the American Academy of Pediatrics (AAP; American Academy of Pediatrics, 2016) also defined school readiness as multidimensional, including children's physical well-being, motor development, social and emotional development, approaches to learning, language development, cognition, and general knowledge. Head Start, the country's biggest preschool program that provides preschool to more than a million children in every U.S. state and territory, recognized school readiness as a multivariable construct and based its educational goals for all Head Start students on developing school readiness (DeParle, 2019; Office of Head Start, 2015). The Head Start Framework highlighted the specific school-readiness goals for its students as cognitive knowledge; perceptual, motor, and physical development; social and emotional development; approaches to learning; and language and literacy skills (Office of Head Start, 2015). As these various definitions from the organizations cited above show, school readiness consistently is defined as a multivariable construct, yet the specific variables that compose school readiness is inconsistent.

Definitions of school readiness similarly are diverse at the research level. Researchers agree that it is multivariate, but they do not agree on which variables best represent school readiness. For example, Meisels (1999) argued that school readiness is composed of cognitive knowledge skills such as familiarity with letters, shapes, numbers, and colors, and that these skills are made possible by social and emotional skills such as confidence, curiosity, intentionality, self-control, and effective communication and cooperation. Mashburn and Pianta (2006) suggested that limiting school readiness to children's cognitive knowledge ignores the strong influence that family relationships and early education have in developing social and emotional skills, motivation to learn, and self-regulation skills—aspects integrally important to school readiness. In their 2007 meta-analysis, Duncan et al. defined school-readiness as cognitive knowledge, attention-related skills, social and emotional skills, and behavior.

Because neither the organizations nor scholars cited above have a shared definition of school readiness, this study seeks to remedy the problem by combining the school-readiness skills and factors from the previously cited organizations and researchers to create a collective definition that could benefit organizations, researchers, and practitioners. Taking into account how these organizations and researchers have defined school readiness, this study connects similar definitions and organizes the variables into six classes, as presented in Table 1. Within each class there are specific variables. These variables are explained in more detail in Chapter III.

Table 1
Six Classes of School-Readiness Variables

1. Cognitive knowledge and skills
2. Social and emotional skills
3. Physical skills and health
4. Family structure and home environment
5. Access to community resources
6. Early school experiences

Purpose of the Study

Even though organizations such as NEGP (Kagan et al., 1995), NAEYC (2009), UNICEF (Britto, 2012), AAP (2016), and Head Start (Office of Head Start, 2015), and authors such as Meisels (1999), Mashburn and Pianta (2006), and Duncan et al. (2007) agree that school readiness is multivariable, only a few studies have examined the effects of *multiple* school-readiness variables on future student academic success. For example, the meta-analysis by Duncan et al. (2007) investigated six longitudinal data sets to examine how two classes of school-readiness variables (cognitive knowledge and social and emotional skills) predicted later student academic achievement. Duncan et al. (2007)

excluded variables of physical skills and health, family structure and home environment, access to community resources, and early school experiences. Besides Duncan et al.'s (2007) meta-analysis, the research cited in this study's literature review (Chapter II) demonstrate further that school-readiness variables usually are studied independently of one another rather than together, which ignores the fact that school readiness is multivariable.

Because no study has examined how six classes of school-readiness variables contribute to student academic success, one purpose of this study was to engage a holistic approach to school readiness by examining the relationships between all six classes of school-readiness variables and students' academic achievement. In order to achieve this goal, a secondary analysis of the data set Early Childhood Longitudinal Study 2011 (ECLS-K:2011) was completed. Using a secondary data set allowed this study to access data on six classes of school-readiness variables for more than 18,000 children over 5 years of elementary school (kindergarten through fourth grade). It also provided the data to measure academic achievement and growth in the form of student test scores in reading and mathematics for 5 years. Hierarchical linear growth modeling (HLM growth modeling) was used to determine the relationships between students' school-readiness variables as measured in kindergarten and their academic assessment scores from kindergarten, first grade, second grade, third grade, and fourth grade. HLM growth modeling, which regresses outcome measures over time onto time measurement variables, provided an intercept and slope for each student in the data set. When properly scaled, the intercept indicated the achievement starting point when students entered kindergarten and the slope indicated the rate of academic achievement (growth) during elementary school. This study related the intercepts and the slopes to school-readiness variables from the six classes.

Significance of the Study

Given the importance of school readiness as a portent for academic achievement, this study is novel in both its approach and its contribution to the current literature. First, as stated, no current study has examined the relationship between six classes of school-readiness variables to students' initial academic achievement in kindergarten and academic growth in elementary school. A comparison of school-readiness variables is essential to best educate teachers about school-readiness and also to understand the relationships between each variable and academic success. After the relative importance of each variable is determined, educational resources can be used with optimal efficiency to develop the more important school-readiness skills in students, educators can make the best decisions to prepare children for school, and students can receive the interventions that will make the biggest difference in their future academic careers.

Second, no previous school-readiness study has used such a sizable longitudinal data set as the ECLS-K:2011 to examine school readiness. This data set included data for all the explanatory and response variables needed for this study, which were (a) direct cognitive measurements (e.g., reading and mathematics assessments; executive function assessments), (b) indirect cognitive variables (e.g., social and emotional skills surveys), (c) measurements of the children's health, family structure, and home environment (e.g., socioeconomic status), (d) use of community resources (i.e., libraries, museums), and (e) previous preschool experience. By studying these variables together, this study provides a more comprehensive examination of school readiness than previously published studies, which contributes to a better understanding of how the variables relate to academic success.

Third, the ECLS-K:2011 contains data for a nationally representative sample of more than 18,000 students. Using a data set with such a large sample size to answer this study's research questions reduced sampling error (Creswell, 2012). Also, the data set created and used a sample of children representative of the general population of the United States, which helps this study's results be more generalizable to the national population (Tsang, 2014).

Finally, this study employed HLM growth modeling, which is used by education researchers interested in how academic achievement changes over time (Anderson, 2012). HLM growth modeling produces more accurate results than ordinary least squares regression because it produces a growth curve for each individual in a data set rather than obtaining mean regression parameters for all individuals (Anderson, 2012). For this study, the students' growth curves were used to evaluate how each school-readiness variable predicted their academic achievement in fall kindergarten and the rate of their academic growth from fall kindergarten through fourth grade. No other study has attempted to examine the relationships between school-readiness variables and initial kindergarten reading and mathematics assessment scores *and* school-readiness variables and academic growth in reading and mathematics in elementary school.

Theoretical Framework

If school readiness is accepted as a multivariable construct, then it is of the utmost importance that *multiple* school-readiness variables be studied together to determine their relationships with academic success. This study's holistic approach to school readiness employs the theoretical framework of Urie Bronfenbrenner's (1979) ecological systems theory, which describes how a child's personal development is influenced by *multiple* environments. School-readiness variables can be found in Bronfenbrenner's description of influencers in a child's development. Bronfenbrenner defined the ecology of human development as "the scientific study of the progressive, mutual accommodation, throughout the life span, between a growing human organism and the changing immediate environments in which it lives" (Bronfenbrenner, 1977, p. 514). In subsequent work, Bronfenbrenner added that human development is most heavily affected by people's relationships within and between different systems, which he defined as "place[s] where people can readily engage in face-to-face interaction—home, day care center[s], playground[s], and so on" (Bronfenbrenner, 1979, p. 22). Bronfenbrenner labeled these systems as the *microsystem*, *mesosystem*, *exosystem*, and *macrosystem*. The following sections will summarize each of these systems and relate them to school readiness.

The *microsystem* is "a pattern of activities, roles, and interpersonal relations experienced by the developing person in a given setting with particular physical and material characteristics" (Bronfenbrenner, 1979, p. 22). In terms of school readiness, a child's microsystem includes home, childcare, or preschool institutions, which influence cognitive and social or emotional growth. The materials and environment of a child's home and school are important not only because they provide the child with a safe, secure, and nurturing environment but also because a child's microsystem greatly influences their psychological growth (Bronfenbrenner, 1979). This study acknowledges that a child's microsystem may influence their behavior and that much of their psychological growth is influenced by the home environment and previous preschool experiences.

The *mesosystem* “comprises the interrelations among major settings containing the developing person at a particular point in his or her life” (Bronfenbrenner, 1977, p. 515). A mesosystem consists of the relationships between home, school, and community. A child is the link between home and school, the communicator between both settings, and the conduit for interaction between the two. School readiness is enhanced if a child’s family supports the transition to school (Bronfenbrenner, 1979).

Exosystem refers to “one or more settings that do not involve the developing person as an active participant, but in which events occur that affect, or are affected by, what happens in the setting containing the developing person” (Bronfenbrenner, 1979, p. 25). For a developing child, this is their local community. Bronfenbrenner (1979) hypothesized that the exosystem can be an important part of human development if resources are allocated and decisions are made to benefit children and the adults who help raise them. Additionally, the more relationships and support a community provides to a developing child, the more the child benefits. For example, when a health-care clinic serves disadvantaged families, a child’s health may be affected positively by access to health care, which may help increase school readiness. Furthermore, children who have access to playgrounds and public parks have the opportunity to exercise and spend time outdoors, which may help promote physical skills and good health.

Macrosystem refers to the consistency of specific settings observed within a culture (Bronfenbrenner, 1979). For example, all U.S. post offices operate much the same way, and the operations of two restaurants might be quite similar. This is not true for schools and educational institutions. There are many different types of schools (e.g., public, private, independent, and charter), and students attending different schools have access to different programs (e.g., athletic, academic, and technical), teachers (e.g., credentialed or not), and resources (e.g., counseling services, tutoring services, and technology). Any disparity in children's macrosystems can lead to differing levels of school-readiness skills. For example, children who attended a more academic prekindergarten program are better prepared for the academic rigors of kindergarten than children who attended home day cares (Sadowski, 2006). Furthermore, schools with a majority low-income population often perform academically lower on standardized tests compared with schools with middle- or high-income students (Duncan & Murnane, 2011), which could be attributed to what Sadowski (2006) labeled a *school-readiness gap*, or "the variations in academic performance and certain social skills among children entering kindergarten and first grade" (p. 1). In terms of Bronfenbrenner's (1979) ecological systems theory, a school-readiness gap may be the result of children with unequal macrosystems.

Using Bronfrenbrenner's (1979) ecological systems perspective as this study's theoretical framework facilitated the examination of the connection between children's school readiness and their life circumstances. Bronfenbrenner's various systems may help us better understand how to improve school readiness for various types of children based on their unique life circumstances. For example, children lacking social and emotional skills may need someone within their microsystem (e.g., a preschool teacher or daycare provider) to better support their development. Children lacking physical skills or have poor heath may need more support within their exosystem; perhaps their neighborhoods do not have safe outdoor spaces or public playgrounds to promote exercise and play. Bronfenbrenner's ecological systems perspective is another way to understand where school-readiness variables exist and how they develop within children.

Table 2 lists the six classes of school-readiness variables according to the ecological systems to better connect Bronfenbrenner's (1979) environmental systems with school readiness. This theory also provided a way in which to order the school-readiness variables from microsystem to macrosystem, which this study defines as areas of development proximal to the child (e.g., cognitive development, social and emotional skills, physical skills and health) to those more distal (e.g., family structure and home environment, access to community resources, and preschool experience). The school-readiness classes and variables are presented in the order listed in Table 2 throughout this study.

Table 2
Bronfrenbrenner's Ecological Systems and School-Readiness Variables

System	Variables
Microsystem	Cognitive knowledge and skills
	Social and emotional skills
Mesosystem	Physical skills and health
	Family structure and home environment
Exosystem	Access to community resources
Macrosystem	Early school experiences

Background and Need

The achievement gap is a decades-old educational problem (Mashburn & Pianta, 2006; Sadowski, 2006). Federal policies have attempted to address the achievement gap. For example, Lyndon Johnson's Elementary and Secondary Education Act of 1965 (ESEA), which was part of his "War on Poverty," lent about $2 million—adjusting for inflation, $16 million in 2018—to programs that sought to improve educational opportunities for underprivileged U.S. children. Head Start was one outgrowth of the ESEA and that initial funding (Diorio, 2017; Johnson, 1965). Unfortunately, Head Start did not solve the school-readiness gap, thus the achievement gap continues to be an educational problem today.

Sadowski (2006) suggested that eliminating the achievement gap starts by understanding and addressing the *school-readiness gap*: the differences in academic skills and social skills among children entering kindergarten. Therefore, school readiness and how it helps students academically succeed must be better understood. If early-education teachers (e.g., preschool, prekindergarten, and Head Start teachers) can identify students with weak school-readiness skills before kindergarten, then they can work with those students to develop school-readiness skills, thus increasing opportunities for academic achievement in elementary school and eventually work toward closing the achievement gap.

This study aimed to help address the school-readiness gap and, consequently, the achievement gap by including the six-classes of school-readiness variables and by using a large-scale sample that can generalize to the U.S. student population. The ECLS-K:2011 was used to help achieve this goal as it provided data for this study's school-readiness variables and achievement measures from a nationally representative sample of about 18,000 children from public and private schools, full-day and part-day kindergarten, and from diverse socioeconomic, language, and racial backgrounds. Succinctly, the goal of this study was to use the ECLS-K:2011 data to study multiple school-readiness variables and how they related to academic achievement and growth.

Research Questions

One purpose of this study was to understand how students' academic starting points in fall kindergarten and subsequent growth throughout elementary school were represented in the ECLS-K:2011 data set. Additionally, this study aimed to determine how six classes of school-readiness variables related to the students' starting points and growth. This study had three research questions:

1. How are the six classes of school-readiness variables related to a child's starting point in kindergarten, and what are their growth rates from kindergarten to fourth grade in reading?
2. How are the six classes of school-readiness variables related to a child's starting point in kindergarten, and what are their growth rates from kindergarten to fourth grade in mathematics?
3. How do the starting points (intercepts) and growth rates (slopes) of reading and mathematics compare?

Definitions of Terms

Below is a list of vocabulary and definitions essential to this study. The definitions have been framed to aid in understanding their applications and relevancy to this study. Many of the definitions are taken from the ECLS-K:2011 User's Manuals (Tourangeau et al., 2015, 2018).

Achievement gap is the standardized test score differences between various racial, socioeconomic status, and ethnicity groups, which starts before children enter kindergarten and continues throughout all years of school. The achievement gap has plagued the U.S. education system for decades (Mashburn & Pianta, 2006; Sadowski, 2006).

Approaches to learning, as defined by the ECLS-K:2011 User's Manual (Tourangeau et al., 2015), are a student's learning behaviors including the ability to keep belongings organized, eagerness to learn new things, ability to work independently, ability to adapt to changes in routine, persistence in completing tasks, ability to pay attention, and ability to follow classroom rules.

Cognitive knowledge refers to the direct measurement of children's knowledge using reading and mathematics assessments. In this study, cognitive knowledge is measured by the reading and mathematics assessments administered to children by ECLS administrators. The ECLS used item response theory (IRT) to place all the assessment scores on the same scale so they could be compared across years. The cognitive knowledge variables from the ECLS data set that were used in this study included students' reading and mathematics test scores from fall kindergarten, spring kindergarten, spring first grade, spring second grade, spring third grade, and spring fourth grade.

Cognitive skills are a measure of a child's executive functions, which are "interdependent processes that work together to regulate and orchestrate cognition, emotion, and behavior and that help a child to learn in the classroom" (Tourangeau et al., 2015, p. 3.15). The cognitive skills variables used in this study are the Dimensional Change Card Sort (Zelazo, 2006) which measured cognitive flexibility and the Numbers Reversed subtest of the Woodcock-Johnson III Tests of Cognitive Abilities (Woodcock, McGrew, & Mather, 2001) which measured working memory.

Community resources included programs and additional activities outside the home, such as community sports leagues, libraries, museums, concerts, zoos, and aquariums. This was measured during the fall kindergarten parent survey.

Distal refers to school-readiness variables that occur in children's surrounding environments. This includes their socioeconomic status, home language, home educational activities, use of community resources (e.g., libraries, museums), and preschool experience.

Early school experiences include a child's time in day care and various types of preschool (public, private, or Head Start). This was measured during the fall kindergarten parent survey.

Explanatory variable means independent variable. There were 13 school-readiness variables that were the explanatory variables in this study.

Family structure and home environment included the educational experiences a child had at home (e.g., singing, reading, playing games), what language the family spoke at home, and the family's socioeconomic status (SES). These variables were measured during the fall kindergarten parent survey.

Health was determined by a calculation of a child's age, weight, and height to produce a body mass index score (BMI). This determined if a child was overweight, underweight, or on track (healthy BMI). ECLS administrators used a digital scale to weigh the children and a Shorr Board to measure their height during fall kindergarten.

Physical skills were a measurement of the children's gross motor skills as determined by a question about children's coordination on the spring kindergarten parent survey.

Proximal refers to school-readiness variables that develop within the child. This includes their cognitive knowledge and abilities, their social and emotional skills and abilities, and physical health.

Response variable means dependent variable. This study used the ECLS-K:2011 reading and mathematics assessment scores from five years of elementary school (kindergarten through fourth grade) as response variables.

School-readiness variables are a combination of skills and behaviors that develop in early childhood and are essential for school success, academically and otherwise. School readiness "implies the mastery of certain basic skills or abilities that, in turn, permit a child to function successfully in a school setting, both academically and socially" (Hair et al., 2006, p. 432). This study organized school-readiness variables into six classes: (a) cognitive knowledge and skills, (b) social and emotional skills, (c) physical skills and health, (d) family structure and home environment, (e) access to community resources, and (f) early school experiences.

Social-emotional skills were measures of social competence such as self-control, interpersonal skills (social interaction), externalizing behavior problems (impulsive and overactive behaviors), and internalizing behavior problems (feelings of sadness and loneliness). These variables were measured using a survey about the children's social-emotional skills during the kindergarten parent survey and kindergarten teacher survey.

Socioeconomic status (SES) was described as a combination of the child's parent(s) or primary caregivers' education level, occupation, and household income (Tourangeau et al., 2015). The ECLS measured each child's SES during the fall kindergarten parent survey.

CHAPTER II

REVIEW OF THE LITERATURE

As stated in Chapter I, the purpose of this study was to examine the relationships between six classes of school-readiness variables and students' academic achievement in elementary school using the Early Childhood Longitudinal Study from 2011 (ECLS-K:2011). The research on school readiness reviewed in this chapter provides a better understanding of school-readiness variables' relationships to academic achievement. First, the findings of a school-readiness research review by Linder, Ramey, and Zambak (2013) are summarized. Then, the three Early Childhood Longitudinal Study (ECLS) data sets are described. Finally, school-readiness studies that used one of the ECLS data sets are reviewed and organized by Bronfenbrenner's (1979) ecological systems.

Most of the studies reviewed in this chapter used variables measured at the beginning of kindergarten to represent school readiness. This chapter includes studies from the six classes of school-readiness variables that were established in Chapter I: (a) cognitive knowledge and skills, (b) social and emotional skills, (c) physical skills and health, (d) family structure and home environment, (e) access to community resources, and (f) early school experiences. A review of school-readiness literature did not find a study that includes variables from all six classes so this chapter does not include one. Most of the studies reviewed used assessment scores after fall kindergarten to represent student academic achievement.

School Readiness Research Review

Linder et al. (2013) reviewed school-readiness research about school-readiness variables and their relationships to academic achievement published in peer-reviewed journals from 1995 to 2013. Their review organized the school-readiness variables most commonly associated with later academic success in reading and mathematics into seven categories: (a) performance on mathematical and literacy based tasks, (b) social behavior, (c) learning-related skills, (d) children's health and socioeconomic status, (e) home environment, (f) family structure and parenting, and (g) childcare experiences. Compared to the six classes used in this study, the reviewed study by Linder, et al. (2013) did not include research about children's access to community resources. The major findings of this review are presented below.

1. Children who engaged in *mathematical thinking tasks*, such as playing numerical board games or constructing complicated designs with blocks and Legos, displayed greater success in reading and mathematics during elementary, middle, and high school than students who did not. The review also found that children who engaged in *literacy tasks* that developed phonological awareness, decoding skills, awareness of print, and letter identification had higher levels of academic success in school.

2. *Social skills* may help kindergarten students perform better on first-grade academic tests. Students with low-to-average cognitive skills and average social skills performed worse on academic tests than students with average cognitive ability and higher social skills. Kindergarten students with high cognitive abilities performed the best on first-grade academic assessments, regardless of their social skills. Kindergarten students with high levels of cognitive self-control performed better on first-grade academic assessments than their peers with low levels of cognitive self-control. Children with more aggressive behaviors had a harder time completing academic tasks, which led to poorer student

achievement. Children who participated in early mathematics intervention were less likely to display negative social behaviors such as aggression and low attention span.

3. *Learning-related skills* helped children succeed academically. Kindergarteners and second-grade students who followed directions, took turns during group activities, and stayed on task had higher mathematics assessment scores than their peers without learning-related skills. Additionally, having strong learning-related skills, such as self-regulation and social competence in kindergarten, positively correlated to higher reading and mathematics test scores from kindergarten to sixth grade.

4. *Premature birth weight, poor health, male gender, and low socioeconomic status* (SES) negatively influenced school readiness. Low SES was found consistently to be most detrimental to developing school readiness: children from low-SES families were twice as likely to have difficulty with school readiness than children from middle- or high- SES families. Children from low-SES households were disadvantaged compared with children from middle- or high-SES households: children from low-SES homes scored lower on number skills, problem solving, and memory assessments. Health was found to be important: compared to girls, boys born premature were twice as likely to be less ready for formal schooling.

5. Providing children with *literacy activities at home* may promote school readiness. Children who engaged with literacy activities at home, such as reading the newspaper, and received direct literacy instruction at home, such as reading books with an adult, had higher oral-language skills, word-decoding skills, and phonological skills.

6. *Parenting style* may influence children academically. Children whose parents expected them to earn high academic grades and succeed academically scored higher on pre-

reading and pre-mathematics assessments, compared with children whose parents had no expectations for high academic grades or academic success. This review also found that parental involvement helped students with school readiness: higher parent involvement correlated to higher levels of student achievement.

7. *High-quality childcare* may help develop school readiness. This review identified seven characteristics of childcare programs that are essential to developing school readiness: encouraging student exploration; mentoring basic skills; celebrating developmental advances; rehearsing and extending new skills; protecting students from inappropriate disapproval, teasing, and punishment; communicating to students richly and responsively; and guiding and limiting student behavior.

In conclusion, the school readiness review by Linder et al. (2013) provided a comprehensive overview of variables of school readiness and their influence on reading and mathematics success, as cited in peer-reviewed journals from 1995 to 2013. The authors found seven school-readiness themes that can be likened to the six classes of school-readiness variables used for this study, as shown in Table 3.

Table 3
ECLS School-Readiness Variables of this Study Compared with School-Readiness Variables from Linder, Ramey, and Zambak (2013)

This Study	Linder, Ramey, and Zambak
• Cognitive knowledge and skills	• Learning related skills • Mathematical and literacy-based tasks
• Social and emotional skills	• Social behavior
• Physical skills and health	• Health and SES
• Family structure and home environment	• Family structure and parenting • Home environment
• Early school experiences	• Childcare experiences
• Access to community resources	• (Not included in review)

The Early Childhood Longitudinal Study Programs

The Early Childhood Longitudinal Study (ECLS) programs are conducted by the National Center for Education Statistics (NCES), part of the Institute of Education Sciences (IES) of the United States Department of Education. Two ECLS data sets are complete (ECLS-B and ECLS-K), and at the completion of this dissertation in April 2019, data from the third data set (ECLS-K:2011) kindergarten through spring fourth grade of was available for public use (Tourangeau et al., 2015, 2018).

The three ECLS programs were designed to collect data about children's early school experiences, child development, and school progress (including the six classes of school-readiness variables used in this study). The ECLS programs collected information about all variables through several methods and sources: administering assessments to the children participants directly and collecting data from the children's parents, teachers, and school staff through automated phone interviews and paper surveys. Many of the assessments and surveys are available to the public through the ECLS website (https://nces.ed.gov/ecls/index.asp). The ECLS data sets are intended for public use in studying child development and developing educational policy.

The first ECLS program called ECLS-B was the birth cohort, a nationally representative sample of about 14,000 children born in 2001. The ECLS-B collected data from parents, childcare centers, and schools about children's cognitive, social, emotional, and physical development from birth to kindergarten entry in 2006. The ECLS-B was designed to provide detailed information about children's early experiences of health, development, care, and education to policy makers, researchers, childcare providers, and parents. Studies using this ECLS-B data set are not included in this study's literature review because the ECLS-B did not collect data past the cohort's kindergarten year. Detailed information about the ECLS-B assessments and domains tested are available online (https://nces.ed.gov/ecls/birth.asp).

The second ECLS data set was the kindergarten class of 1998 (ECLS-K). This study was a nationally representative sample of about 21,000 children attending public and private schools, full-day and part-day kindergarten from diverse socioeconomic, language, and racial backgrounds. Children who qualified for special-education services were included in this study. Unlike the ECLS-B, the ECLS-K began when the children entered kindergarten in the fall of 1998 and followed the cohort until spring of eighth grade in 2007. Seven rounds of data were collected: fall of 1998 and spring of 1999 (kindergarten), fall of 1999 and spring of 2000 (first grade), spring of 2002 (third grade), spring of 2004 (fifth grade), and spring of 2007 (eighth grade).

Like the ECLS-B, data about the children's cognitive, social, emotional, and physical development were collected from home, classroom, and school environments about home educational activities, classroom curriculum, and teacher qualifications. Information was gathered directly from the children participants through cognitive assessments and from teachers, parents, families, and school administrators using phone and paper surveys. Like the ECLS-B, the ECLS-K was designed to provide comprehensive data to policymakers and researchers. Detailed information about the ECLS-K assessments and data collection procedures is available online (https://nces.ed.gov/ecls/kinderinstruments.asp). Studies using this data set are included in this dissertation.

The third ECLS was the kindergarten class of 2010–11 (ECLS-K:2011). Like the ECLS-K, this study was a nationally representative sample of about 18,000 children—attending public and private schools, full-day and part-day kindergarten—from diverse socioeconomic, language, and racial backgrounds. Children who qualified for special-education services were included in this study. This ECLS study began in fall 2010 when the children entered kindergarten. Data were collected every semester until spring 2016, when the children were in fifth grade. Because this ECLS data set includes information about all six classes of school readiness, used a large, national sample that represented elementary-school students, and was available for public use, it was used for this study.

As of April 2019, the ECLS-K:2011 data from kindergarten and grades one, two, three, and four were available to the public online (https://nces.ed.gov/ecls/ index.asp); the NCES had not released the data from fifth grade for public use. This data set contained information on the same or similar variables and from similar sources as ECLS-K using the same data collection methods: direct assessments of the children and phone and paper surveys of parents, teachers, and school administrators. Minor changes were made to update the cognitive assessments given to the children participants to reflect new school standards and curriculum. An updated ECLS allows comparisons between different generations of children, reveals effects of educational policies, and allows studies of different educational and demographic environments.

Studies Using ECLS Data Sets

Studies that used the ECLS-K or ECLS-K:2011 data sets to examine how children's school readiness measured at the beginning of kindergarten contributed to their academic success in school are reviewed in this section which is organized by the school-readiness variables reviewed in each article by school-readiness classes. The articles reviewed here used school-readiness variables as explanatory variables and academic achievement as measured by test scores as response variables. A list of the articles reviewed with their classes of variables is provided in Table 4.

Cognitive knowledge and skills

Chatterji (2006) estimated reading achievement gaps between ethnic, gender, and socioeconomic groups of young schoolchildren using the ECLS-K data set. The researcher focused on four research areas. The second area, explained below, is most relevant to this study.

Chatterji's (2006) second research area was the relationship between kindergarten entry reading achievement to first-grade reading achievement. The research questions were "To what extent do prekindergarten reading levels account for first-grade reading variance over and above sociodemographic variables? Controlling for prekindergarten reading levels (at kindergarten entry) and other child background characteristics, does a child's membership in specific subgroups still result in significant within-school reading achievement differentials at the end of first grade?" (p. 492).

Chatterji (2006) used data from the ECLS-K to answer her research questions. For her second area of focus, the explanatory variables were the kindergarten reading assessment scores from the fall and spring of kindergarten, and the response variable was the reading assessment score from spring of first grade. Data were analyzed using two-level hierarchical linear modeling. The researcher did not include children whose data were missing. Additionally, she included only children who did not repeat or skip kindergarten. The final sample size used was 2,296 children from 184 schools.

Table 4
Six Classes of School-Readiness Represented in Articles that Used ELCS Data Sets

Researcher(s)	Cognitive knowledge and skills	Social and emotional skills	Physical skills and health	Family structure and home environ.	Access to community resources	Early school experiences
Chatterji (2006)	x					
DiPerna, Lei, & Reid (2007)	x	x				
Duncan, Dowsett, Claessens, Magnuson, Huston, Klebanov…& Japel (2007)	x	x				
Georges, Brooks-Gunn, & Malone (2012)		x				
Grissmer, Grimm, Aiyer, Murrah, & Steele (2010)			x			
Hair, Halle, Terry-Humen, Lavelle, & Calkins (2006)	x	x	x			
Isaacs (2012)				x		
Magnuson, Ruhm, & Waldfogel (2007)						x
Reaney, Denton, & West (2002)					x	

Results indicated a positive correlation between fall kindergarten reading scores, which represented student cognitive knowledge at the beginning of kindergarten, and spring first-grade reading scores ($\beta = .88$). The researcher interpreted the result to mean that for every scale score point increase in kindergarten reading the first-grade scale scores increased by almost one point. She concluded that prekindergarten reading experiences are important for academic success in first-grade reading. Her results suggest that continuing efforts to improve children's literacy preparation in early childhood will likely improve reading outcomes in elementary school.

Social and emotional skills

DiPerna et al. (2007) studied the relationship between students' social and emotional skills (internalizing behaviors, externalizing behaviors, interpersonal skills, and approaches to learning) and their growth in mathematics. The authors defined *internalizing behaviors* as feelings of anxiousness and withdrawal; *externalizing behaviors* as aggressiveness, hyperactivity, and regulation of behavior; *interpersonal skills* as cooperation and assertion; and *approaches to learning* as persistence, staying on task, following teacher directions, and participating in groups (DiPerna et al., 2007). Their research question was "Are there direct relationships between young children's behaviors at the beginning of kindergarten and their growth in mathematics skills during the primary grades?" (p. 371).

They used data from the ECLS-K data set to answer their research questions. The researchers selected children who spoke English as their first language, did not repeat kindergarten, and stayed in the same school from kindergarten to third grade. The resulting sample was 6,905 children. The explanatory variables were teachers' Social

Skills Rating System (SSRS) values of their students on four behavior variables during the fall of kindergarten: interpersonal skills, externalizing behaviors, internalizing behaviors, and approaches to learning. The response variables were four mathematics assessment scores from each student: fall of kindergarten, spring of kindergarten, spring of first grade, and spring of third grade.

Data were analyzed using latent growth modeling to examine predictive relationships between children's behaviors, as measured in the fall of kindergarten, and their mathematical assessment scores in kindergarten, first grade, and third grade, controlling for age and general knowledge from fall of kindergarten. Results are presented in Table 5.

Table 5
Correlation Matrix for Cognitive Knowledge and Skills and Academic Achievement

	1	2	3	4	5	6	7	8	9
1 FKM	1.00								
2 SKM	.79	1.00							
3 S1M	.69	.75	1.00						
4 S3M	.63	.67	.74	1.00					
5 IS	.22	.22	.20	.18	1.00				
6 Ext	-.14	-.14	-.12	-.11	-.57	1.00			
7 Int	-.15	-.15	-.15	-.12	-.35	.25	1.00		
8 AL	.38	.35	.32	.30	-.70	-.50	-.35	1.00	
9 GK	.59	.54	.52	.51	.22	-.12	-.12	.32	1.00
10 Age	.27	.25	.19	.12	.08	-.03	-.06	.18	.30

Note: Abbreviation key: FKM = fall kindergarten mathematics score, SKM = spring kindergarten mathematics score, S1M = spring first-grade mathematics score, S3M = spring third-grade mathematics score, IS = interpersonal skills, Ext = externalizing behavior problems, Int = internalizing behavior problems, AL = approaches to learning, GK = general knowledge

DiPerna et al. (2007) concluded that internalizing behaviors, externalizing behaviors, and interpersonal behaviors failed to predict mathematical growth in young students. They concluded that there might be a small positive relationship between approaches to learning and mathematical growth. Their results were similar to those of previous research conducted on student behavior predicting academic achievement.

When the authors included general knowledge, however, a medium correlation was found, which was the strongest correlation, although general knowledge was not part of the authors' goals. Finally, the authors concluded that approaches to learning might represent the most important behavioral domain in promoting classroom learning. They suggested that future research be done to examine the relationship between approaches to learning and other subjects, such as mathematics and science, to learn whether it is a skill worth promoting in instructional practices.

Cognitive knowledge and skills; Social and emotional skills

The meta-analysis by Duncan et al. (2007) reviewed six longitudinal studies to estimate the relationship between three variables of school readiness and later academic achievement. The school-readiness variables were early academic achievement, attention skills, and social and emotional skills. The research question was "What is the relationship between children's early academic achievement, attention skills, and social and emotional skills [socioemotional skills] and their later academic achievement?" They answered their research question by examining six longitudinal data sets from Canada, Great Britain, and the United States, including the ECLS-K. The procedures, analysis, and results relating to the ECLS-K are summarized below.

Duncan et al. (2007) used data from 10,779 children in their study. The explanatory variables were the fall kindergarten student reading and mathematics scores, and the fall kindergarten teacher Social Skills Rating System (SSRS) values. The two assessment scores represented early student academic achievement, and the teacher SSRS values represented student attention skills and social and emotional skills. The authors separated the five SSRS subcategories into two areas: (a) approaches to learning represented a student's attention ability and (b) externalizing behaviors, internalizing behaviors, self-control, interpersonal skills represented a student's social and emotional skills. By breaking the teacher's SSRS values into two categories, the authors were able to stay with their original purpose of examining how student attention ability and student social and emotional skills are related to academic achievement.

The response variables were the students' spring of third-grade reading and mathematics scores. Data were analyzed using multiple regression. Reading and mathematics outcomes were regressed on school entry variables. Duncan et al. (2007) controlled for student socioeconomic status and gender. The study's regression results are presented in Table 6.

Table 6
Regression Results for Kindergarten Cognitive Knowledge and Skills and Social and Emotional Skills with Third-Grade Academic Achievement

	Third-Grade Achievement Test Score		Third-Grade Teacher-Rated Cognitive Knowledge	
Kindergarten	Reading	Mathematics	Reading	Mathematics
Reading	.18	.05	.15	.09
Mathematics	.27	.53	.31	.34
Attention	.04	.10	.14	.12
Externalizing	.00	.00	.00	-.01
Internalizing	.00	.00	-.01	-.02
Self-control	.01	.00	.01	.01
Interpersonal skills	.02	-.02	.01	-.01
R^2	.44	.50	.39	.32

Note: Results are regression coefficients.

Results indicated that kindergarten reading and mathematics assessments were the strongest predictors of later reading and mathematics achievement, whereas behavior and social and emotional skills were not associated with later academic achievement. Duncan et al. (2007) concluded that the reason early academic achievement appears to be the best predictor of later academic achievement might be that cognitive knowledge can be measured more accurately than behavior and social and emotional skills. Additionally, the authors posed that behavior and social and emotional skills may matter more for other school-related outcomes, such as graduation rates, than for academic test scores.

Cognitive knowledge and skills; Physical skills and health

Grissmer, Grimm, Aiyer, Murrah, and Steele's study (2010) had three objectives: "(1) provide new empirical evidence that fine motor skills, a developmental skill measured at school entry but not included in Duncan et al.'s (2007) analysis, is strongly predictive of later scores; (2) present several sensitivity analyses that extend Duncan et al.'s findings including assessing the predictive power of a child's knowledge of the world; and (3) review the developmental and neuroscience literature to assess and suggest mechanisms for a link between early motor skills and later achievement" (p. 1009). The first two objectives apply to this study and thus are examined and summarized below.

Grissmer et al. (2010) intended to expand upon the research of Duncan et al. (2007), who did not include the variables of fine and gross motor skills or general knowledge in their review of six longitudinal data sets. This study used data from 7,814 children in the ECLS-K. The explanatory variables were two measures of the children's psychomotor skills (fine-motor skills and gross-motor skills), general knowledge score, and social and emotional skills. The response variables were the children's fifth-grade mathematics, reading, and science test scores. Data were analyzed using ordinary least squares. The authors controlled family and home variables.

Similar to Duncan et al. (2007), Grissmer et al. (2010) found that early reading and mathematics scores were the best predictor of later reading and mathematics achievement scores, when compared with children's attention scores and psychomotor scores. When the authors included the kindergarten general-knowledge assessment score, results indicated it was the strongest predictor of fifth-grade reading and mathematics test scores. The results of this study are presented in Table 7.

Table 7
Regression Results for Kindergarten Cognitive Test Scores, Physical Skills, and Attention with Fifth-Grade Academic Achievement

Predictor Variables	Fifth-Grade Reading Test Score	Fifth-Grade Math Test Score	Fifth-Grade Science Test Score
Fine motor	.07	.14	.08
Gross motor	-.02	.00	-.02
Social skills	-.03	-.01	.01
Externalizing behavior	.01	-.00	.01
Internalizing behavior	.03	.02	.03
Self-control	-.01	-.04	-.02
Approaches to learning	.16	.21	.11
Reading	.08	.01	.04
Math	.20	.33	.14
General knowledge	.30	.16	.40
R^2	.55	.56	.57

Note: Results are regression coefficients.

Cognitive knowledge and skills; Social and emotional skills; Physical skills and health

The study by Hair et al. (2006) had two purposes. First, to examine how the multiple dimensions of children's school readiness function together at the start of kindergarten and second, how they collectively predict academic and social adjustment at the end of first grade" (p. 432). The multiple dimensions of school readiness included were children's cognitive, language, social and emotional skills, and health variables. For the first purpose, Hair et al. hypothesized that profiles of school readiness were present in kindergarteners, meaning that children entering kindergarten were developing well in multiple variables of school readiness or lacking in development. They hypothesized that even though school readiness varies greatly among children, children would fall into a limited set of school-readiness profiles. Research questions were not provided.

In examining how the multiple dimensions of children's school readiness function together at the start of kindergarten, Hair et al. (2006) used data from 17,219 children from the ECLS-K data set. They selected ECLS-K participants who were entering kindergarten for the first time and excluded children who repeated kindergarten. The National Education Goals Panel (Kagan et al., 1995) was used to identify school-readiness variables that were developmentally appropriate for incoming kindergarteners: physical health, social and emotional development, approaches to learning, language development, and cognitive development.

To accommodate using cluster methodology to identify school-readiness patterns, the authors rescaled the variables so that they were all on the same dichotomous scale. The authors coded the children as *conservative* or *liberal* within each variable to indicate whether or not a child had a strong representation of a particular developmental characteristic. Coding was based on ECLS-K parent reports, teacher reports, and assessment items. Cut-off points for coding were determined for each school-readiness variable. For example, a child was coded as having liberal social and emotional development if parents and teachers rated the child as having less self-control, more temper tantrums, or more hyperactivity. Likewise, a child was rated as having conservative social and emotional development if parents and teachers rated the child as having more self-control, no temper tantrums, and no hyperactivity.

Next, cluster analysis helped to identify different profiles or patterns that emerged among the children. Four school-readiness profiles were identified: comprehensive positive development; social, emotional, and health strengths; social and emotional risk; and health risk. Comprehensive positive development included children who scored above the mean on all four dimensions of school readiness, which was about 30% of the sample (*n* = 5,229) using liberal indices. Social, emotional, and health strengths included children who were about average in health and physical well-being and social and emotional well-being but were below average in the dimensions of language and cognition. This was about 34% of the sample (*n* = 5,845) using liberal indices. Social and emotional risk included children who were below average on all four dimensions of readiness and were significantly below the mean on social and emotional well being at the beginning of kindergarten, which was about 13% of the sample (*n* = 2,280) using liberal indices. Health risk included children who were distinguished by being more than one standard deviation below the mean in health and physical well-being and below the mean in language and cognition, which was about 22% of the sample (*n* = 3,865) using liberal indices.

Hair et al. (2006) concluded that four different school-readiness profiles were present in the ECLS-K sample using their cut-off points, although they acknowledged that if different cut-off points were used, different school-readiness profiles might be found. They argued, however, that because their results were similar to those of previous studies, their cut-off points were acceptable. The authors concluded that the children in two specific profiles—social and emotional risk, and health risk—were more likely to possess only limited school-readiness skills. Children in the other two profiles—comprehensive positive development and social, emotional, and health strengths—entered kindergarten with stronger school readiness skills.

Hair et al.'s (2006) second study examined how school-readiness profiles predict academic and social adjustment at the end of first grade. Since the total percentage of children in risk profiles was similar to findings from another study, the liberal indices were used to determine the school-readiness profiles. The authors hypothesized that at the end of first grade, children with the comprehensive positive development profile would perform best on academic and social measures.

Hair et al. (2006) used data from children who were not missing data of the required variables and who did not drop out of the ECLS-K study (*N* = 13,397). First, the demographics of each school-readiness profile were examined to determine if they differed based on children's background characteristics. Children from the comprehensive positive development group were found most likely to have individual and family characteristics deemed to be economically and socially advantageous. For example, children who fit this profile were more likely to be female and Caucasian and less likely to have low birth weights. They were also more likely to speak English at home and have two parents at home, smaller average household sizes, parents who were married, and parents with higher than average education levels. In contrast, children in the social, emotional, and health strengths profile group were more likely to live in a household where English was not spoken at home.

Children who fit the social- and emotional- risk profile were the least likely to live with two parents. Children from the health-risk profile were less likely to be of "normal" weight, more likely to have a limiting condition or be diagnosed with a disability, and more likely to possess poor fine and gross motor skills. When compared with the two strength profiles, children from the two risk profiles were more likely to be from economically disadvantaged families, have parents with less education, mothers who were teenagers at the time of the child's birth, and/or mothers who were unmarried at the child's birth, be male, and be born at a low birth weight.

Hair et al. (2006) also tested the extent to which school-readiness profile membership at the beginning of kindergarten predicted children's academic and social outcomes at the end of first grade. The authors controlled for background characteristics and kindergarten-year experiences. Background characteristics included individual traits such as the child's age, gender, race, premature birth weight, and disability diagnosis, but also family factors such as children with teen mothers, parents' marital status, and household SES were included. Kindergarten-year experiences included whether the child attended full-day or half-day, whether the child went to a public or private school, the number of students in the child's kindergarten class, the years of teaching experience the child's teacher had, and the education credentials and academic degrees held by the child's teacher.

The response variables of spring first-grade academic and social outcomes were regressed onto the explanatory variables of school-readiness profiles, demographic variables, and school variables. The authors chose five response variables equivalent to the five components they chose to use in their school-readiness profiles: (a) the child's general health, as measured by a parent rating, (b) the child's social and emotional development, as measured by the first-grade teacher rating of child self-control, (c) approaches to learning, as measured by teacher rating of the child's "work ethic," (d) the child's language skills, as measured by the reading assessment and (e) the child's mathematics skills, as measured by the mathematics assessment.

Regression results indicated that children from the comprehensive positive development profile performed best on three outcomes—approaches to learning, reading assessment, and mathematics assessments—even when controlling for background characteristics of the child and kindergarten experiences (presented in Table 8). This group did not outperform the comparison group on general health and social-emotional development. Children from the health risk and social-emotional risk profiles had lower effect sizes than children from the comparison group on all response variables.

Table 8
Regression Results of School-Readiness Profiles on Academic and Social Outcomes at the End of First Grade

Profile	General Health	Social and Emotional Development	Approaches to Learning	Reading Test Score	Math. Test Score
1. Comprehensive positive development profile	n/a	n/a	.21	.55	.42
2. Social, emotional, and health strengths profile	-	-	-	-	-
3. Social and emotional risk profile	-.12	-.65	-.50	-.40	-.42
4. Health risk profile	-.28	-.19	-.24	-.40	-.53
R^2	.14	.32	.29	.13	.07

Note: Profile 2 was used as reference group: effect sizes were calculated comparing first-grade child outcomes for children in this group with other profiles. Results are regression coefficients.

Based on their studies about kindergarten school readiness and first-grade outcomes, Hair et al. (2006) concluded that children from disadvantaged backgrounds are more likely to be in the “risk” school-readiness profiles in kindergarten, and children in the “risk” school-readiness profiles are more likely to underperform on first-grade academic and social measures than children who are considered more ready for school. They recommended further research to study kindergarten school readiness and subsequent effects on academic and social outcomes beyond first grade, to learn if children with “risk” profiles catch up to children who start school with a greater degree of school readiness.

Approaches to learning; Externalizing behaviors

Georges, Brooks-Gunn, and Malone (2012) investigated the relationship between children’s behavior and later academic achievement. Their three research questions were “To what extent are attention and aggressive behavior problems associated with mathematics and reading scores? Are these associations stronger than those for SES and ethnic test score gaps? To what extent is the behavior of other children associated with a child’s mathematics and reading scores?” (p. 962).

After excluding children with missing test-score data, Georges et al. (2012) used data from 14,537 children from ECLS-K. Multiple imputation was engaged to find the missing values of predictor variables. They used the ECLS-K variables from the teachers’ surveys from fall of kindergarten. The first variable, approaches toward learning, was a composite of seven survey items about students’ exhibited learning behaviors such as being organized, eagerness to learn new things, working independently, paying attention, and following classroom rules. For the second variable, the authors used the teachers’ survey responses for aggressive behavior, a composite that measured students’ frequency of fighting, anger, impulsivity, and disturbing others.

Georges et al. (2012) employed cluster analysis using the K-Means algorithm to specify groups based on the distribution of attention and aggressive behavior. They found four specific attention and aggression groups: a group with both problems (11%), a group with low attention (26%), a group with high aggression (23%), and a group with neither (40%). These groups were compared using multivariate analysis variance (MANOVA), and the results indicated specific differences for each group. For example, children categorized in the high aggressive-behavior group had higher reading and mathematics test scores than children categorized in the attention-problem group.

Estimating two models to investigate whether group membership is associated with spring kindergarten test scores, Georges et al. (2012) controlled for child characteristics such as race or ethnicity, gender, and SES. Results indicated that children in two groups—the group that scored higher on low-attention behaviors and the group that scored higher on aggressive behaviors—had lower test scores than children with high aggression (effect sizes -.18 and -.16 for mathematics, and -.20 and -.18 in reading, respectively). The authors found that for children in the group with both behavior and attention problems, their combination of high aggression and low attention had a bigger influence on their test score gaps than SES, gender, or race or ethnicity.

To answer their third research question, Georges et al. (2012) found that being in a classroom with children with aggressive behavior did not change the test scores of the other students (effect sizes -.12 for mathematics, -.13 for reading). Finally, the researchers found that children in the lower-attention group made slower gains in mathematics (effect sizes -.10 for lower-attention group, -.09 for higher misbehaviors group) and reading (effect sizes -.11 for lower-attention group, -.09 for higher misbehaviors group) than children in the aggressive-behavior group and children in the low behavior-problems group.

Georges et al. (2012) concluded that children who were categorized with behavior problems and attention problems had lower kindergarten test scores than children categorized with no behavior problems or children categorized with only aggressive behavior, thus creating a test-score gap. The results of this study suggest that children who have lower social and emotional skills survey scores may have a more difficult time learning than children who have higher on social and emotional skills survey scores. The authors suggested that helping students strengthen social and emotional skills at the start of kindergarten might help prevent school failure and prevent future aggressive behavior in society.

Home environment

Comparing children in poverty with children not in poverty, Isaacs (2012) reported on the differences in their school readiness and their later academic performance. For her article, Isaacs (2012) defined poverty as an annual income of $18,000 for a family of three or $23,000 for a family of four. Her research question was: "Why are poor children less ready for school than their non-poor peers?" (p. 2). The data from 4,300 children from the ECLS-B data set was used to answer this question. First, Isaacs (2012) classified children as "school ready" or "not school ready" based on their assessment scores on fall kindergarten reading and mathematics tests, overall health status measures taken from the fall kindergarten parent survey, and two behavioral variables from the kindergarten teacher (approaches to learning and externalizing behavior). The variables were standardized into *z* scores to compare the measures, and children were rated "school ready" as long as they did not score more than one standard deviation below the mean on any of the school-readiness measures.

Isaacs (2012) conducted a regression analysis to compare how children who were ready for school compared with children not ready for school in the areas of poverty, parents' education level, mother's overall health (smoking habits and depression), race or ethnicity, child's health, child's preschool experience, mother's parenting style, and child's cognitive stimulation at home. The results indicated a large school-readiness gap of 27 percentage points between children in poverty and children not in poverty, suggesting that poverty affects school readiness for all races or ethnicities, parent education levels, and preschool experience. Isaacs theorized that poor children suffer the negative outcomes of lack of financial resources and poor parenting skills—characterized by Isaacs as a "harsh and less supportive parenting style" (p. 5)—both of which play a large role in a child's life. The children whom Isaacs labeled "poor" and "not ready" for school had less-supportive environments at home.

As concluded by Isaacs (2012), children living in poverty are more likely to have parents with less than a high-school diploma, which may mean they are unaware of how to provide their children with academic stimulation, compared with children whose parents have more than a high school diploma. She also found that children living in poverty are more likely to have mothers who smoke, which may lead to more health concerns in the children. Isaacs' research found that programs that educate single mothers in parenting skills, programs that provide mothers with smoking cessation programs, and preschool programs for poor children may help children overcome some of poverty's obstacles and be more school ready when they begin kindergarten.

Early school experiences

Magnuson et al. (2007) investigated how prekindergarten attendance and behavior influence school readiness as measured by students' academic performance in the spring of first grade. Their three research questions summarized are (a) Does prekindergarten experience increase school readiness at kindergarten entry? (b) Do the effects persist or dissipate over time? (c) Do the results differ for children with disadvantaged backgrounds?

ECLS-K data from 10,224 children was used to answer these research questions. Children who were missing kindergarten or first-grade data and children who had moved to new schools for first grade were excluded from this study. The explanatory variable was preschool experience, and Magnuson et al. (2007) used information from the fall of kindergarten parent survey in which parents responded to questions about the student's childcare in the year prior to kindergarten. Based on the survey responses, pre-kindergarten experience included preschool (45%), prekindergarten (17%), parental care (16%), other types of nonparent care such as a nanny (12%) and Head Start (10%). The response variables, from the fall of kindergarten, were the children's reading and mathematics test scores from the ECLS-K data set, which were direct cognitive assessments of the children's reading and mathematics knowledge.

Magnuson et al. (2007) used regression to analyze the children's academic outcomes as a function of prekindergarten attendance. They controlled for child, family background, and neighborhood characteristics, which included demographic and family characteristics such as ethnicity, age, birth weight, height, weight, gender, SES, parental education, region of the country where living, family structure and size, and language spoken at home.

Results indicated that compared with other types of childcare, prekindergarten attendance predicted higher reading and mathematics scores in the fall of kindergarten. Reading scores were 1.20 points higher (effect size .12) and mathematics scores were .95 points higher (effect size .10) for prekindergarten children, which means that children who attended prekindergarten correctly answered one more assessment question than children who did not. Magnuson et al. (2007) also found that children who attended prekindergarten had more externalizing behavior problems and lower self-control in the fall of kindergarten than children who did not attend prekindergarten (effect sizes .11 and -.07, respectively).

To answer their second research question, Magnuson et al. (2007) tested to investigate if the effects of prekindergarten persisted over time. They found that in fall of first grade, the academic advantages associated with prekindergarten disappeared. The effect sizes were .03 for reading and mathematics for prekindergarten students, about one-fifth of the effect sizes in the fall of kindergarten. For their third research question, the authors tested to see if disadvantaged students (students in poverty or with a less-educated parent) had results different from those of nondisadvantaged students. Results indicated that for disadvantaged students, reading and mathematics scores were raised more by prekindergarten than by other programs. Disadvantaged children who attended prekindergarten had fall of kindergarten reading scores in the 44th percentile, whereas disadvantaged children who did not attend prekindergarten had reading scores in the 33rd percentile. The effects of prekindergarten on behavior were the same for disadvantaged students: prekindergarten children had higher levels of self-control problems and externalizing behaviors than children with no prekindergarten.

Magnuson et al.(2007) concluded that prekindergarten attendance did raise academic test scores in reading and mathematics more than nonprekindergarten programs such as preschool, Head Start, and nonparent care. The authors noted that the education levels of teachers in the prekindergarten programs was higher compared with the education levels of the teachers in other programs, so prekindergarten teachers might be better prepared to teach academics to young children. Also, because they usually are located within elementary schools, prekindergarten programs might have better access to reading and mathematics curriculum that is similar to kindergarten curriculum. Behavior problems were more prevalent in children who attended prekindergarten, possibly because teachers in those programs spend more time on direct instruction and less time correcting behavior. Also, children have less time for positive social experiences with peers and to practice self-control during unstructured playtime.

The conclusion of the study was the academic advantages of prekindergarten fade over time and that other students eventually catch up to the prekindergarten students as reading and mathematics are taught. Finally, the authors concluded that higher-quality early-childhood education programs such as prekindergarten helped raise test scores for disadvantaged children. This conclusion suggested that higher-quality early-childhood education is a good investment for public education, because it helps disadvantaged children prepare academically for kindergarten.

Access to community resources

Reaney, Denton, and West's study (2002) explored children's engagement in a wide range of experiences, both inside and outside the home, and examined the relationship between children's engagement in these activities and their reading knowledge, general knowledge, and mathematics knowledge in kindergarten. The research questions summarized were (a) What percentage of kindergarteners engage in certain home educational activities and extracurricular activities and use particular community resources? (b) Does the level of their participation differ by certain child and family characteristics? (c) Is there a relationship between kindergarteners' participation in home educational activities and extracurricular activities, their use of community resources, and their knowledge and skills? and (d) Does this relationship exist for both children not in poverty and children in poverty?

ECLS-K data from 18,934 children were used for Reaney et al.'s (2002) study. The explanatory variables were taken from the ECLS-K parent interviews from fall 1998 and spring 1999 during the children's kindergarten year. The three explanatory variables were children's engagement in home educational activities (fall interview), extracurricular activities (spring interview), and use of community resources (spring interview). Home educational activities included how often family members engaged with the child in reading, telling stories, singing to the child, doing art activities, doing chores, playing games, talking about nature, building things, and playing sports. Parents responded by indicating either (a) not at all, (b) once or twice a week, (c) three to six times a week, or (d) every day. Extracurricular activities included participation in activities outside of school, such as dance lessons, organized athletic events, organized clubs (such as Scouts), music lessons, drama classes, art lessons, organized performances (such as choirs), and craft classes. Children's use of community resources included how many times per month the child visited a library, art gallery, museum, historical site, zoo, aquarium, or farm or attended a play, concert, sporting event, or other live show. The response variables were children's spring of kindergarten reading, mathematics, and general knowledge scores from the ECLS-K data set.

Data were analyzed using linear regression, controlling for children's race and ethnicity. Two models were run for each response variable: one for children in poverty, and one for children not in poverty. (The authors did not provide a definition for "poverty" and "not in poverty.") Data were taken from fall 1998 and spring 1999 to determine if a child was considered in poverty or not; the parents responding to the survey were asked to indicate whether or not they were living in poverty. In this data set, 22% of parents responded they were "poor," whereas 78% of parents responded they were "not poor." (The authors did not provide a definition for "poor" and "not poor.") Results are summarized in Table 9.

The results indicated that for both poor and not poor children, participation in extracurricular activities related to higher reading achievement, participation in home educational activities and extracurricular activities related to higher performance in mathematics, and participation in extracurricular activities and community resources related to higher general knowledge achievement. Participation in home educational activities also related to higher general knowledge scores, though only for not poor children. Results also indicated that benefits of extracurricular activities seem to be more than twice as strong for not poor children than for poor children.

Table 9
Regression Results for Home Educational Activities, Extracurricular Activities, and Use of Community Resources with Spring Kindergarten Achievement

Activities and Resources	Reading	Mathematics	General Knowledge
Children not in poverty			
Home educational activities	.05	.08	.05
Extracurricular activities	.08	.09	.09
Access to community resources	.03	.02	.08
R^2	.04	.08	.14
Children in poverty			
Home educational activities	.05	.08	.05
Extracurricular activities	.08	.09	.09
Access to community resources	.03	.02	.08
R^2	.04	.08	.14

Note: Results are standardized regression coefficients.

Reaney et al. (2002) concluded that all children benefit from participation in home educational activities, extracurricular activities, and community resources, but the effects seem to be greater for children not living in poverty. One reason for this result may be lack of access to quality community programs or activities for children living in “poverty.” The authors suggested that future research explore how frequency, quality, and accessibility of activities influence children’s participation in activities and programs and their level of academic achievement.

Summary of Studies That Used ECLS Data Sets

The articles reviewed in this chapter used ECLS data sets to answer their research questions and to examine how various school-readiness variables are related to students’ academic achievement, as measured by assessment scores. School readiness, however, is a multivariable construct, and none of these articles looked at *all* six classes of variables to investigate which variables most influence academic success. The next paragraphs summarize the articles reviewed.

For cognitive variables, a positive correlation between kindergarten reading scores and spring first-grade reading scores was found in one study (Chatterji, 2006), and early reading and mathematics assessments were the strongest predictors of later reading and mathematics achievement in another study (Duncan et al., 2007). A third study found general knowledge to be a strong predictor of later academic achievement (Grissmer et al., 2010). Finally, children who attended prekindergarten performed better on later reading and mathematics assessments than children who participated in non-prekindergarten programs such as preschool and Head Start, or nonparent care such as home daycares (Magnuson et al., 2007).

DiPerna et al. (2007) concluded that internalizing, externalizing, and interpersonal behaviors failed to predict mathematical growth in young students, although there might be a small positive relationship between approaches to learning and mathematical growth. Similarly, Duncan et al. (2007) concluded that behavior and social and emotional skills were not associated with later academic achievement. In contrast, a study by Georges et al. (2012) found that children with low scores on attention skills surveys and higher scores on aggressive behavior surveys had lower spring kindergarten test scores compared with their peers. Grissmer et al. (2010) did not find a strong relationship between children’s fine or gross motor skills at kindergarten entry and later academic achievement.

When school-readiness variables were combined, children who were above the mean in cognitive, language, social and emotional skills, and health measurements performed better on reading and mathematics assessments than children who were below the mean in those four areas (Hair et al., 2006). Hair et al. (2006) also reported that children who were above average in one area of school readiness (cognitive skills, language skills, or social and emotional skills) tended to be above average in other areas as well, and children who were lower on social-emotional skills and had poor health did not score as well on subsequent academic assessments as children who were higher on social and emotional skills or who had no health risks.

Isaacs (2012) found that children who are not school ready are more likely to be from low-income households (labeled as "poor" in her article). She investigated the commonalities among children from poor households and found that poor children are more likely to come from single-mother homes, have parents with no more than a high school diploma, or have mothers who are depressed (as labeled by a self-administered survey), smoked, and lacked parenting skills that were characterized by Isaacs (2012) as a "harsh and less supportive parenting style" (p. 5). Children labeled as "poor" also came from households that lacked resources to provide an academically rich and supportive home environment, as defined by lack of academic activities at home to stimulate a child's cognition, such as reading books, telling stories, and singing songs (Isaacs, 2012). Reaney et al. (2002) found that all children (poor or not poor) who participated in home educational activities, extracurricular activities, and community resources had higher reading and mathematics scores compared with children who did not participate, but the effects were greater for children not living in poverty.

Unlike the reviewed school-readiness research in this chapter, which examined one or a few school-readiness variables, this study examined six classes of school-readiness variables. Like the reviewed literature, this study used an ECLS data set (ECLS-K:2011) to answer research questions. Examining how six classes of school-readiness variables related to academic achievement using the most current ECLS data set, this study presents a more complete picture of school readiness and academic achievement than previous literature. This study's model is presented in Figure 1

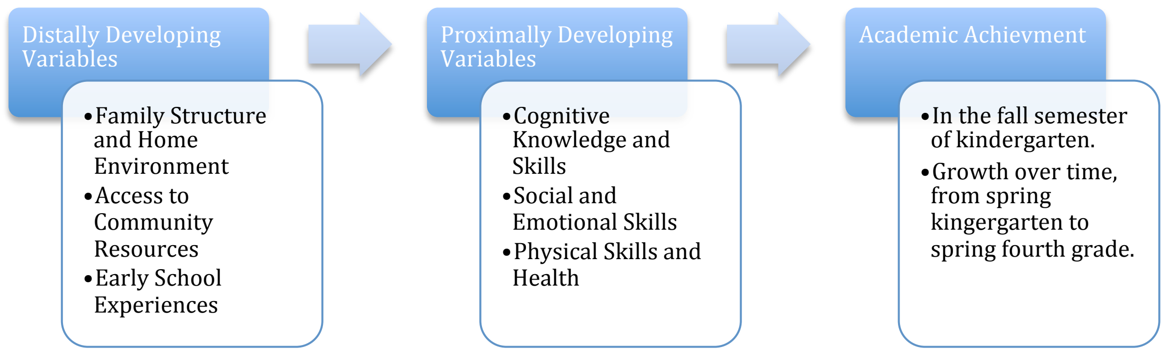

Figure 1. Study model: The six classes of school-readiness variables and their relationships to fall kindergarten achievement and academic growth in elementary school.

CHAPTER III

METHODOLOGY

The purpose of this study was to examine the relationships between six classes of school-readiness variables with students' academic achievement in reading and mathematics in elementary school. The six classes were (a) cognitive knowledge and skills, (b) social and emotional skills, (c) physical skills and health, (d) family structure and home environment, (e) access to community resources, and (e) early school experiences. To accomplish this purpose this study used hierarchical linear growth modeling (HLM growth modeling; Anderson, 2012; Heck, Thomas, & Tabata, 2014; Raudenbush & Bryk, 2002) to analyze the Early Childhood Longitudinal Study: Kindergarten Class of 2010–11 (ECLS-K:2011), a longitudinal study of more than 18,000 students, which was available online at https://nces.ed.gov/ecls/kindergarten2011.asp (Tourangeau et al., 2015, 2018). This study's research design, sample, data sources and instrumentation, data-collecting process, and how this study's variables were created and selected from the ECLS data set are explained in this chapter. Version 25 of IBM's Statistical Package for the Social Sciences (SPSS), released in 2017, was used for all data analysis.

The ECLS data set and the methodology explained in this chapter were used to answer this study's research questions, which were:

1. How are the six classes of school-readiness variables related to a child's starting point in kindergarten, and what are their growth rates from kindergarten to fourth grade in reading?

2. How are the six classes of school-readiness variables related to a child's starting point in kindergarten, and what are their growth rates from kindergarten to fourth grade in mathematics?
3. How do the starting points (intercepts) and growth rates (slopes) of reading and mathematics compare?

Research Design

This study was a secondary data analysis of the ECLS-K:2011 data set. This nationally representative data set is a longitudinal study of 18,174 children, beginning with their kindergarten year in 2010 and continuing until fifth grade in 2016. At the time of this study, data from fall kindergarten through spring fourth grade were available for public use (https://nces.ed.gov/ecls/ kindergarten2011.asp). There were more than 21,000 variables in the ECLS data set, all aimed to provide information about children's early educational experiences, including demographics and data about the children, their caregivers, teachers, principals, and schools. The children were from diverse backgrounds, public and private schools, and general- and special-education classes.

The first part of this study's methodology was selecting the explanatory and response variables from the ECLS data set. Based on a review of school-readiness definitions (summarized in Chapter I) and a review of the variables in the ECLS data set, 60 school-readiness variables were selected as explanatory variables and organized into six classes from proximally developing to distally developing based on Bronfenbrenner's (1979) ecological systems theory. Using so many variables, however, complicated the data analysis, so through a process of data reduction, to be explained later in this chapter, the number of explanatory variables was reduced to 13.

To represent the children's academic achievement in reading and mathematics, 12 ECLS assessment variables were selected as response variables (six for reading and six for mathematics) over 5 years of elementary school: fall and spring kindergarten, plus the spring semesters of first, second, third, and fourth grades. The 13 explanatory variables and 12 response variables, plus some demographic variables, time variables, and weights were saved as their own SPSS file and used as the final data set for this study.

The second part of this study's methodology addressed developing the HLM growth model to answer the study's research questions (Anderson, 2012; Heck et al., 2014; Raudenbush & Bryk, 2002). HLM growth modeling was selected because it addresses explanatory factors (school-readiness variables) affecting (a) the students' initial fall kindergarten scores in reading and mathematics and (b) student growth rates in reading and mathematics from beginning kindergarten to spring fourth grade. Including multiple school-readiness variables in the model showed how different variables influenced students' academic starting points at the beginning of kindergarten (as intercepts) and how the students' academic achievement changed over time (as slopes). Also, HLM growth modeling is used with longitudinal data and where the repeated measures can be conceptualized as nested within each student (e.g., assessment scores nested in students over 5 years). An overview of HLM is provided in the next paragraphs.

HLM growth-modeling procedures regress response variables onto time and explanatory measures. If the time variables are centered, giving them a meaningful zero point, then the intercept of the regression gives the starting achievement level and the regression coefficients for the time variables give the growth rate. The regression coefficients for the explanatory variables include the main effects, and the regressions for the interaction between the explanatory variables and the time variables indicate if there are differences in growth rates for persons at different levels of the explanatory variables.

The HLM growth model included two levels: Level 1 represented the within-students model and Level 2 represented the between-students model (Anderson, 2012). Level 1 modeled students' individual change in response scores in either reading or mathematics from fall kindergarten to spring fourth grade. Level 2 modeled the influence of the six classes of explanatory variables in school readiness scores measured during kindergarten. A more detailed explanation of the basic concepts of HLM growth modeling is provided in Appendix A.

The basic Level 1 growth model is represented by the equation

$$Y_{ti} = \pi_{0i} + \pi_{1i}a_{ti} + e_{ti}$$

where Y_{ti} is the outcome measure (reading or mathematics assessment score) at time *t* for individual *i* (*time* nested within *individuals*), π_{0i} is the intercept for the regression of the response variables onto the time variable (*t* is zero), π_{1i} is the regression coefficient representing the rate of academic growth (slope), a_{ti} is the time variable for individual *i* at time *t*, and e_{ti} is the residual (error) for individual *i* at time *t*. The intercept is a random variable and the slopes can be fixed or random variables (in this study they always are random variables).

The Level 2 model attempted to predict the variability of these random variables (the intercept and slopes) by adding explanatory variables. Level 2 is represented by

$$\pi_{0i} = \beta_{00} + r_{0i}$$

$$\pi_{1i} = \beta_{10} + r_{1i}.$$

Adding regression equations for each term in the Level 1 model (π_{0i} for the intercept and π_{1i} for the slope) produces two new outcome measures, where β_{00} is the mean intercept with r_{0i} as the residual and β_{10} is the mean growth rate with r_{1i} as the residual. When explanatory variables (represented as C1 through C6 for the six classes of school-readiness variables) are entered at Level 2, they are represented as follows:

$$\pi_{0i} = \beta_{00} + \beta_{01}(\mathrm{C1}) + \beta_{02}(\mathrm{C2}) + \beta_{03}(\mathrm{C3}) + \beta_{04}(\mathrm{C4}) + \beta_{05}(\mathrm{C5}) + \beta_{06}(\mathrm{C6}) + r_{0i}$$

$$\pi_{1i} = \beta_{10} + \beta_{11}(\mathrm{C1}) + \beta_{12}(\mathrm{C2}) + \beta_{13}(\mathrm{C3}) + \beta_{14}(\mathrm{C4}) + \beta_{15}(\mathrm{C5}) + \beta_{16}(\mathrm{C6}) + r_{1i}.$$

Now β_{00} and β_{10} represent the mean intercept and mean slope for all students adjusted for the explanatory variables. Combining the Level 1 and Level 2 equations, the final HLM growth model for this study can be represented by

$$Y_{ti} = \pi_{0i} + \pi_{1i}a_{ti} + e_{ti}$$

$$\pi_{0i} = \beta_{00} + \beta_{01}(\mathrm{C1}) + \beta_{02}(\mathrm{C2}) + \beta_{03}(\mathrm{C3}) + \beta_{04}(\mathrm{C4}) + \beta_{05}(\mathrm{C5}) + \beta_{06}(\mathrm{C6}) + r_{0i}$$

$$\pi_{1i} = \beta_{10} + \beta_{11}(\mathrm{C1}) + \beta_{12}(\mathrm{C2}) + \beta_{13}(\mathrm{C3}) + \beta_{14}(\mathrm{C4}) + \beta_{15}(\mathrm{C5}) + \beta_{16}(\mathrm{C6}) + r_{1i}.$$

Before executing this two-level model, this study attempted to determine (a) the best explanatory and response variables, (b) the best way to conceptualize time, (c) the best way to model the covariance matrix of the repeated measures, and (d) the best way to model the Level 2 covariance matrix among the intercept and growth rate parameter estimates. The procedures used to address these needs are explained later in this chapter.

Sample

The ECLS sample for this study was a large cohort of children from the United States who were studied from their kindergarten year in fall 2010 to fifth grade in spring 2016. To obtain a national probability sample, ECLS administrators used a three-stage process: (a) the United States was divided into 90 primary sampling units (PSUs) consisting of groups of counties, (b) samples of public and private schools were selected from each PSU, and (c) children were selected from each school, which created a self-weighting sample of children, with the exception of Asian Pacific Islanders (APIs), who were over sampled to meet sample-size goals. The final sample size was 18,174 children from 968 schools from general- and special-education classrooms with approximately 49% female and 51% male. This study used data from all children in the sample. The demographics of the participants are listed in Table 10.

Table 10
Demographics from Fall 2010 Kindergarteners

Characteristic	Total
U.S. census region	
Northeast	3,010
Midwest	3,870
South	6,640
West	4,660
Race or ethnicity	
Caucasian	8,508
African American	2,413
Hispanic American	4,531
Asian American	1,558
Native Hawaiian or other Pacific Islander	114
Native American	180
Other	870

Protection of Human Subjects

Students who wish to conduct research on human subjects at the University of San Francisco (USF) are required to gain approval from the USF Institutional Review Board for the Protection of Human Subjects (IRBPHS). USF guidelines, however, state "research that involves only passive observation or archival data (accessible to the public) does not require IRBPHS approval" (https://www.usfca.edu/catalog/policies/ obtaining-approval-for-research-on-human-subjects). This study did not use new information collected from human subjects and no personal identities were revealed. Because this study used a data set available publicly online for statistical uses (https://nces.ed.gov/ecls/kindergarten2011.asp) and the ECLS participants were anonymous, IRBPHS approval was not required prior to this study.

Data Sources and Instrumentation

The explanatory and response variables used in this study are outlined next. Definitions were taken from the ECLS User's Manuals (Tourangeau et al., 2015, 2018). First, the explanatory variables are described. If the variables were the same as identified in the ECLS manual, the ECLS name was used. If the original ECLS variable was changed in some way (e.g., composited or reduced) a new name was given for this study's data set. Finally, the response variables are explained.

Explanatory variables

The 60 explanatory variables that comprised the six classes of school-readiness variables are described in this section, one class at a time. The classes are presented in order of Bronfenbrenner's (1979) ecological systems theory from proximal areas of development to distal. The variables' descriptions include definitions, how the data were collected, and how the variables were changed to suit this study's needs. Tables with the variables' ECLS names and descriptive statistics are located in Appendix B.

All explanatory variables' data were collected during the fall semester of kindergarten except the variables that measured the children's coordination and use of community resources, which were measured during the spring semester of kindergarten. The word *parent* is used to designate a child's custodial caregiver, who might be the biological parent, foster parent, adoptive parent, or general caregiver. The word *child* is used interchangeably with *student* and refers to the ECLS participants.

Class 1: Cognitive knowledge and skills

This class represented two measures of the children's mental capabilities: cognitive knowledge and cognitive skills. First, the cognitive knowledge composite created from 25 variables is explained. Then, the two variables used to represent cognitive skills are described.

Cognitive knowledge referred to a child's general academic knowledge. This study used the kindergarten teachers' Academic Rating Scale (ARS) variables (listed in Table B1 in Appendix B) to represent the students' cognitive knowledge in the fall of kindergarten. The ARS, a survey of 25 questions in language arts, mathematics, and science was designed to rate the students' academic knowledge about each question on a 5-point scale ranging from "*not yet*" to "*proficient*." Teachers also had the option to answer "*not applicable*." Questions addressed typical kindergarten learning standards such as predicting what comes next in a story, using the five senses to describe the immediate environment, and sorting and classifying objects. The 25 ECLS variables, one for each question, are listed in Table 11.

Instead of using 25 variables to represent cognitive knowledge, this study created a single ARS composite for each student. First, variables that were not answered (left blank) or answered with "*not applicable*" were recoded in SPSS as missing data. That process revealed that more than 50% of the data were missing for 11 ARS variables. These 11 variables assessed more advanced kindergarten knowledge, and many teachers had chosen the "*not applicable*" response to these questions. These 11 variables were eliminated, and the remaining 14 variables, each of which had more than 50% of their data present, were retained. The variables kept included eight language arts variables, one science variable, and five mathematics variables. Table 12 lists the 14 variables kept and 11 variables eliminated.

Table 11
Academic Rating Scale (ARS) Variables

Variable Name	Variable Description
T1CMPSEN	Q1 Uses complex sentence structure
T1STORY	Q2 Interprets story read to him/her
T1LETTER	Q3 Names upper and lower case
T1PRDCT	Q4 Predicts what happens in stories
T1READS	Q5 Reads simple books independently
T1USESTR	Q6 Uses different strategies with unfamiliar words
T1WRITE	Q7 Shows early writing behaviors
T1CMPSTR	Q8 Composes simple stories
T1PRINT	Q9 Understands conventions of print
T1OBSRV	Q10 Uses senses to explore and observe
T1EXPLN	Q11 Bases explanation on observations
T1CLSSFY	Q12 Groups living and non-living things
T1SCIPRD	Q13 Logical scientific predictions
T1COMSC	Q14 Communicates science information
T1PHYSCI	Q15 Understands physical science concepts
T1LIFSCI	Q16 Understands life science concepts
T1ERSPSC	Q17 Understands early and space science
T1SORTS	Q18 Sorts math materials by criteria
T1ORDER	Q19 Orders group of objects by criteria
T1RELAT	Q20 Understands quantity relationships
T1SOLVE	Q21 Solves problems with numbers and objects
T1GRAPH	Q22 Understands graphing activities
T1MEASU	Q23 Uses instruments for measuring
T1STRAT	Q24 Uses strategies for math problems
T1FRACTN	Q25 Models, reads, and compares fractions

A principal component analysis was computed on the remaining 14 ARS variables. A single component with eigenvalues >1 was identified, with loadings ranging between .76 and .87. A single component score was generated using the SPSS Dimension Reduction module to give each student one ARS value, which was named TAcadKnow (teachers' ratings of students' general academic knowledge). The procedure that created the principal component analysis also standardized the variable. This variable was a relatively broad measure of the children's general knowledge of early-kindergarten academic skills upon kindergarten entry.

Table 12
ARS Variables Kept and Eliminated

Kept	Eliminated
T1CMPSEN	T1CMPSTR
T1STORY	T1EXPLN
T1LETTER	T1CLSSY
T1PRDCT	T1SCIPRD
T1READS	T1COMSC
T1USESTR	T1PHYSCI
T1WRITE	T1LIFSCI
T1PRINT	T1ERSPSC
T1OBSRV	T1SOLVE
T1SORTS	T1MEASU
T1ORDER	T1FRACTN
T1RELAT	
T1GRAPH	
T1STRAT	

Two variables were used to represent *cognitive skills*, which ECLS called executive functions defined as “interdependent processes that work together to regulate and orchestrate cognition, emotion, and behavior” (Tourangeau et al., 2015, p. 3.15). The ECLS measured two types of cognitive skills: cognitive flexibility and working memory.

The variable X1DCCSTOT was the students’ cognitive flexibility test score measured using the Dimensional Change Card Sort (DCCS) test by Zelazo (2006). Administrators verbally asked the children to sort 22 cards in three different ways: color of the objects, shape of the objects, and color of the cards’ borders. Each student received a total score from zero to 18. For this study, this variable was standardized and renamed ZX1DCCSTOT.

Working memory was measured through the Numbers Reversed subtest of the Woodcock-Johnson III Tests of Cognitive Ability (Woodcock, McGrew, & Mather, 2001). Administrators gave each child a series of numbers and then asked the child to reverse the order of those numbers. For example, if an assessor said “3, 4, 5,” the child was expected to respond “5, 4, 3.” The number sequences became increasingly longer, up to eight numbers, and the test ended when a child responded incorrectly to three sequences in a row. Each child had a total score between 403 and 581. This variable was unique because about 39% of the kindergarteners scored at the assessment’s lowest score possible (403). This posed a problem because having a large amount of students at the low end of the score range had the possibility to skew results of data analyses. To help remedy this, scores 404 or lower were coded as “missing.” Subsequently, the missing number of assessments was 8,942 (about 49%). This large percentage of missing scores was resolved when the data set was imputed, which is described in a later section. This variable was standardized and renamed ZX1NRWABL for this study.

In summary, three variables represented the first class of school-readiness: TAcadRating, ZX1DCCSTOT, and ZX1NRWABL. Based on an assessment of cognitive knowledge, TAcadRating represented the children’s understanding of basic kindergarten knowledge (their general knowledge). ZX1DCCSTOT and ZX1NRWABL represented the children’s cognitive skills based on two assessments of their executive functioning skills: cognitive flexibility and working memory.

Class 2: Social and emotional skills

The second class of school-readiness variables was the children’s *social and emotional skills*, which came from teachers’ and parents’ ratings of the students’ social and emotional behaviors and skills. First, the ECLS variables are described and then the composites created for this study are summarized.

In the fall of kindergarten, teachers and parents were surveyed about five categories of the students' positive and negative behaviors via questionnaires and interviews. They were asked to rate how often the child displayed certain positive and negative behaviors and skills, using a frequency scale from one (*never*) to four (*very often*). High scores indicated more presence of the behaviors. There was also an option for "*not yet observed*."

Positive behaviors included three categories: the children's approaches to learning, self-control, and social interaction. Approaches to learning represented eagerness to learn, interest in different things, creativity, persistence, concentration, and sense of responsibility. Self-control represented the children's ability to control their own behavior. Social interaction represented the children's ability to play with others, how well they maintained friendships, and how often they helped others.

Negative behaviors were organized into two categories: externalizing and internalizing. Externalizing behaviors included outward displays of emotion such as anger, arguing, fighting, impulsiveness, and disturbing others. Internalizing behaviors were emotions that existed within the children: anxiousness, loneliness, low self-esteem, and sadness.

A principal component analysis was computed on the 10 variables (five parent and five teacher). Three components were identified with eigenvalues > 1. The loadings are listed in Table 13. From these components, three composites were created for this study: TRatingSE, PRatingSE1, and PRatingSE2. This also standardized the variables.

Table 13
Principal Component Analysis Loadings for Teacher and Parent Survey Items

Composite	Category	I	II	III
TRatingSE	Self-control	**.900**	-.119	.000
	Interpersonal skills	**.874**	-.073	.116
	Approaches to learning	**.856**	-.095	.097
	External behavior problems	**-.796**	.190	.078
	Internal behavior problems	**-.426**	-.063	-.229
PRatingSE1	Social interaction	.039	-.110	**.855**
	Approaches to learning	.136	-.173	**.777**
PRatingSE2	Self-control	.111	**-.771**	.156
	Sad or lonely behaviors	.018	**.671**	-.252
	Impulsive or overactive behaviors	-.163	**.802**	.081

In summary, three variables were created to represent the children's social and emotional skills at the beginning of kindergarten: TRatingSE (ratings of positive and negative behaviors; the negative loadings of external behavior problems and internal behavior problems indicated the absence of the behaviors), PRatingSE1 (ratings of positive behaviors), and PRatingSE2 (ratings of negative behaviors).

Class 3: Physical skills and health

Two student variables represented class three: a *coordination* variable and a *body mass index* (BMI) variable. The ECLS variable P2COORD was used to represent the children's overall physical skills. During the spring kindergarten survey, parents rated their child's arm and leg coordination compared with other children the same age on a scale from one (*better than other children*) to four (*less than other children*), or declined to answer. This variable was reverse coded for this study so a score of one indicated below-average coordination and four was above-average coordination to match the pattern of the other variables in this study (lower scores represented less of a variable). This new variable was named Coord and was used as a general measure of the children's physical skills.

In the fall of kindergarten, an ECLS administrator measured the children's height and weight to calculate their BMI, a numerical representation of health. This ECLS variable was labeled X1BMI. According to the Centers for Disease Control and Prevention, an underweight BMI is less than the 5^{th} percentile, a healthy BMI is the 5^{th} to 85^{th} percentile, and an overweight BMI is 85^{th} percentile and above ("About Child and Teen BMI," 2018). It was determined that a healthy BMI for a child 5.5 years old (the mean age of the kindergarteners in the fall semester) was between 15 and 18.5. Children with BMIs 15 to 18.5 were recoded as one (healthy), and children with BMIs below 15 or above 18.5 were recoded as zero (unhealthy). This dummy variable was labeled BMIDummy and used to represent the children's overall health.

Class 4: Family structure and home environment

This class included three variables: *socioeconomic status* (SES), *home language*, and frequency parents did certain *activities at home* with the children. These variables were measured with the fall kindergarten parent survey. SES was a broad measure, defined by the User's Manual as a composite of the child's household income, parent or guardian education level, and parent or guardian occupation (Tourangeau et al., 2015). This ECLS variable (X12SESL) was standardized and relabeled ZX12SESL.

Parents were asked to identify the language spoken at home: English, another language, or English and another language used equally (bilingual households). This ECLS variable (X12LANG) was recoded to a dummy variable (0 = non-English households and 1 = English and bilingual households) and renamed LangDummy.

To measure home environment, parents indicated how often they engaged in certain activities with their children at home. Questions included, "How often do you sing songs at home?" and "How often do you read books at home?" The scale ranged from one (*not at all*) to four (*every day*), and parents also had the choice to not respond or answer "*don't know*." These 10 ECLS home activity variables are listed in Table 14.

Table 14
Home Environment Activities

Variable	Description
P1TELLST	Tell stories at home
P1SINGSO	Sing songs at home
P1HLPART	Do art at home
P1CHORES	How often child does chores
P1GAMES	Play games at home
P1NATURE	Talk about nature at home
P1BUILD	Build things at home
P1SPORT	Do sports at home
P1NUMBRS	Practice reading and writing numbers at home
P1READBK	Read books at home

A principal component analysis was computed on the 10 variables. All 10 variables loaded onto one component with loadings ranging from .50 to .61. A single component score was produced and labeled HomeEnv, which also standardized the variable.

Class 5: Access to community resources

The children's *access to community resources* was measured during the spring kindergarten parent interview. Parents responded "*yes*," "*no*," or "*don't know*" to questions asking if their child had visited certain places in their communities in the past month. Questions included "In the past month, did the child visit a museum?" and "In the past month, did the child visit a library?" The six ECLS variables for this class are listed in Table 15.

Table 15
Access to Community Resources

Variable	Description
P2LIBRAR	Visited the library
P2BKSTOR	Visited a bookstore
P2CONCRT	Went to a play, concert, or other live show
P2MUSEUM	Visited an art gallery, museum, or historical site
P2ZOO	Visited a zoo, aquarium, or petting farm
P2SPORT	Attended an athletic or sporting event as spectator

A principal component was computed for the six variables and a single component was identified with loadings ranging from .42 to .61. A single component score was created for each child, named CommRes, which also standardized the variable.

Class 6: Early school experiences

The students' *early-school experiences* measured with the fall kindergarten parent survey referred to the primary type of childcare prior to kindergarten year. This ECLS variable (X12PRIMPK) had 10 response options: (a) no non-parental care, (b) relative care in child's home, (c) relative care in another's home, (d) relative care, (e) location varies, (f) nonrelative care in child's home, (g) nonrelative care in another home, (h) nonrelative care, (i) center-based program (private preschool or public preschool, such as Head Start), or (j) two or more types of care with equal hours. Parents also had the option to not respond.

This variable was converted to a dummy variable in which zero indicated no center-based program (non-parental care, relative care in child's home, relative care in another's home, relative care, location varies, nonrelative care in child's home, nonrelative care in another home, or nonrelative care) and one indicated center-based program (private preschool or public preschool, such as Head Start). This variable was renamed CenterDummy.

Explanatory variables summary

Sixty school-readiness variables from the ECLS data set were used to create the explanatory variables for this study. First, they were organized into the six classes. Then, the variables were composited, standardized, or transformed to dummy variables when appropriate. This reduction process reduced the final explanatory variable total to 13, as presented in Table 16.

Table 16
Final 13 Explanatory Variables

Class	Variable	Description
1. Cognitive knowledge and skills	TAcadRating	Kindergarten teacher rating of general academic knowledge
	ZX1DCCSTOT	Card sort test score
	ZX1NRWABL	Working memory test score
2. Social and emotional skills	TRatingSE	Teacher rating of SE skills
	PRatingSE1	Parent rating of SE skills
	PRatingSE2	Parent rating of SE skills
3. Physical skills and health	Coord	Coordination
	BMIDummy	Overall health
4. Family structure and home environment	ZX12SESL	SES status
	LangDummy	Primary language at home
	HomeEnv	Home environment rating
5. Access to community resources	CommRes	Use of community resources
6. Early school experiences	CenterDummy	Formal preschool experience

Response variables

The 12 response variables (6 reading and 6 mathematics) for this study were ECLS students' reading and mathematics assessment scores from six different time points during the 5 years of the study: fall and spring kindergarten, and spring semesters of first, second, third, and fourth grades. ECLS supervisors visited each school site and administered assessments individually to the students. The assessments were created by the ECLS administrators and matched grade-level standards. For example, the fall kindergarten reading assessment tested students' knowledge of early alphabet and phonics, rhyming, syllables, and name writing. The fall kindergarten mathematics assessment included items about counting and recognizing numbers to 10, naming shapes, completing simple patterns, and one-digit addition and subtraction problems.

The assessments began with a routing test where all the students were asked the same questions. Based on their routing test score, the assessment continued with a set of questions appropriate to each student's demonstrated knowledge. For example, a second-grade student who demonstrated below second-grade knowledge on the mathematics routing test would continue the assessment with below second-grade-level mathematics questions. Item Response Theory (IRT), a method for modeling and equating assessment data, was used to calculate students' final assessment scores for all 12 assessments. The IRT scores placed all children on the same scale, which made it possible to compare scores across years and to compare scores even though the difficulty or ease of assessment questions was different or that different students had different test questions. IRT-based scale scores are overall measures of achievement and thus appropriate for longitudinal analyses (Tourangeau et al., 2015). The 12 assessment variables used for this study are listed in Table 17. The descriptive statistics are located in Appendix C.

Table 17
Response Variables: Reading and Mathematics Assessment Variables

Time of Testing	Reading	Mathematics
Fall kindergarten 2010	X1RSCALK4	X1MSCALK4
Spring kindergarten 2011	X2RSCALK4	X2MSCALK4
Spring first grade 2012	X4RSCALK4	X4MSCALK4
Spring second grade 2013	X6RSCALK4	X6MSCALK4
Spring third grade 2014	X7RSCALK4	X7MSCALK4
Spring fourth grade 2015	X8RSCALK4	X8MSCALK4

Data-Collection Process

The data set and study materials used for this study were available online. The public-use ECLS data set was downloaded from the National Center for Education Statistics website (https://nces.ed.gov/ecls/dataproducts.asp). IBM's computer software Statistical Package for the Social Sciences (SPSS, version 25, 2017) was used to organize the data and conduct data analyses. The ECLS User Manuals and Electronic Codebook (ECB) were available online and examined prior to this study. They provided explanations of the variables, information about the assessments used, descriptive statistics of variables, a timeline of when data were collected, and how variables were labeled. The assessments and surveys used to collect the data were downloaded from the NCES website (https://nces.ed.gov/ecls/instruments2011.asp), although some were copyrighted and not available for downloading.

Selecting the Time Variable

After the final 13 variables were determined, the next step for this study was selecting the time variable. The coding of time and determining the best functional form for the data are important steps of HLM growth modeling to avoid making false inferences or miss-specifying the model, which threatens the study's validity (Anderson, 2012). One procedure to do this is to create different ways to code time of the study (e.g., as months, semesters, or years) as time variables, and then test the different time variables to determine which ones are the best "fit" for the data's functional form. First, the different types of functional form and what types were chosen to test for this data are explained, then how the time variables were created and coded is summarized, and finally the best functional form for this data is described.

There are four commonly encountered functional forms: linear, decelerating quadratic, accelerating quadratic, and cubic (Anderson, 2012), as shown in Figure 2. With educational data, two types commonly are encountered: linear and decelerating quadratic.

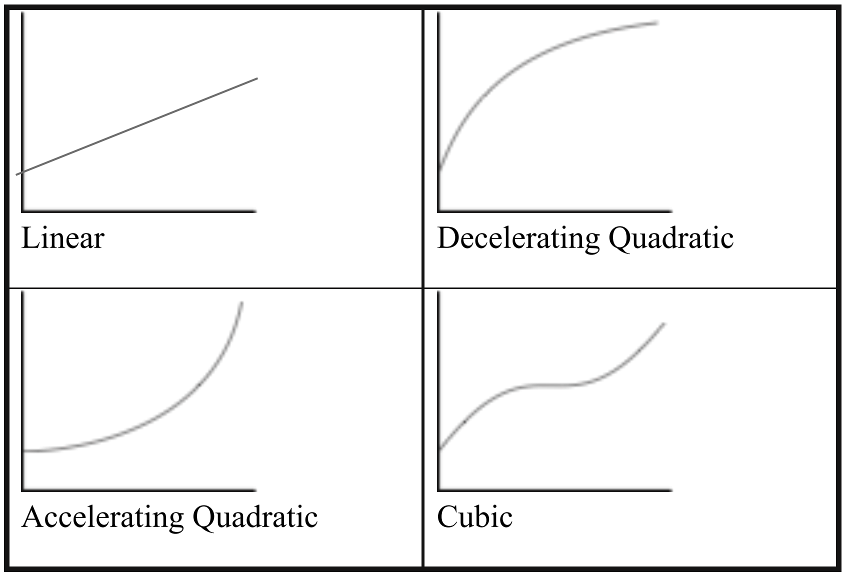

Figure 2. Four Types of Functional Form. Reprinted "Hierarchical Linear Modeling (HLM): An Introduction to Key Concepts Within Cross-Sectional and Growth Modeling Frameworks (Technical Report No. 1308)," by D. Anderson, 2012, Behavioral Research and Teaching, University of Oregon. Copyright [2012] by Daniel Anderson. Reprinted with permission.

A fifth type of functional form also was considered: a discontinuous form (called two-piece linear form; Raudenbush & Bryk, 2002; Singer & Willett, 2003). Because the students' academic growth trajectory was over 5 years of elementary school, there was reason to believe that a shift in the academic growth rates (slopes) of the students may have occurred. For example, during kindergarten and first grade, the students may have learned more rapidly than during second, third, and fourth grade. These differences in academic growth rates would be reflected in different slopes during the first half of the test scores (fall and spring kindergarten, spring first grade) and second half of the test scores (spring second, third, and fourth). An example of a discontinuous growth model is displayed in Figure 3.

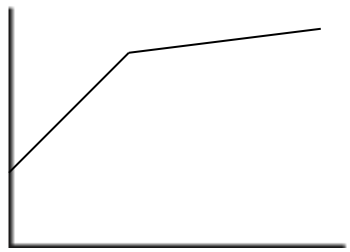

Figure 3. Example of a Discontinuous Growth Model with a Change in Slope

Singer and Willet (2003) suggested theory and reasoning guide the researcher in choosing what functional forms should be tested. Therefore, an initial investigation of the reading and mathematics data trajectories was conducted. The reading (top line) and mathematics (bottom line) mean achievement for the students across the 5 years (six time points) is presented in Figure 4.

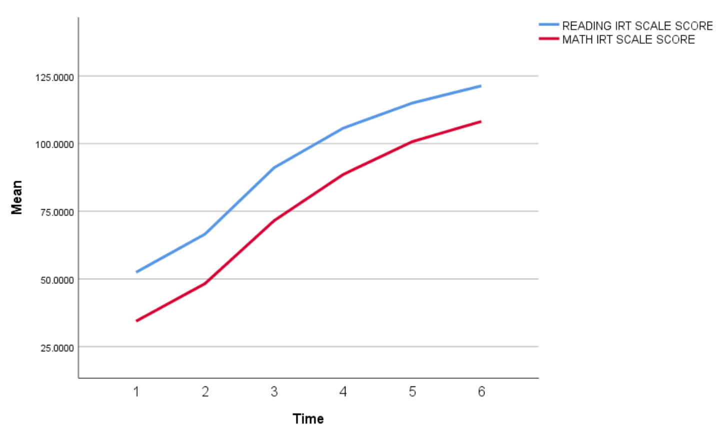

Figure 4. Data Trajectories for Reading Mean Achievement (Top Line) and Mathematics Mean Achievement (Bottom Line).

A visual inspection of line graphs of the students' achievement data revealed that two types of functional form should be tested: decelerating quadratic and, since the data trajectories appeared curvilinear, two-piece linear. Next, the process used to create and code the time variables is explained.

First, different time variables were created in order to test the two types of functional forms (quadratic and two-piece linear). Four sets of time variables were created to test the decelerating quadratic form and two time variables were created to test the two-piece functional form. The length of time for the data set was 5 years, but the time variables represented time in different ways (e.g., semesters or months) and had different starting points (e.g., at zero, or another number), which was reflected in the coding schemes.

Four time variables were created to test the decelerating quadratic form: (a) Zeroindex and Zeroindex^2, (b) ECLSTime and ECLSTime^2, (c) Test and Test^2, and (d) ZeroTime and ZeroTime^2. Notice that the second term in each pair is the square of the first, which represented the quadratic term. The coding of these four time variables is outlined below:

1. Zeroindex started with 0 as fall kindergarten semester and coded the assessments sequentially (0 = fall kindergarten, 1 = spring kindergarten, 2 = spring first grade, 3 = spring second grade, 4 = spring third grade, 5 = spring fourth grade). Zeroindex^2 was the square of Zeroindex (0 = fall kindergarten, 1 = spring kindergarten, 4 = spring first grade, 9 = spring second grade, 16 = spring third grade, 25 = spring fourth grade).
2. The ECLSTime variables were the ECLS variables of age in months of the student at the time of their testing (for each of the six assessment semesters). ECLSTime^2 was the square of each of these variables. For example, if a child was 60 months (5 years old) at fall kindergarten testing, then ECLSTime^2 was 3,600.
3. The Test time variable subtracted the mean of the students' age in months at time of testing at fall kindergarten (67.45 months) from each test time to center the time periods,

which did not standardize each test period but centered each student's intercept. Test^2 was the square of Test.

4. ZeroTime recoded the ECLS time variables of month of testing for each of the six testing semesters. These variables are listed in Table 18. ZeroTime coded the first

Table 18
Age in Months at Time of Assessment

Variable	Semester
X1ASMTMM	Fall kindergarten
X2ASMTMM	Spring kindergarten
X4ASMTMM	Spring first grade
X6ASMTMM	Spring second grade
X7ASMTMM	Spring third grade
X8ASMTMM	Spring fourth grade

month during fall kindergarten zero and continued sequentially to the end of fourth grade, which created a continuous time variable for this study. The first kindergarten test was given in July 2010 and was coded zero, August was one, September was two, and so on until the last test in July 2015. This coding is listed in Table 19. ZeroTime^2 was the square of ZeroTime. The reason this was done was because ECLS had a testing window at each time period of four to five months. The ZeroTime procedure more accurately measured time as months from the first assessment (September 2010).

Two two-piece linear time variables were created: (a) Earlytime and Latetime, and (b) Early and Late. Two-piece linear time variables were tested because the data trajectories appeared curved, which may make interpreting a single time variable difficult. The coding schemes for these two sets followed examples from Anderson (2012) and Raudenbush and Bryk (2002). The coding for these two time variables is outlined below.

1. Earlytime allowed the first three testing periods to form a linear functional form (0 =

fall kindergarten, 1 = spring kindergarten, 2 = spring first grade, 2 = spring second grade, 2 = spring third grade, 2 = spring fourth grade), whereas Latetime allowed the last three testing periods to create a linear functional form (0 = fall kindergarten, 0 = spring kindergarten, 0 = spring first grade, 1 = spring second grade, 2 = spring third grade, 3 = spring fourth grade).

Table 19
Time Variables for Zerotime and Zerotime^2

Variable	Assessment Window	Coding
Time1	Fall kindergarten	0 = September 2010
		1 = October 2010
		2 = November 2010
		3 = December 2010
Time2	Spring kindergarten	6 = March 2011
		7 = April 2011
		8 = May 2011
		9 = June 2011
		10 = July 2011
Time4	Spring first grade	18 = March 2012
		19 = April 2012
		20 = May 2012
		21 = June 2012
Time6	Spring second grade	30 = March 2013
		31 = April 2013
		32 = May 2013
		33 = June 2013
Time7	Spring third grade	42 = March 2014
		43 = April 2014
		44 = May 2014
		45 = June 2014
Time8	Spring fourth grade	54 = March 2015
		55 = April 2015
		56 = May 2015
		57 = June 2015
		58 = July 2015

2. Early and Late created a two-piece linear model. Early represented the early months of testing and Late represented the late months of testing. Because Early and Late represented the months of testing instead of semesters, it was a more specific two-piece

linear model than Earlytime and Latetime. The coding schemes for both two-piece linear time variables are displayed in Table 20.

In summary, six time variables were created to help determine the best functional form for this data set: four decelerating quadratic and two two-piece linear. The next step was to test the different time variables in the growth model and determine which ones best fit the data.

Table 20
Coding for Two-Piece Linear Time Variables

Testing Semester	Earlytime	Latetime	Early	Late
Fall K	0	0	0, 1, 2, 3	-
Spring K	1	0	6, 7, 8, 9, 10	-
Spring 1st	2	0	18, 19, 20, 21	-
Spring 2nd	2	1	-	30, 31, 32, 33
Spring 3rd	2	2	-	42, 43, 44, 45
Spring 4th	2	2	-	59, 60, 61, 62, 63

The time variables were tested using a SPSS Mixed Model module. The results included deviance statistics and fixed effects for the intercept and slope. The deviance statistic represented the lack of fit, and the lower the deviance statistic the better the data fit for the model (Anderson, 2012). Therefore, the deviance statistic was a major factor for selecting the best time variables and functional form. Additionally, quadratic regressions can be difficult to interpret so a two-piece linear form was preferred. Because the correlation coefficient for the reading and mathematics achievement scores for the six testing periods was high (.7 and higher for all correlation coefficients), only the reading achievement measure was used as the dependent variable for this testing.

The first four time variables tested were quadratic, with ZeroTime and ZeroTime^2 as the best. Next, the two-piece linear time variables were tested, with Early and Late as the best overall based on the deviance statistic. Therefore, these time variables were selected for the study. To better define what these variables represented, they were renamed EarlyGrades (fall kindergarten, spring kindergarten, and spring first grade) and LateGrades (spring semesters of second, third, and fourth grades). The fixed effects for the time variables tested are listed in Table 21. The first four variables are the quadratic, and the last two are the two-piece linear.

Table 21
Fixed Effects for Time Variables

		Fixed Effects			
Functional Form	Variables	Intercept	a	b	Deviance Statistic
Quadratic	Zeroindex $Zeroindex^2$	50.07	23.33	-1.78	815,113.73
Quadratic	ECLStime $ECLStime^2$	-174.25	4.58	-0.02	656,886.98
Quadratic	Test $Test^2$	54.65	2.21	-0.02	656,886.98
Quadratic	Zerotime $Zerotime^2$	49.89	2.48	-0.02	646,291.88
Two-piece linear	Earlytime Latetime	50.25	20.74	10.66	817,331.13
Two-piece linear	Early Late	49.66	2.15	0.52	613,543.20

Note: The slopes for the two time variables are a and b, respectively.

Selecting the Level 1 and Level 2 Covariance Structures

In HLM growth modeling, there are two covariance matrices to consider: the error structure among the six response variables (for reading and mathematics) and the Level 2 covariance matrix among the regression parameters. The Level 1 model describes the within-individual academic growth. The error term (e_{ti}) implies that there was some error (e) in measuring the students' academic growth (individual i for time t), which is unobserved (Heck et al., 2014). Because academic growth is an unobserved variable, different structures of the variance-covariance matrix can be used. Different models were tested to see which structure fit the data best. Testing different error structures was important because an incorrect assignment of the random effect (error) covariance structure might result in biased estimation, which could affect the estimation of the standard errors and the test of significance of the fixed effects (Kwok et al., 2008).

The default variance-covariance matrix in SPSS, called the scaled identity matrix, estimates a single variance (parameter) for all outcome measures (Heck et al., 2014), which means that the error structure is assumed to be the same for all individuals, with a mean of zero (i.e., no covariances between testing occasions) and a common variance σ^2 (Anderson, 2012). This error structure is written as

$$e_{ti} \sim N(0, \sigma_e^2).$$

For this study, with six testing occasions, this error structure (the same for each individual) is represented as

$$\begin{bmatrix} \sigma^2 & & & & & \\ 0 & \sigma^2 & & & & \\ 0 & 0 & \sigma^2 & & & \\ 0 & 0 & 0 & \sigma^2 & & \\ 0 & 0 & 0 & 0 & \sigma^2 & \\ 0 & 0 & 0 & 0 & 0 & \sigma^2 \end{bmatrix}.$$

This default error structure does not work well for the academic growth modeling of this study because the data are nested: six assessments for each student for six testing occasions (for reading and mathematics). Also, this error structure assigns the same within-individual residual for every testing occasion, which does not describe testing data well, because within-individual testing scores usually are correlated: more strongly when they are closer together and less strongly as time increases (Heck et al., 2014).

Instead of one error term for all individuals, at the other extreme is the unstructured covariance matrix, which estimates all 21 parameters in this study (six variances and 15 covariances for each student), which is shown in Figure 5. Along the main diagonal are the variances, with covariances in the off diagonals. The unstructured covariance matrix is the best for this study because it estimates all 21 parameters for each student, but often does not converge, and did not converge with this study's data.

$$
\begin{array}{cccccc}
\text{Fall K} & \text{Spring K} & \text{Spring 1} & \text{Spring 2} & \text{Spring 3} & \text{Spring 4} \\
\end{array}
$$

$$
\begin{bmatrix}
\sigma_1^2 & & & & & \\
\sigma_{2,1} & \sigma_2^2 & & & & \\
\sigma_{3,1} & \sigma_{3,2} & \sigma_3^2 & & & \\
\sigma_{4,1} & \sigma_{4,2} & \sigma_{4,3} & \sigma_4^2 & & \\
\sigma_{5,1} & \sigma_{5,2} & \sigma_{5,3} & \sigma_{5,4} & \sigma_5^2 & \\
\sigma_{6,1} & \sigma_{6,2} & \sigma_{6,3} & \sigma_{6,4} & \sigma_{6,5} & \sigma_6^2
\end{bmatrix}
$$

Figure 5. Unstructured error variance-covariance matrix for all individuals.

Therefore, different error structures were tested in SPSS to find the model with the lowest deviance statistic but also estimating the most parameters (variance and covariance).

A linear mixed model was calculated using SPSS with the reading assessment scores as the dependent variable, EarlyGrades and LateGrades as the random factors, and the Level 2 covariance matrix defined as unstructured. The Level 2 covariance matrix included the variances and covariances among the regression parameters, and because there are fewer parameter estimates to make, this structure is usually easier to estimate.

Like the testing of the time variables, the deviance statistic indicates a relative lack of fit, with the lowest deviance statistic indicating the best-fitting model (Anderson, 2012). Because the correlation coefficient for reading and mathematics achievement scores for the six testing periods was high (.7 and higher for all correlations), only the reading achievement measure was tested. The four different error structures were tested in SPSS and their resulting parameters and deviance statistics are listed in Table 22.

Table 22
Parameters and Deviance Statistics for Five Error Structure Models

Name of Error Structure	Number of Parameters	Deviance Statistic
Scaled Identity	10	782,595.71
Diagonal	15	780,131.68
AR(1)	11	782,102.98
ARMA(1, 1)	12	782,075.94

Even though the diagonal error structure had the lowest deviance statistic, some of the later growth models would not converge. Therefore AR(1), where all the growth models converged, was selected as the best compromise.

In summary, different types of variance-covariance matrices for the HLM growth modeling error structure were tested in SPSS with the intention of using the best-fitting error structure, which was based on lowest deviance statistic, highest number of parameters, and convergence without error. Consequently, the AR(1) error structure was the best for this data set and was selected in SPSS as the Level 1 repeated covariance type. The Level 2 error structure was unstructured.

Selecting the Weights

According to the User's Manual (Tourangeau et al., 2015), the data set "must be weighted to compensate for differential probabilities of selection at each sampling stage and to adjust for the effect nonresponse can have on the estimates" (p. 4.14). The manual also provided information about the calculation, use, and types of the 17 weights created for the data set. According to the manual, the researcher must choose the weight that best fits the study. For this study, the case weight W8C18P_8T180 was selected. The description for this weight can be found in Tourangeau et al. (2018) on page 4.30.

Unfortunately, the SPSS Mixed Model module does not allow the use of a case weight in multilevel modeling. The results of two-level analyses can give a preliminary indication of relationships but should not be relied on to provide final, unbiased estimates (Heck, 2014). For this reason, additional linear regressions were conducted with the same explanatory and response variables as the HLM growth models. The results from the linear regressions helped verify the results from the HLM growth modeling. These results are explained in Chapter IV.

Missing Data

The ECLS data set included 18,174 children (cases). Before the data were reduced, there were more than 80 variables for this study (60 explanatory variables plus response, time, and demographic variables). Because the data set was large in number of individuals and variables, there were missing data for all variables. The process used to impute the data set is explained in this section.

First, in the ECLS SPSS file, the cases that had variables marked with -9 (*not ascertained*), -1 (*not applicable*), -8 (*don't know*), or -7 (*refused*) were recoded as "missing" so that SPSS would not use those values in principal component analyses, calculations of composites, dummy variables, or averages. Depending on how ECLS administrators scored some variables and how children responded, some variables (such as the working memoryvariable) had additional special treatment so that SPSS would not miscalculate the data and results would not be specified incorrectly. Lists of missing cases for the explanatory and response variables are located in Appendix D.

A single imputation was performed to resolve all missing data using the SPSS Multiple Imputation module. All explanatory, response, and time variables were imputed and used as predictors. For categorical variables and time variables, the minimums and maximums were restricted to stay in the range of the variable. After imputation, each variable had 18,151 cases except for the working memory test (ZX1NRWABL), which had 17,752. This variable had more than 50% of its original data missing, so the imputation procedure did not impute as much data as for the other variables.

Data Analyses

The primary data analysis used in this study was HLM growth modeling. Before this could occur the 13 school-readiness variables and 12 assessment variables were finalized, the time variables were determined, the Level 1 and Level 2 covariance structures were chosen, and the data set was imputed. The large number of variables, however, posed a problem for HLM growth modeling. Because a two-piece time model was decided (EarlyGrades and LateGrades), there were three Level 1 parameters to estimate with 13 variables each, and 39 Level 2 parameters (13 times 3). Consequently, it was determined that an explanatory variable selection strategy would be implemented to reduce the number of variables even more. This process is explained in the following sections.

To help determine the explanatory variables to be used in the final growth models, a simple correlation analysis was performed between the 13 explanatory variables and the fall kindergarten and spring fourth-grade assessment scores (the first and last response variables) for reading and mathematics (Table 23). The correlation analyses provided a way to include the school-readiness variables with the strongest relationships with academic achievement in the HLM growth models, while excluding the variables with little or no relationship.

The criterion used to determine which variables were included in the final model was a .200 or higher correlation with the fall kindergarten assessment scores. Statistical significance was not used to determine if the variable was included, because the large sample size (*N* = 18,151) makes virtually all nonzero correlations statistically significant. The coefficient .200 was selected because it represented only four percent shared variance between the two variables, a relatively low percentage. The intercorrelations and correlations shown in Table 23 are summarized in the next sections.

The intercorrelations in the first class (cognitive knowledge and skills) showed that the teacher-reported academic rating scale (ARS) composite for general knowledge (TAcadRating), cognitive flexibility (ZX1DCCSTOT), and working memory (ZX1NRWABL) had weak-positive relationships. The highest correlation coefficient in this class was between general knowledge and working memory score (.311), suggesting a slight positive relationship between a child's general knowledge and their working memory ability.

The correlations between the three variables in the first class with fall kindergarten assessment scores suggested stronger relationships than the intercorrelations. There were medium-positive correlation coefficients between general knowledge and the reading and mathematics assessment scores (.576 and .556, respectively). Medium-positive correlation coefficients between working memory and the reading and mathematics assessment scores (.436 and .498, respectively) also were found. These relationships were similar to the relationship between general knowledge and working memory.

The correlations between cognitive flexibility and fall kindergarten assessment scores were weak positive (.267 for reading and .332 for mathematics). Working memory maintained a medium correlation between fourth-grade reading and mathematics

Table 23
Intercorrelations and Correlations for 13 Explanatory Variables with Fall Kindergarten and Spring Fourth Grade Assessment Scores

Class	Variable	Intercorrelations			Fall K Reading	Fall K Math	Spring 4th Reading	Spring 4th Math
		1	2	3				
1. Cognitive knowledge and skills	1 TAcadRating	1.000			.576	.556	.381	.365
	2 ZX1DCCSTOT	.243	1.000		.267	.332	.270	.304
	3 ZX1NRWABL	.311	.219	1.000	.436	.498	.403	.391
		1	2	3				
2. Social and emotional skills	1 TRatingSE	1.000			.248	.274	.255	.237
	2 PRatingSE1	.181	1.000		.175	.203	.193	.173
	3 PRatingSE2	-.247	-.280	1.000	-.111	-.133	-.141	-.125
		1	2					
3. Physical skills and health	1 Coord	1.000			.030	.082	.061	.088
	2 BMIDummy	.047	1.000		.063	.067	.061	.052
		1	2	3				
4. Family structure and home environment	1 ZX12SESL	1.000			.406	.435	.397	.390
	2 LangDummy	.256	1.000		.129	.163	.116	.080
	3 HomeEnv	.129	.221	1.000	.095	.094	.081	.066
5. Access to community resources	1 CommRes				-.124	-.124	-.122	-.102
6. Early school experiences	1 CenterDummy				.139	.136	.088	.076

Note: All correlations statistically significant.

assessment scores (.403 for reading and .391 for mathematics). This variable had the highest correlations with fourth-grade reading and mathematics assessment scores out of all 13 school-readiness variables.

The second school-readiness class examined was the students' social and emotional skills. The three variables in this class were TRatingSE (behavior), PRatingSE1 (parent rating of students' positive behaviors), and PRatingSE2 (parent rating of students' negative behaviors). PRatingSE2 had the strongest relationships with TRatingSE (-.247) and the PRatingSE1 (-.280). All of these variables had weak relationships with fall kindergarten assessment scores (correlations from -.111 to .274), suggesting a weak relationship between students' social and emotional skills and their academic achievement at the beginning of kindergarten. The correlations of these variables with fourth-grade assessments were lower (-.125 to .255). In summary, the children's social and emotional skills generally had weak relationships with academic achievement in fall kindergarten and at the end of fourth grade.

The third school-readiness class examined was physical skills and health. The two variables in this category were the parents' rating of their child's coordination (COORD) and the children's general health as assessed by their BMI (BMIDummy). These variables had a small positive correlation with each other (.047), suggesting practically no relationship between a child's coordination and BMI. These two variables also had weak relationships with the fall kindergarten reading and mathematics assessments (.030 to .082), and weak relationships with the spring fourth-grade reading and mathematics assessments (.052 to .088). These low correlations suggest that a child's coordination and BMI, two measures of physical skills and health, are not related to a child's academic achievement in fall kindergarten or at the end of fourth grade.

The fourth school-readiness class examined was family structure and home environment. The three variables in this class were the children's SES (ZX12SESL), home language (LangDummy), and home environment rating composite (HomeEnv). The highest of the three variables' intercorrelations was between SES and home language (.256). The correlations between SES and fall kindergarten reading and mathematics were the highest in this class (.406 and .435, respectively), which suggested a medium-positive relationship between SES and academic achievement at the beginning of kindergarten. The correlations for the other two variables with fall kindergarten assessments were not as strong (.095 to .129). The correlations between SES and the fourth-grade assessment scores were close to the fall kindergarten correlations: .397 for reading and .390 for mathematics. The correlations between home language and home environment with spring fourth-grade assessment scores were weak (.080 to .116).

The final two classes of school-readiness variables, access to community resources and early school experiences, had only one variable in each class: a rating of the children's use of community resources (CommRes), and a measure of the children's preschool experience (CenterDummy). Community resources had weak-negative relationship with fall kindergarten and spring fourth-grade assessment scores (-.102 to -.124, respectively). The correlations between preschool experience and fall kindergarten and spring fourth assessment scores were weak positive (.076 to .139). The correlations for both of these variables suggested weak relationships between a preschool experience and SES with academic achievement at the beginning of kindergarten and end of fourth grade.

In conclusion, among the 13 variables, general knowledge (TAcadRating) had the strongest relationship to fall kindergarten reading and mathematics assessment scores, working memory (ZX1NRWABL) was second, and SES (ZX12SESL) was third. In fourth grade, the rank order was different: working memory was first, SES was second, and general knowledge was third. Among these three variables, the change in the correlations between SES and fall kindergarten scores and SES with the fourth-grade scores was the smallest (.009 lower for reading and .063 lower for mathematics), which may suggest that SES has a more lasting relationship with a child's academic achievement in elementary school than their general knowledge and working memory.

An additional correlation analysis was performed between the 13 explanatory variables and the fall kindergarten reading and mathematics assessment scores while controlling for the children's age at kindergarten entry to learn if controlling for age made a difference in coefficients. These correlations are presented in Table 24.

Table 24
Correlations Between Explanatory Variables and Fall Kindergarten Reading and Mathematics Assessment Scores

	Control Age at K Entry	
Variable	Fall K Reading	Fall K Math
TAcadRating	.581	.563
ZX1DCCSTOT	.258	.320
ZX1NRWABL	.432	.496
TRatingSE	.251	.274
PRatingSE1	.165	.189
PRatingSE2	-.103	-.128
Coord	.020	.072
BMIDummy	.061	.070
ZX12SESL	.398	.432
LangDummy	.124	.155
HomeEnv	.090	.088
CommRes	-.120	-.124
CenterDummy	.133	.133

Note: All *Ns* are 18,151 except ZX1NRWABL (17,752).

Comparing the correlation coefficients in Table 23 with Table 24 revealed a few differences. Controlling for age at kindergarten entry made most of the correlation coefficients smaller (21 correlations). Two correlations were the same: between TRatingSE and mathematics (.274) and between CommRes and mathematics (-.124). Controlling for age resulted in slightly higher correlations for three variables: between general knowledge and reading and mathematics scores (from .576 to .581 for reading, .556 to .563 for mathematics), between TRatingSE and reading scores (from .248 to .251), and between BMI and mathematics (from .067 to .070). Out of the 21 correlations that were smaller after controlling for age, the biggest differences, though not by much, were between PRatingSE1 and fall mathematics (.014 lower) and cognitive flexibility and fall mathematics (.012 lower). In summary, the slight changes between the results seen in Table 23 and Table 24 suggested that controlling for age at kindergarten entry created slightly weaker correlations between most of the school-readiness variables and academic achievement in kindergarten, though not by much.

In conclusion, before HLM growth modeling, the data analysis for this dissertation began with a correlation analysis conducted between the 13 school readiness variables and fall kindergarten and spring fourth grade reading and mathematics assessment variables, which helped simplify the final growth models by determining which variables would be used. Using the criterion of retaining the school-readiness variables with correlations .200 and higher with fall kindergarten assessment scores, the variables included in the final growth model were general knowledge (TAcadRating), cognitive flexibility (ZX1DCCSTOT), working memory (ZX1NRWABL), behavior (TRatingSE), and SES (ZX12SESL).

Methodology Summary

This study began with more than 80 variables from the ECLS 2011 data set, including 60 school-readiness variables, 12 academic assessment variables, time variables, and demographic variables. First, the 60 school-readiness variables were categorized into six classes based on school-readiness definitions and organized according to Bronfenbrenner's (1979) ecological systems theory: (a) cognitive knowledge and skills, (b) social and emotional skills, (c) physical skills and health, (d) family structure and home environment, (e) access to community resources, and (f) early school experiences. Then, the number of variables was reduced using principal component analysis, compositing, transforming to dummy variables, and standardized. The variables were given new names to reflect the changes made to them and to distinguish them from their original ECLS variable names. The final number of school-readiness variables was 13.

The response variables were the reading and mathematics assessments from fall and spring kindergarten and from spring of first, second, third, and fourth grades, which made 12 total assessment variables (six reading and six mathematics). Unlike the explanatory variables, these variables were not changed and their ECLS names were retained. The 13 explanatory variables and 12 response variables, plus some demographic variables, time variables, and weights were saved as the final SPSS data set for this study.

All variables were imputed to resolve missing data, which brought the total number of participants to 18,151, except for the working memoryvariable (ZX1NRWABL), which had 17,752 participants. During preliminary analysis, a single time variable was considered. However, the data were found to be curvilinear so the most appropriate time variable was a two-piece linear model with the variables EarlyGrades and LateGrades. The best Level 1 error structure was determined to be AR(1), and the Level 2 error structure was unstructured. The final explanatory and response variables with their correlation matrices and descriptive statistics are listed in Appendix E.

As outlined at the beginning of this chapter, the HLM growth model for this study included two levels: Level 1 modeled the within-students academic growth and Level 2 modeled the between-students academic growth. The two-level HLM growth model equation with the six classes of explanatory variables (shown as C1 through C6) and time variables was

$$\Upsilon_{ti} = \pi_{0i} + \pi_{1i} EarlyGrades + \pi_{2i} LateGrades + e_{ti}$$

$$\pi_{0i} = \beta_{00} + \beta_{01}(\text{C1}) + \beta_{02}(\text{C2}) + \beta_{03}(\text{C3}) + \beta_{04}(\text{C4}) + \beta_{05}(\text{C5}) + \beta_{06}(\text{C6}) + r_{0i}$$

$$\pi_{1i} = \beta_{10} + \beta_{11}(\text{C1}) + \beta_{12}(\text{C2}) + \beta_{13}(\text{C3}) + \beta_{14}(\text{C4}) + \beta_{15}(\text{C5}) + \beta_{16}(\text{C6}) + r_{1i}$$

$$\pi_{2i} = \beta_{20} + \beta_{21}(\text{C1}) + \beta_{22}(\text{C2}) + \beta_{23}(\text{C3}) + \beta_{24}(\text{C4}) + \beta_{25}(\text{C5}) + \beta_{26}(\text{C6}) + r_{2i}.$$

Because a two-piece linear time variable was selected, the equation had a slope for EarlyGrades (π_{1i}) and a slope for LateGrades (π_{2i}).

Even after reducing the final variable count to 13 explanatory variables and 12 response variables, there were still too many variables for the two-level HLM growth model. Therefore, a simple correlation analysis was performed between the 13 explanatory variables and fall kindergarten assessment scores and spring fourth grade assessment scores to determine which variables had the strongest relationships to academic achievement at the start of kindergarten and at the end of fourth grade. These results showed five school-readiness variables with correlations above .200 with the fall kindergarten assessments: general knowledge (TAcadRating), cognitive flexibility

(ZX1DCCSTOT), working memory (ZX1NRWABL), behavior (TRatingSE), and SES (ZX12SESL). Ultimately, these five variables were selected to be the explanatory variables in the two-level HLM growth models.

Because five explanatory variables were ultimately chosen, the final model equation was

$$\Upsilon_{ti} = \pi_{0i} + \pi_{1i} EarlyGrades + \pi_{2i} LateGrades + e_{ti}$$

$$\pi_{0i} = \beta_{00} + \beta_{01}(\text{TAcadRating}) + \beta_{02}(\text{ZX1DCCSTOT}) + \beta_{03}(\text{ZX1NRWABL})$$
$$+ \beta_{04}(\text{TRatingSE}) + \beta_{05}(\text{ZX1SESL}) + r_{0i}$$

$$\pi_{1i} = \beta_{10} + \beta_{11}(\text{TAcadRating}) + \beta_{12}(\text{ZX1DCCSTOT}) + \beta_{13}(\text{ZX1NRWABL})$$
$$+ \beta_{14}(\text{TRatingSE}) + \beta_{15}(\text{ZX1SESL}) + r_{1i}$$

$$\pi_{2i} = \beta_{20} + \beta_{21}(\text{TAcadRating}) + \beta_{22}(\text{ZX1DCCSTOT}) + \beta_{23}(\text{ZX1NRWABL})$$
$$+ \beta_{24}(\text{TRatingSE}) + \beta_{25}(\text{ZX1SESL}) + r_{2i}.$$

The correct time variables, error structures, five school-readiness variables, and assessment variables were entered into the SPSS Mixed Models module to conduct the HLM growth modeling. The results of this study's three research questions, plus the results of additional analyses, are presented in Chapter IV.

CHAPTER IV

RESULTS

The purpose of this study was to describe the relationships between six classes of school-readiness variables with students' academic achievement in reading and mathematics in elementary school. Specifically, this study examined how school-readiness variables related to children's academic starting points in fall kindergarten in reading and mathematics and how the school-readiness variables related to their subsequent academic growth in reading and mathematics from fall kindergarten to spring fourth grade. The hierarchical linear growth modeling (HLM growth modeling) results that addressed the study's three research questions, plus two additional analyses, are summarized in this chapter. The results of research questions one and two are summarized in the first two sections. Then, Research Question 3, which was updated to reflect the new two-piece linear time variables EarlyGrades and LateGrades, is summarized. An additional analysis related to preschool instruction is explained and then the results of linear regressions performed to help verify the HLM growth modeling results are summarized. Effect sizes (ES) were calculated by dividing the explanatory variables estimates for intercepts and slopes by the assessment's standard deviation.

All the statistical tests run in this chapter were run at the .05 level of statistical significance. Because a fair number of regression coefficients are estimated in some of the HLM growth models, it was deemed necessary to control for the type 1 error rate. Controlling the error rate when a number of statistical tests are made in the same model allows the error rate to remain at .05. To do this, Kirk (1995) suggests dividing .05 by the number of statistical tests. This was done for each of the models presented in Chapter IV.

These error rates are noted in the Notes section of the results tables.

Research Question 1

How are the six classes of school-readiness variables related to a child's starting point in kindergarten, and what are their growth rates from kindergarten to fourth grade in reading?

To answer Research Question 1, the SPSS Mixed Models module was used with a stacked—also called long or tall (Holt, 2008)—data set. Stacking the data set gave each student six rows of data (equal to the number of response variables). Each student's reading and mathematics scores were represented as six rows of data, one for each assessment period, creating six rows of data per student. The top three rows were the three assessment time periods for EarlyGrades (fall and spring kindergarten and spring first grade) and the bottom three rows were the three assessment time periods for LateGrades (spring of second, third, and fourth grades).

The first part of question one involves how the six classes of school-readiness variables are related to reading achievement. The correlation analysis at the end of Chapter III suggested only three classes for the final HLM growth models: cognitive knowledge and skills, social and emotional skills, and family structure and home environment. The variables representing those classes are TAcadRating (general knowledge), ZX1DCCSTOT (cognitive flexibility), ZX1NRWABL (working memory), TRatingSE (behavior), and ZX1SESL (socioeconomic status [SES]). These variables were all measurements of the students' abilities, behavior, or status, taken during fall kindergarten. Before growth modeling was conducted, it was concluded that three school-readiness classes—physical skills and health, access to community resources, and early school experiences—did not have strong relationships with students' academic achievement, so variables from these classes were not included in the final HLM growth modeling.

Three models were tested to answer Research Question 1, all with reading assessments as the response variable. Model 1, the unconditional growth model, was computed with EarlyGrades and LateGrades as the time variables. Four variables were introduced in Model 2 as covariates: TAcadRating, ZX1DCCSTOT, ZX1NRWABL, and TRatingSE. Finally, ZX12SESL was introduced to Model 3 as a covariate. The reason three models were run was to enter the variables in the order of Bronfenbrenner's (1979) ecological systems theory from proximally to distally developing variables. Model 1 represented the students' growth without explanatory variables, Model 2 added the variables closest to the students (proximally developing), and Model 3 added the one variable most removed from the student (distally developing). This order aligned with Bronfenbrenner's (1979) theory that the variables most influential on child development are those closest to the child, such as cognitive knowledge and skills and behavior. The SES variable has more to do with a child's circumstances, so it was included in Model 3.

The stacked reading assessments were entered as the dependent variables in these models. The results of the three models are presented in Table 25. Model 1 had a mean intercept of 49.73, which was the mean item response theory (IRT) reading assessment score at fall kindergarten, not adjusted for explanatory variables, for all the students. The regression coefficient estimates of EarlyGrades and LateGrades were 2.14 and 0.52, respectively, which means that the average student was growing 2.14 reading assessment IRT points per month from fall kindergarten through spring first grade (EarlyGrades),

Table 25
HLM Growth Modeling Results of Reading Achievement

	Unconditional Growth Model 1			Proximal Model 2			Distal Model 3		
Fixed Effects	Est.	SE	*t*	Est.	SE	*t*	Est.	SE	*t*
Intercept	49.73	.08	574.74	49.88	.07	703.72	49.88	.07	724.69
EarlyGrades	2.14	.01	402.24	2.15	.01	420.02	2.14	.01	423.84
LateGrades	0.52	.00	353.87	0.52	.00	365.38	0.52	.00	366.11
TAcadRating				4.72	.08	59.24	4.20	.08	53.19
ZX1DCCSTOT				1.06	.07	14.13	0.83	.07	11.32
ZX1NRWABL				2.97	.07	39.21	2.64	.07	35.66
TRatingSE				0.44	.07	5.77	0.37	.07	4.98
TAcadRating*EarlyGrades				0.00	.01	-0.50	-0.02	.01	-4.12
ZX1DCCSTOT*EarlyGrades				0.07	.01	13.95	0.07	.01	12.24
ZX1NRWABL*EarlyGrades				0.12	.01	21.48	0.10	.01	19.06
TRatingSE*EarlyGrades				0.11	.01	19.28	0.10	.01	18.93
TAcadRating*LateGrades				-0.03	.00	-18.88	-0.03	.00	-16.91
ZX1DCCSTOT*LateGrades				-0.01	.00	-4.96	-0.01	.00	-4.15
ZX1NRWABL*LateGrades				-0.03	.00	-17.24	-0.02	.00	-16.03
TRatingSE*LateGrades				-0.02	.00	-11.07	-0.01	.00	-10.86
ZX12SESL							2.41	.07	32.94
ZX12SESL*EarlyGrades							0.10	.01	18.20
ZX12SESL*LateGrades							-0.01	.00	-8.13
Random Effects		Model 1			Model 2			Model 3	
Level 1 Residual		40.95			41.58			41.54	
Intercept		98.37			50.89			45.79	
EarlyGrades		0.29			0.24			0.23	
LateGrades		0.02			0.01			0.01	
Deviance		782,102.98			753,805.79			751,544.72	
Parameters		11.00			23.00			26.00	

Note: All fixed effects statistically significant except Model 2 TAcadRating*EarlyGrades, which is statistically not significant. All estimates of covariance parameters statistically significant using Wald's Z. Reading assessment scale is 0-155. Adjusted error rate is .017 for Model 1, .003 for Model 2, and .003 for Model 3.

and 0.52 reading assessment IRT points per month from spring second grade through spring fourth grade (LateGrades). The random effects of Model 1 indicated there was residual variance in intercepts (intercept variance = 98.37), and residual variance in slopes for EarlyGrades (slope variance = 0.29) and LateGrades (slope variance = .02), all statistically significant, which suggested there was sufficient variance to explain for the explanatory variables.

Four explanatory variables were introduced in Model 2: TAcadRating (general knowledge), ZX1DCCSTOT (cognitive flexibility), ZX1NRWABL (working memory), and TRatingSE (behavior). The mean intercept at fall kindergarten was 49.88 reading assessment IRT points, and the mean growth rate was 2.15 reading assessment IRT points per month during EarlyGrades and 0.52 reading assessment IRT points per month during LateGrades, all adjusted for the four explanatory variables. Because all school readiness variables were principal components or *z* scores, the unstandardized partial regression coefficients can be compared. The regression coefficient for each explanatory variable represented how much reading assessment scores could be expected to change, in the form of reading assessment IRT points, for a one-unit change in that variable, holding all other variables constant. Because all the variables were standardized, the unstandardized coefficients were, in effect, rough effect sizes. The coefficient for TAcadRating ($\beta_{01} = 4.72$; ES = .42), which is the largest coefficient, suggests that students with one standard deviation higher than the mean on general knowledge had a fall kindergarten reading achievement score 4.72 reading assessment IRT points higher than students with average general knowledge, which means their mean reading assessment score was 54.6 (49.88 + 4.72). The second largest coefficient was working memory (β_{03} = 2.97; ES = 0.26), then cognitive flexibility (β_{02} = 1.06; ES = 0.09), and finally behavior (β_{04} = 0.44; ES = 0.04).

The regression coefficients of the four explanatory variables in Model 2 showed an order of importance. Because it had the largest regression coefficient (β_{01} = 4.72), general knowledge (TAcadRating) contributed, on average, the most IRT points to fall reading assessment scores, followed by working memory, cognitive flexibility, and behavior. In terms of school-readiness classes, this suggested cognitive knowledge and skills was the class with the strongest positive influence on fall kindergarten reading assessment scores.

Eight interaction terms were introduced in Model 2: the four explanatory variables with EarlyGrades and the four explanatory variables with LateGrades. These interaction estimates showed the academic growth rates in reading of students with above-average variable values in fall kindergarten compared with average students, in terms of reading assessment IRT points per month. A positive growth rate suggested that students above the mean of that variable demonstrated more academic growth compared with students at the mean for that variable, whereas a negative growth rate suggested that students above the mean for that variable demonstrated less academic growth compared with students at the mean for that variable (Heck et al., 2014).

A pattern is seen when the growth rates for early versus late grades are compared. Students with higher scores on all predictors show slightly negative growth (less growth) or no growth in late grades. For example, students with above-average general knowledge (TAcadRating) in fall kindergarten showed no academic growth during EarlyGrades compared with students at the mean (β_{11} = 0; ES = 0) and slightly less academic growth during LateGrades compared with students at the mean (β_{21} = -0.03; ES = 0). For cognitive flexibility (ZX1DCCSTOT), students above the mean showed slightly more academic growth in reading during EarlyGrades (β_{12} = 0.07; ES = 0) and slightly less academic growth in reading during LateGrades (β_{22} = -0.01; ES = 0) compared with students at the mean. For working memory (ZX1NRWABL), students above the mean showed more academic growth during EarlyGrades (β_{13} = 0.12; ES = 0.01) and slightly less academic growth during LateGrades (β_{23} = -0.03; ES = 0) compared with students at the mean. For behavior (TRatingSE), students above the mean showed more academic growth during EarlyGrades (β_{14} = 0.11; ES = 0.01) and slightly less academic growth during LateGrades (β_{24} = -0.02; ES = 0) compared with students at the mean. The random effects of Model 2 were statistically significant and indicated residual variance in intercepts (intercept variance = 50.89) and residual variance in slopes (slope variance EarlyGrades = 0.24 and slope variance LateGrades = 0.01) even after the influences of the four explanatory variables and the cross-level interactions, which suggested there is additional variance for other explanatory variables to explain.

Model 3 introduced a fifth explanatory variable, SES (ZX12SESL), which was also standardized so that it could be compared with the other variables. Model 3 had a mean intercept of 49.88, which was the mean reading assessment score at fall kindergarten adjusted for all five explanatory variables. The fixed effects estimates of EarlyGrades and LateGrades were 2.14 and 0.52, respectively, which meant the average student is growing 2.14 reading assessment IRT points per month during EarlyGrades and 0.52 reading assessment IRT points per month during LateGrades, adjusted for all five explanatory variables. The regression coefficient for TAcadRating (β_{01} = 4.20; ES = 0.37) was the highest, which suggested that above-average students on the general knowledge variable had a fall kindergarten reading achievement score 4.20 reading assessment IRT points higher than students with average general knowledge, which meant their mean reading assessment score was 54.08 (49.88 + 4.20). The second largest coefficient was working memory (β_{03} = 2.64; ES = 0.24), then SES ($\beta_{05} = 2.41$; ES = 0.21) then cognitive flexibility (β_{02} = 0.83; ES = 0.07), and finally behavior (β_{04} = 0.37; ES = 0.03).

Contrasted with Model 2, the addition of SES in Model 3 changed the order of importance for the school-readiness variables. Comparable to Model 2, general knowledge and working memory had the strongest relationships to fall kindergarten reading assessment scores, but SES was third in Model 3, rather than cognitive flexibility, which was fourth in Model 2. Behavior remained fifth, resembling Model 2. In Model 3, two school-readiness classes showed the strongest relationships to fall kindergarten reading assessment scores: cognitive knowledge and skills and home environment, which meant that variables proximally developing to the child (general knowledge and working memory) and distally developing to the child (SES) both had relatively strong relationships to fall kindergarten reading assessment scores.

Ten interaction terms were introduced in Model 3: the five explanatory variables with EarlyGrades and the five explanatory variables with LateGrades. These interaction estimates showed the reading growth rates of students with above-average variable values in fall kindergarten compared with students with average variable values, in terms of reading IRT assessment points per month. Students with above-average general knowledge (TAcadRating) in fall kindergarten showed slightly less academic growth during EarlyGrades (β_{11} = -0.02; ES = 0) and LateGrades (β_{21} = -0.03; ES = 0) compared with students with average general knowledge. For cognitive flexibility (ZX1DCCSTOT), students above the mean showed slightly more academic growth during EarlyGrades (β_{12}= 0.07; ES = 0.01) and no academic growth during LateGrades (β_{22} = 0; ES = 0) compared with students at the mean. For working memory (ZX1NRWABL), students above the mean showed more academic growth during EarlyGrades (β_{13} = 0.10; ES = 0.01) and slightly less academic growth during LateGrades (β_{23} = -0.02; ES = 0) compared with students at the mean. For behavior (TRatingSE), students above the mean showed more growth during EarlyGrades (β_{14} = 0.10; ES = 0.01) and less academic growth during LateGrades (β_{24} = -0.01; ES = 0) compared with students at the mean. For SES (ZX12SESL), students above the mean showed more academic growth during EarlyGrades (β_{15} = 0.10; ES = 0.01) and slightly less academic growth during LateGrades (β_{25} = -0.01; ES = 0) compared with students at the mean. The random effects of Model 3 were statistically significant and indicated there was residual variance in intercepts to be explained (intercept variance = 45.54) and residual variance in slopes to be explained (slope variance EarlyGrades = 0.23 and slope variance LateGrades = 0.01) even after the influence of the five explanatory variables.

Research Question 2

How are the six classes of school-readiness variables related to a child's starting point in kindergarten, and what are their growth rates from kindergarten to fourth grade in mathematics?

Similar to Research Question 1, Research Question 2 used a stacked data set with the five explanatory variables in three different models, but the response variable was the mathematics assessments. Model 1, the unconditional growth model, was conducted with

EarlyGrades and LateGrades as the time variables. General knowledge (TAcadRating), cognitive flexibility (ZX1DCCSTOT), working memory (ZX1NRWABL), and behavior (TRatingSE) were introduced in Model 2 as covariates. Finally, SES (ZX12SESL) was introduced in Model 3 as a covariate. The HLM growth modeling results of these three models are presented in Table 26.

Model 1 had an intercept of 31.81, which was the mean IRT mathematics assessment score at fall kindergarten, not adjusted for explanatory variables. The estimates of EarlyGrades and LateGrades were 2.03 and 0.63, respectively, which meant the average student was growing 2.03 mathematics IRT assessment points per month from fall kindergarten through spring first grade (EarlyGrades), and 0.63 mathematics IRT assessment points per month from spring second grade through spring fourth grade (LateGrades). The random effects of Model 1 indicated there was residual variance in intercepts (intercept variance = 95.08), in EarlyGrades (slope variance = .21), and LateGrades (slope variance = 0.02), all statistically significant, which suggested there was sufficient variance to explain for the explanatory variables.

Four explanatory variables were introduced in Model 2: TAcadRating (general knowledge), ZX1DCCSTOT (cognitive flexibility), ZX1NRWABL (working memory), and TRatingSE (behavior). The mean intercept at fall kindergarten was 32.02 mathematics IRT assessment points, and the mean growth rate was 2.04 mathematics IRT assessment points during EarlyGrades and 0.63 mathematics IRT assessment points during LateGrades, all adjusted for four explanatory variables. Because all the school-readiness variables were standardized, the unstandardized regression coefficients were, in effect, rough effect sizes.

Table 26

HLM Growth Modeling of Mathematics Achievement

	Unconditional Growth Model 1			Proximal Model 2			Distal Model 3		
Fixed Effects	Est.	SE	*t*	Est.	SE	*t*	Est.	SE	*t*
Intercept	31.81	.08	385.97	32.02	.06	499.78	32.00	.06	520.86
EarlyGrades	2.03	.01	438.44	2.04	.00	454.29	2.04	.00	457.57
LateGrades	0.63	.00	471.54	0.63	.00	476.96	0.63	.00	477.04
TAcadRating				3.80	.07	52.72	3.24	.07	45.99
ZX1DCCSTOT				1.73	.06	25.60	1.48	.06	22.78
ZX1NRWABL				3.57	.06	52.21	3.23	.06	48.74
TRatingSE				0.80	.06	11.59	0.72	.06	10.92
TAcadRating*EarlyGrades				0.03	.01	5.72	0.01	.01	2.45
ZX1DCCSTOT*EarlyGrades				0.08	.01	17.52	0.08	.01	16.00
ZX1NRWABL*EarlyGrades				0.08	.01	15.99	0.07	.01	13.82
TRatingSE*EarlyGrades				0.06	.01	12.74	0.06	.01	12.36
TAcadRating*LateGrades				-0.02	.00	-13.87	-0.02	.00	-13.01
ZX1DCCSTOT*LateGrades				-0.07	.00	-4.70	0.00	.00	-4.40
ZX1NRWABL*LateGrades				-0.02	.00	-10.72	-0.01	.00	-10.25
TRatingSE*LateGrades				-0.01	.00	-7.90	-0.01	.00	-7.81
ZX12SESL							2.57	.06	39.36
ZX12SESL*EarlyGrades							0.08	.01	16.07
ZX12SESL*LateGrades							0.00	.00	-2.89
Random Effects		Model 1			Model 2			Model 3	
Level 1 Residual		33.74			33.75			33.79	
Intercept		95.08			44.52			38.63	
EarlyGrades		0.21			0.17			0.17	
LateGrades		0.02			0.01			0.01	
Deviance		777,584.30			749,003.21			746,964.72	
Parameters		11.00			23.00			26.00	

Note: All fixed effects statistically significant at except Model 3 TAcadRating*EarlyGrades and ZX12SESL*LateGrades, which are not significant. All estimates of covariance parameters statistically significant using Wald's Z. Mathematics assessment scale is 0-146. Adjusted error rate is .017 for Model 1, .003 for Model 2, and .003 for Model 3

The regression coefficient for each explanatory variable represented how much mathematics assessment scores could be expected to change, in the form of IRT points, for a one-unit change in that variable, holding all other variables constant. For example, the coefficient for TAcadRating (β_{01} = 3.80; ES = 0.33) suggested that students higher than the mean on general knowledge had a fall kindergarten reading achievement score 3.80 mathematics assessment IRT points higher than students with average general knowledge, which meant their mean mathematics assessment score was 35.82 (32.02 + 3.80). The second largest coefficient was working memory (β_{03} = 3.57; ES = 0.31), then cognitive flexibility (β_{02} = 1.73; ES = 0.15), and finally behavior (β_{04} = 0.80; ES = 0.07).

The regression coefficients of the four explanatory variables in Model 2 showed an order of importance. Because it had the largest regression coefficient ($\beta_{01} = 3.80$), general knowledge (TAcadRating) was the variable with the largest contribution of IRT points on fall scores, followed by working memory, cognitive flexibility, and behavior. In terms of school-readiness classes this meant cognitive knowledge and skills was the class with the strongest positive influence on fall kindergarten mathematics assessment scores.

Eight interaction terms were introduced in Model 2: the four explanatory variables with EarlyGrades and the four explanatory variables with LateGrades. These interaction estimates showed the academic growth rates in mathematics of students with above-average variable values in fall kindergarten compared with average students in terms of mathematics assessment IRT points per month. A positive growth rate suggested that students above the mean of that variable demonstrated more academic growth compared with students at the mean for that variable, whereas a negative growth rate suggested that students above the mean for that variable demonstrated less academic growth compared with students at the mean for that variable (Heck et al., 2014). For example, students with above-average general knowledge (TAcadRating) in fall kindergarten showed slightly more academic growth in mathematics during EarlyGrades compared with students at the mean (β_{11} = 0.03; ES = 0) and slightly less academic growth during LateGrades compared with students at the mean (β_{21} = -0.02; ES = 0). For cognitive flexibility (ZX1DCCSTOT), students above the mean showed slightly more academic growth in mathematics during EarlyGrades (β_{12} = 0.08; ES = 0.01) and slightly less academic growth in mathematics during LateGrades (β_{22} = -0.07; ES = -0.01) compared with students at the mean. For working memory (ZX1NRWABL), students above the mean showed slightly more academic growth during EarlyGrades (β_{13} = 0.08; ES = 0.01) and slightly less academic growth during LateGrades (β_{23} = -0.02; ES = 0) compared with students at the mean. For students' behavior ratings (TRatingSE), students above the mean showed slightly more academic growth in mathematics during EarlyGrades (β_{14} = 0.06; ES = 0) and slightly less academic growth in mathematics during LateGrades (β_{24} = -0.01; ES = 0) compared with students at the mean. The random effects of Model 2 were statistically significant and indicated there was residual variance in intercepts (intercept variance = 33.75) and residual variance in slopes (slope variance EarlyGrades = 0.17 and slope variance LateGrades = 0.01) even after the influences of the four explanatory variables and the cross-level interactions, which suggested there was additional variance for the explanatory variables to explain.

A fifth explanatory variable, SES (ZX12SESL), which was standardized so it could be compared with the other variables, was introduced in Model 3. The mean intercept of Model 3 is 32.0, which was the mean mathematics assessment IRT score at fall kindergarten adjusted for all five explanatory variables. The fixed effects estimates of EarlyGrades and LateGrades were 2.04 and 0.63, respectively, which meant the average student was growing 2.04 mathematics assessment IRT points per month from fall kindergarten through spring first grade (EarlyGrades) and 0.63 mathematics assessment IRT points per month from spring second grade through spring fourth grade (LateGrades), adjusted for all five explanatory variables. The coefficient for general knowledge (TAcadRating; $\beta_{01} = 3.24$; ES = 0.28) suggested that students with one standard deviation higher than the mean had a fall kindergarten mathematics achievement score 3.24 mathematics assessment IRT points higher than students with average general knowledge, which meant their mean mathematics assessment score was 35.24 (32.0 + 3.24). The second largest coefficient was working memory (β_{03} = 3.23; ES = 0.28), then SES ($\beta_{05} = 2.57$; ES = 0.22) then cognitive flexibility (β_{02} = 1.48; ES = 0.13), and finally behavior (β_{04} = 0.72; ES = 0.06).

Similar to Model 2, the addition of SES in Model 3 changed the order of importance. Compared to Model 2, general knowledge and working memory had the strongest relationships to fall kindergarten mathematics assessment scores, but SES was third in Model 3, rather than cognitive flexibility, which was fourth in Model 2. Behavior remained fifth, just as in Model 2. Two school-readiness classes showed the strongest relationships to mathematics assessment scores in fall kindergarten: cognitive knowledge and skills and home environment, which meant the variables proximally developing to the child (general knowledge and working memory) and distally developing to the child (SES) had strong relationships to fall kindergarten mathematics assessment scores.

Ten interaction terms were introduced in Model 3: the five explanatory variables with EarlyGrades and the five explanatory variables with LateGrades. These interaction estimates showed the mathematics growth rates of students with above-average variable values in fall kindergarten contrasted with average students, in terms of mathematics assessment IRT points per month. Students with above-average general knowledge (TAcadRating) in fall kindergarten showed slightly more academic growth in mathematics during EarlyGrades ($\beta_{11} =$ 0.01; ES = 0) and slightly less academic growth in mathematics during LateGrades (β_{21} = -0.02; ES = 0) compared with students with average general knowledge. For cognitive flexibility (ZX1DCCSTOT), students above the mean showed more academic growth during EarlyGrades (β_{12}= 0.08; ES = 0.01) and no academic growth during LateGrades (β_{22} = 0; ES = 0) compared with students at the mean. For working memory (ZX1NRWABL), students above the mean showed slightly more academic growth during EarlyGrades ($\beta_{13} =$ 0.07; ES = 0.01) and slightly less academic growth during LateGrades (β_{23} = -0.01; ES = 0) compared with students at the mean. For behavior (TRatingSE), students above the mean showed slightly more academic growth during EarlyGrades (β_{14} = 0 .06; ES = 0) and slightly less academic growth during LateGrades (β_{24} = -0.01; ES = 0) compared with students at the mean. For SES (ZX12SESL), students above the mean showed slightly more academic growth during EarlyGrades (β_{15} = 0.08; ES = 0.01) and no academic growth during LateGrades (β_{25} = 0; ES = 0). The random effects of Model 3 were statistically significant and indicated there was residual variance in intercepts (intercept variance = 38.63) and residual variance in slopes (slope variance EarlyGrades = 0.17 and slope variance LateGrades = .01) even after the influence of the five explanatory variables.

Research Question 3

How do the starting points (intercept variance) and growth rates (slopes) of reading and mathematics compare for EarlyGrades and LateGrades?

The reading and mathematics assessment intercepts and slopes could not be compared because they were different academic subjects and IRT scales for two different time periods. The reading and mathematics assessment questions were not part of the same test. The rank order of the five school-readiness variables from Research Questions 1 and 2, however, can be compared. Therefore, the rank order of the variables will be explained in this section. The rank order of the variables are in terms of the largest fixed effect estimate to smallest, which shows the variable with the biggest influence on assessment scores to the variable with the smallest influence. The rank order of the five explanatory variables is listed in Table 27.

Table 27
Rank Order of Five Explanatory Variables for Reading and Mathematics

Reading	Est.	Mathematics	Est.
1. TAcadRating	4.20	1. TAcadRating	3.24
2. ZX1NRWABL	2.64	2. ZX1NRWABL	3.23
3. ZX12SESL	2.41	3. ZX12SESL	2.57
4. ZX1DCCSTOT	0.83	4. ZX1DCCSTOT	1.48
5. TRatingSE	0.37	5. TRatingSE	0.72

Even though the reading and mathematics assessments are different subjects so the coefficients cannot be compared, it is interesting to see that the rank order for both was the same. General knowledge (TAcadRating), a broad measure of the students' general academic knowledge at the beginning of kindergarten, was the variable with the strongest relationship to fall kindergarten assessment scores for both reading and mathematics, followed by working memory (ZX1NRWABL), SES (ZX12SESL), cognitive flexibility (ZX1DCCSTOT), and behavior (TRatingSE).

HLM Growth Modeling with Center Instruction

Because of the importance of preschool, additional HLM growth modeling was performed to investigate how preschool experience influences fall kindergarten academic assessment scores and academic growth rates. Previous research (e.g., Magnuson et al., 2007) suggested that preschool experience is an important positive influence on academic test scores. Two analyses were performed to investigate this claim further. First, an HLM growth model regression was performed with reading achievement and the CenterDummy variable. Then, a second HLM growth model was performed with mathematics achievement and the CenterDummy variable. This dummy variable was a school-readiness variable indicating students' educational experience before kindergarten, where zero indicated no preschool experience (no center-based program, i.e., daycare or parental care only), and one indicated preschool experience (center-based program, i.e., private preschool or public preschool, such as Head Start). The purpose of these analyses was to investigate the differences of the reading and mathematics intercept and slope estimates when the CenterDummy was the only explanatory variable, compared with the estimates with CenterDummy and five additional explanatory variables.

These analyses were performed similarly to the growth modeling used to answer Research Question 1 and Research Question 2. Three models were conducted for both reading and mathematics with a stacked data set using the achievement scores as the dependent variables. Model 1 was the unconditional growth model with the time variables EarlyGrades and LateGrades as the time variables, Model 2 added the CenterDummy variable as an explanatory variables, and Model 3 added the five school-readiness explanatory variables from Research Questions 1 and 2: TAcadRating, ZX1DCCSTOT, ZX1NRWABL, TRatingSE, and ZX12SESL. The results for reading are presented in Table 28.

The regression coefficients for Model 1 and Model 3 for reading are the same or similar to those found for Research Question 1. The regression coefficient of interest is that for CenterDummy in Model 2 and Model 3 to compare how the coefficients change when CenterDummy is the only explanatory variable (Model 2) and then when five additional explanatory variables are added (Model 3). When the HLM growth modeling included only the CenterDummy variable (Model 2), the regression coefficient is 2.92 (ES = 0.26), which was interpreted as the additional amount of reading assessment IRT points students with preschool experience had on their fall kindergarten reading assessment compared to students without preschool experience. In other words, the fall kindergarteners with preschool experience have a mean reading assessment score of 51.03 (2.92 + 48.11) assessment IRT points compared to students without preschool experience, who were at the mean (48.11 assessment IRT points).

When the five explanatory variables were added in Model 3, the regression coefficient for CenterDummy changed to 0.47 reading assessment IRT points (ES = 0.04). In other words, when the other school-readiness variables were accounted for, the CenterDummy variable regression coefficient dropped 2.45 points. One reason for this change might be the difference in racial demographics between the children with preschool experience and those without; the groups were not equivalent. For example, 62.1% of Asian students had preschool experience and 37.9% did not, which was a large

Table 28

HLM Growth Modeling Results of Reading Achievement with CenterDummy

	Unconditional Growth Model 1			Proximal Model 2			Distal Model 3		
Fixed Effects	Est.	SE	*t*	Est.	SE	*t*	Est.	S.E.	*t*
Intercept	49.73	.08	574.74	48.11	.12	373.94	49.61	.10	475.30
EarlyGrades	2.14	.01	402.24	2.13	.01	267.72	2.17	.01	283.09
LateGrades	0.52	.00	353.87	0.52	.00	238.64	0.51	.00	239.50
CenterDummy				2.92	.17	16.93	0.47	.14	3.31
CenterDummy*EarlyGrades				0.01	.01	0.98	-0.05	.01	-4.77
CenterDummy*LateGrades				-0.01	.00	-3.29	0.01	.00	2.39
TAcadRating							4.17	.08	52.77
ZX1DCCSTOT							0.82	.07	11.27
ZX1NRWABL							2.64	.07	35.62
TRatingSE							0.38	.07	5.15
ZX12SESL							2.37	.07	32.13
TAcadRating*EarlyGrades							-0.02	.01	-3.73
ZX1DCCSTOT*EarlyGrades							0.07	.01	12.32
ZX1NRWABL*EarlyGrades							0.10	.01	19.14
TRatingSE*EarlyGrades							0.10	.01	18.66
ZX12SESL*EarlyGrades							0.10	.01	18.71
TAcadRating*LateGrades							-0.03	.00	-17.04
ZX1DCCSTOT*LateGrades							-0.01	.00	-4.19
ZX1NRWABL*LateGrades							-0.02	.00	-16.07
TRatingSE*LateGrades							-0.02	.00	-10.72
ZX1SESL*LateGrades							-0.01	.00	-8.39

Random Effects	Model 1	Model 2	Model 3
Level 1 Residual	40.95	40.97	41.54
Intercept	98.37	96.25	45.74
EarlyGrades	0.29	0.29	0.23
LateGrades	0.02	0.02	0.01
Deviance	782,102.98	781,802.22	751,535.11
Parameters	11.00	14.00	29.00

Note: All fixed effects significant except Model 3 CenterDummy*LateGrades, which is insignificant. All estimates of covariance parameters significant using Wald's Z. Reading assessment scale is 0-155. Adjusted error rates are .017 for Model 1, .008 for Model 2, and .002 for Model 3.

difference. By including the other school-readiness variables, demographics may be accounted for or controlled. The demographics for CenterDummy are listed in Table 29.

Table 29
Percentage of Racial Demographics of CenterDummy Variable

Race	No Center Experience	Center Experience
White, non-Hispanic	41.9	58.1
African American	44.9	55.1
Hispanic	51.3	48.7
Asian	37.9	62.1
Native Hawaiian or Pacific Islander	68.0	32.0
American Indian or Alaska Native	43.6	56.4
Two or more races	44.4	55.6

The results for the CenterDummy HLM growth model with mathematics were similar to the reading results. Again, three models were computed, with the same explanatory variables as the reading analysis. The results of the mathematics HLM growth modeling are located in Table 30. Similar to the results for reading, there was a difference in the regression coefficient for CenterDummy in Model 2 (2.83; ES = 0.25) compared with Model 3 (0.35; ES = 0.03) of about two mathematics assessment IRT points. Before the other five school-readiness variables were accounted for, it appeared that children with preschool experience scored, on average, two mathematics assessment IRT points higher on the fall kindergarten mathematics assessment compared to students without preschool experience. Again, this difference may be because the racial demographics of the two groups (preschool experience versus no preschool experience) were not equal.

In summary, the additional HLM growth models for reading and mathematics with the CenterDummy variable show how not accounting for differences of group racial

Table 30
HLM Growth Modeling Results of Mathematics Achievement with CenterDummy

	Unconditional Growth Model 1			Proximal Model 2			Distal Model 3		
Fixed Effects	Est.	S.E.	*t*	Est.	S.E.	*t*	Est.	S.E.	*t*
Intercept	31.81	.08	385.97	30.23	.12	246.81	31.80	.09	341.23
EarlyGrades	2.03	.01	438.44	2.03	.01	291.41	2.06	.01	304.93
LateGrades	0.63	.00	471.54	0.64	.00	317.56	0.63	.00	314.40
CenterDummy				2.83	.16	17.23	0.35	.13	2.86
CenterDummy*EarlyGrades				0.02	.01	1.65	-0.04	.01	-4.29
CenterDummy*LateGrades				-0.01	.00	-3.78	0.00	.00	-0.07
TAcadRating							3.22	.07	45.62
ZX1DCCSTOT							1.48	.07	22.74
ZX1NRWABL							3.22	.07	48.69
TRatingSE							0.73	.07	11.06
ZX12SESL							2.54	.07	38.54
TAcadRating*EarlyGrades							0.01	.01	2.78
ZX1DCCSTOT*EarlyGrades							0.08	.01	16.08
ZX1NRWABL*EarlyGrades							0.07	.01	13.89
TRatingSE*EarlyGrades							0.06	.01	12.13
ZX12SESL*EarlyGrades							0.08	.01	16.53
TAcadRating*LateGrades							-0.02	.00	-12.97
ZX1DCCSTOT*LateGrades							-0.01	.00	-4.40
ZX1NRWABL*LateGrades							-0.02	.00	-10.24
TRatingSE*LateGrades							-0.01	.00	-7.80
ZX1SESL*LateGrades							0.00	.00	-2.85

Random Effects	Model 1	Model 2	Model 3
Level 1 Residual	33.74	33.74	33.79
Intercept	95.08	93.09	38.60
EarlyGrades	0.21	0.21	1.24
LateGrades	0.02	0.02	-0.38
Deviance	777,584.30	777,308.52	746,958.75
Parameters	11.00	14.00	29.00

Note: All fixed effects variables statistically significant except Model 2 CenterDummy*EarlyGrades, Model 3 CenterDummy*LateGrades, and ZX1SESL*LateGrades, Model 3 TAcadRating*EarlyGrades, and CenterDummy*LateGrades are not statistically significant. All estimates of covariance parameters statistically significant using Wald’s Z. Mathematics assessment scale is 0-146.

demographics or controlling for other variables can change variable estimates, which can lead to incorrect conclusions about variables. The results of these additional analyses show the importance of a well-specified model.

Linear Regressions

The ECLS User's Manual (Tourangeau et al., 2015) suggests statistical analyses using the ECLS data set use a weight to "compensate for differential probabilities of selection at each sampling stage and to adjust for the effect nonresponse can have on the estimates" (p. 4.14). The ECLS data set provides weights to be used with analyses. The weight selected for this study was W8C18P_8T180. As stated in Chapter III, however, the SPSS Mixed Model module does not allow the use of case weight in multilevel modeling. Therefore, the results of two-level analyses can give a preliminary indication of relationships but should not be relied on to provide final, unbiased estimates (Heck, 2014). For this reason, an ordinary least squares (OLS) regression was conducted using SPSS with the ECLS case weight W8C18P_8T180.

First, an OLS regression for reading was obtained using six school-readiness variables: TAcadRating (general knowledge), ZX1DCCSTOT (cognitive flexibility), ZX1NRWABL (working memory), TRatingSE (behavior), ZX12SESL (SES), and CenterDummy (preschool experience dummy variable). Because the variables were standardized prior to the OLS regression, the unstandardized coefficients of the linear regressions can be compared. The results of this OLS regression are presented in Table 31 with the coefficients rank ordered from largest to smallest.

The OLS regression coefficients of the explanatory variables were different than the estimates of the HLM growth models. The rank order of importance for the six school-readiness variables, however, was the same for the HLM growth modeling including CenterDummy for reading.

Table 31
OLS Regression Results for Six School-Readiness Variables and Fall Kindergarten Reading Achievement

Variable	Coefficients	SE	*t*
1. TAcadRating	5.15	.13	40.12*
2. ZX1NRWABL	2.57	.12	20.99*
3. ZX12SESL	2.16	.13	17.06*
4. ZX1DCCSTOT	0.78	.13	6.19*
5. CenterDummy	0.14	.23	0.60
6. TRatingSE	-0.01	.13	-0.10

Note: *Statistically significant when the overall error rate was controlled.

General knowledge was the variable with the strongest relationship to reading achievement in fall kindergarten, followed by working memory, SES, cognitive flexibility, preschool experience, and behavior. The OLS regression results suggested that the rank order found using HLM growth modeling was the same as the rank order found using the case weight. This suggested the growth analysis was valid. Next, an OLS regression for mathematics was performed using the same six school-readiness variables. The results of this OLS regression are presented in Table 32 with the coefficients rank ordered from largest to smallest.

Table 32
OLS Regression Results for Six School-Readiness Variables and Fall Kindergarten Mathematics Achievement

Variable	Coefficients	SE	*t*
1. TAcadRating	4.29	.12	35.18*
2. ZX1NRWABL	3.36	.12	28.94*
3. ZX12SESL	2.54	.12	21.19*
4. ZX1DCCSTOT	1.54	.12	12.90*
5. TRatingSE	0.42	.12	3.51*
6. CenterDummy	-0.14	.22	-0.68

Note: *Statistically significant when overall error rate was controlled.

The OLS regression coefficients of the explanatory variables were different than the estimates of the HLM growth models. The rank order of importance for the six school-readiness variables, however, was the same for the HLM growth modeling including CenterDummy for mathematics. General knowledge and working memory were the variables with the strongest relationships to reading achievement in fall kindergarten, then SES, cognitive flexibility, preschool experience, and behavior. This suggested that the rank order found using HLM growth modeling was not invalid. Additionally, even though the coefficients of the school-readiness variables in the HLM growth models were different compared with the coefficients of the school-readiness variables in the OLS regressions, some of the coefficients were close in numerical value, as shown in Table 33. For example, the difference of the coefficients for the variables ZX12SESL, ZX1DCCSTOT, and CenterDummy was less than one.

Table 33
Comparison of Coefficients of Six School-Readiness Variables from HLM Growth Modeling and OLS Regressions

School-Readiness Vars.	Reading HLM Growth Mod. Coefs.	Reading OLS Reg. Coefs.	Math. HLM Growth Mod. Coefs.	Math. OLS Reg. Coefs.
1. TAcadRating	4.17	5.15	3.22	4.29
2. ZX1NRWABL	0.82	2.57	1.48	3.36
3. ZX12SESL	2.64	2.16	3.22	2.54
4. ZX1DCCSTOT	0.38	0.78	0.73	1.54
5. TRatingSE	2.37	0.14	2.54	0.42
6. CenterDummy	0.47	-0.01	0.35	-0.14

Note: OLS regressions include weight; HLM growth models do not.

In summary, two OLS regressions, one for reading and one for mathematics, were performed using six school-readiness variables, which was done to investigate how the results of the OLS regression using a weight compared with the results of HLM growth-modeling. These were not the same models because the HLM growth model was both fixed and random effects and was a growth analysis, not a multiple linear regression.

Although the numerical values for the OLS regression coefficients were not exactly same as the HLM growth analysis estimates, the rank ordering of the variables was the same. This conclusion suggested that the results of the HLM growth analysis were not invalid with the absence of a weight.

Summary

The results of this study's three research questions, the results of an additional HLM growth analysis using the CenterDummy variable, and the results of two OLS regressions were presented in Chapter IV. Research Question 1 investigated the relationships between five school-readiness variables with reading achievement. HLM growth modeling was used to determine the fixed and random effects of three models. Model 1 included the time variables EarlyGrades and LateGrades. Four school-readiness explanatory variables were introduced in Model 2 (general knowledge, cognitive flexibility, working memory, and behavior). One explanatory variable was introduced in Model 3 (SES). The results from these three models showed how the different school-readiness variables related to students' academic starting points in fall kindergarten in reading (as intercepts). The interactions between the school-readiness variables and the two time variables EarlyGrades and LateGrades showed students' academic growth as reading assessment points per month from the beginning of kindergarten to the end of fourth grade (as slopes). Research Question 2 was the same as Research Question 1 except the response variable was the students' mathematics scores. Research Question 3 compared the rank order of the five school-readiness variables for reading and mathematics, which was the same for Model 3 of Research Question 1 and 2.

Two additional HLM growth analyses were computed using the CenterDummy variable to investigate how preschool experience influences academic starting points in fall kindergarten and academic growth in reading and in mathematics from kindergarten to fourth grade. Results of these analyses indicated that adding the CenterDummy variable changed the rank order of variables found in Research Questions 1 and 2. Additionally, the starting points (intercepts) and growth rates (slopes) of CenterDummy changed after adding five additional explanatory variables to the HLM growth model. Finally, two OLS regressions (one for reading and one for mathematics) were conducted using the same explanatory and response variables as Model 3 of the CenterDummy HLM growth model, which was undertaken because of the inability to use the ECLS case weight with multilevel modeling in SPSS. The two OLS regressions validated the rank order of school-readiness variables found in Model 3 of Research Questions 1 and 2.

CHAPTER V

SUMMARY, LIMITATIONS, DISCUSSION, AND IMPLICATIONS

The purpose of this study was to describe the relationships between six classes of school-readiness variables with students' academic achievement in reading and mathematics in elementary school. Specifically, this study examined how school-readiness variables related to children's academic starting points in fall kindergarten in reading and mathematics and how the school-readiness variables related to their subsequent academic growth in reading and mathematics to spring fourth grade. A summary of this study and its limitations, major findings, and implications for future research and practice are presented in this chapter.

Summary of Study

School readiness is defined as a vital, multivariable construct by many organizations and authors, such as the American Academic of Pediatrics (AAP; 2016), Duncan et al. (2007), Head Start (Office of Head Start, 2015), Mashburn and Pianta (2006), Meisels (1999), National Association of the Education of Young Children (NAEYC; 2009), National Education Goals Panel (NEGP; Kagan, Moore, & Bradenkamp, 1995), and United Nations Children's Fund (UNICEF; Britto, 2012). The positive relationship between school-readiness variables and academic achievement is undeniable: children who are better prepared for school are more likely to succeed academically (Duncan et al., 2007). Research suggests that children who are ready to start kindergarten tend to score higher on academic assessments, are more socially and emotionally competent throughout elementary school, and have an easier time acquiring additional academic skills, which in turn facilitates continued academic success throughout their educational careers (Britto, 2012; Duncan & Murnane, 2011; Hair, Halle, Terry-Humen, Lavelle, & Calkins, 2006).

Helping children who perform below academic standards achieve academic success is a common theme in the history of schooling in the United States. Head Start, for example, was established in the mid-1960s as a free preschool program to help children at risk for low school performance gain academic and social skills necessary for success in elementary school. Although some studies report how Head Start students are succeeding in school (Anderson et al., 2003), there is still much room for improvement (DeParle, 2019). A second example is No Child Left Behind (NCLB), the U.S. educational policy signed into law by President George W. Bush in 2002, which mandated that all public-school students be proficient academically by 2014. NCLB introduced a rigorous standardized testing schedule for public school students as a way to hold school districts accountable for their students' academic performance. Head Start and NCLB are examples of national initiatives that attempted to help students achieve academic success and attempted to close the achievement gap, which are the differences in standardized-test scores among various racial, socioeconomic status and ethnicity groups, which has been a long-standing issue in educational research (Mashburn & Pianta, 2006; Sadowski, 2006). Taking a step back from the achievement gap, it becomes obvious that children beginning elementary school are part of a *school-readiness gap*, understood as the differences in academic and social skills among children entering kindergarten (Sadowski, 2006). Sadowski (2006) suggested that eliminating the achievement gap starts by understanding and addressing the school readiness gap. First, however, the relationship between school readiness variables and academic achievement must be understood.

This study's review of school-readiness research identified six classes of school-readiness variables present in the literature: cognitive knowledge and skills, social and emotional skills, physical skills and health, family structure and home environment, access to community resources, and early school experiences. These categories are common themes among many important child-centered organizations and researchers, such as the AAP (2016), Duncan et al. (2007), Head Start (2015), Meisels (1999), Mashburn and Pianta (2006), NAEYC (2009), NEGP (1999), and UNICEF (2012). This study also found that six classes of school-readiness variables and their influence on academic achievement have never been studied together: most school-readiness studies focused on one or a few school-readiness variables and their relationships to academic achievement, which makes it difficult to draw accurate conclusions about the relative importance of *all* school readiness variables on academic success. This lack of knowledge further complicates understanding what creates the school-readiness gap, which complicates understanding the achievement gap. Therefore, the main purpose of this study was to understand how six classes of school-readiness variables relate to students' academic starting points and academic growth throughout elementary school.

The theoretical rationale used to frame school readiness in this study was Urie Bronfenbrenner's (1979) ecological systems theory, which describes how a child's personal development is influenced by multiple environments (systems) that are where school readiness skills are cultivated. For example, a preschool environment helps shape a child's academic knowledge, and a child's home environment helps shape their social and emotional skills. Bronfenbrenner's theory reinforces the idea that school readiness is a complex construct occurring in many areas of a child's life and that children's various experiences in their unique systems contribute to overall school readiness. Understanding how school readiness fits in Bronfenbrenner's (1979) systems can help us understand where school-readiness skills begin. The systems also provided a way to order the school-readiness variables in this study from proximally developing to more distal as shown in Table 2. This organization also helped provide an order to the way the variables were entered into the statistical models in SPSS in this study.

This study used the Early Childhood Longitudinal Study of 2011 (ECLS-K:2011) (Tourangeau et al., 2015, 2018) to examine how school-readiness variables related to children's academic starting points in fall kindergarten and their academic growth over 5 years of elementary school, from spring kindergarten through spring fourth grade. The ECLS-K:2011 is a nationally representative data set of more than 18,000 children that tracked their educational growth by collecting data about their years before kindergarten through fifth grade (data through spring fourth grade was available at the time of this study in April 2019). After a process of organizing and reducing the ECLS variables explained in Chapter III, 13 school-readiness variables (Table 16) and 12 academic assessment scores (six reading and six mathematics over 5 years of elementary school; Table 17) were selected for this study.

The methodology for this study was hierarchical linear growth modeling (HLM growth modeling; Anderson, 2012; Raudenbush & Bryk, 2002; Singer & Willet, 2003), a type of multilevel modeling that accounted for the nested assessment scores (six scores per student, for both reading and mathematics) and longitudinal data set (over 5 years, from fall kindergarten to spring fourth grade). HLM growth modeling required the creation of time variables to represent the testing occasions, which were the variables EarlyGrades and LateGrades, and a determination of the best way to model the error variance-covariance structure, which was AR(1) for Level 1 and Unstructured for Level 2.

Preliminary correlation analyses of the 13 school-readiness variables and fall kindergarten and spring fourth grades assessment scores revealed five school-readiness variables with the strongest relationship to academic assessment scores in fall kindergarten: children's general academic knowledge (TAcadRating), cognitive flexibility (ZX1DCCSTOT), working memory (ZX1NRWABL), teacher's ratings of students' behavior (TRatingSE), and socioeconomic status (SES; ZX12SESL). These five variables were the explanatory variables included in the final HLM growth modeling used, which was used to answer this study's research questions:

1. How are the six classes of school-readiness variables related to a child's starting point in kindergarten, and what are their growth rates from kindergarten to fourth grade in reading?
2. How are the six classes of school-readiness variables related to a child's starting point in kindergarten, and what are their growth rates from kindergarten to fourth grade in mathematics?
3. How do the starting points (intercepts) and growth rates (slopes) of reading and mathematics compare?

Summary of Findings

There are four major findings of this study. First, HLM growth modeling helped determine an order of importance of five school-readiness variables in terms of how they related to children's academic starting points in fall kindergarten for reading and mathematics. The five school-readiness variables examined were children's (a) general academic knowledge, (b) cognitive flexibility, (c) working memory, (d) behavior, and (e) socioeconomic status. The order of importance was determined by the school-readiness variables' estimated fixed effects (intercepts), which indicated the average number of IRT scale assessment points in reading or mathematics the different school-readiness variables raised assessment scores. The rank order of the five variables based on the amount of item response theory (IRT) scale assessment points from most important to least was general knowledge, working memory, SES, cognitive flexibility, and behavior.

A second major finding of this study is the relationship between the school-readiness variables and the children's academic growth in reading and mathematics, which was indicated by the change in the students' assessment scores over time (slopes) in terms of IRT scale assessment points. The time variables used in this study's HLM growth model split the data into two time periods: fall kindergarten to spring first grade (EarlyGrades) and spring second grade to spring fourth grade (LateGrades). In general, the students displayed more academic growth in reading and mathematics in EarlyGrades and less academic growth in reading and mathematics in LateGrades.

A third major finding of this study is that even though the school-readiness variables' estimated effects (intercepts and slopes) are not the same numerical values for reading and mathematics, the rank order of importance of the variables is the same for reading and mathematics. The reading and mathematics assessments are different academic subjects and different IRT scales, so the coefficients could not be compared. Comparing the rank order of the five school-readiness variables, however, revealed that the order of importance in terms of how the school-readiness variables increased the students' IRT scale assessment points was the same. The rank order of the variables, from most important to least, was general knowledge, working memory, SES, cognitive flexibility, and behavior.

The fourth major finding of this study is showing how adding explanatory variables to an HLM growth model changes the rank order of the variables. The additional HLM growth model using the five school-readiness variables mentioned above plus a school-readiness variable indicating the children's preschool experience (CenterDummy) showed how the coefficients changed when preschool was the only explanatory variable in the HLM growth model and then when other school-readiness variables were included. When the preschool variable was the only school-readiness variable included in the HLM growth model the regression coefficient was 2.97 for reading and 2.83 for mathematics. These results suggested that students with preschool experience scored, on average, almost 3 IRT scale assessment points higher on their fall kindergarten assessments, compared with students who did not attend preschool. When the five school-readiness variables were included in the HLM growth models the coefficients for the preschool variable dropped to .47 for reading and .35 for mathematics. The results from this additional HLM growth model showed the importance of accounting for all possible variables during data analyses and also suggested that including other variables possibly accounts for demographic differences. Excluding variables or demographic differences may change a study's results.

Limitations

There are four limitations of this study. First, because this study analyzed secondary data, it relied on accurate measures by the ECLS administrators: accurate test administration, accurate score and measurement reporting, and correct test selection. The ECLS is sponsored by the National Center for Education Statistics (NCES) within the Institute of Education Sciences (IES) of the U.S. Department of Education, with support from other federal agencies and many professional educational organizations. With this background, the ECLS-K:2011 is a credible study and data set, but there is always room for human error in manual processes such as typing test scores or survey answers.

The second limitation with using a secondary data set is relying on the administrators to choose tests that measure constructs, cognitive abilities, and situations correctly. Fortunately, the ECLS User's Manuals (Tourangeau et al., 2015, 2018) and ECLS website (https://nces.ed.gov/ecls/kindergarten2011.asp) provided most of the tests and surveys used and listed definitions of constructs measured. Due to copyright laws, some tests were not provided, such as the cognitive flexibility test (Dimensional Change Card Sort [Zelazo, 2006]) and working memory test (Numbers Reversed subtest of the Woodcock-Johnson III Tests of Cognitive Ability [Woodcock et al., 2001]). Furthermore, the reading and mathematics test questions were not released to the public; explanations of the tests were provided in the User's Manuals (Tourangeau et al., 2015, 2018).

The third limitation is the variables are defined only to the extent that ECLS measured them. The tests and surveys the ECLS administrators used to measure the variables may limit the conclusions drawn from this study. For example, the community-resources variable was a composite of 10 items from a parent survey about children's use of various community resources during the previous month. Although this composite would not be a bad measure the correlations were -.12 between it and the fall kindergarten reading and mathematics assessments. In other words, the more students used community resources, the lower their test scores, which intuitively does not make sense. For this study, there were no follow-up tests or surveys to further study children's use of community resources. Another example was the working memory variable. The Numbers Reversed test (Woodcock et al., 2001) used to measure students' working memory was too difficult for many of the fall kindergarteners, and about 39% scored at the assessment's lowest score possible (403). This assessment became more appropriate as the students aged, but perhaps a different working memory test could have provided a better representation of this ability in the fall kindergarteners. Even though one of the first steps of this study was to ensure the ECLS variables were accurate representations of school-readiness variables, some people may disagree with the variables chosen to represent school readiness for this study.

The fourth limitation is that this study was a longitudinal survey study, not an experiment; therefore, the relationships determined in this study between school-readiness and academic achievement are not causal relationships. This study's results suggest relationships between school-readiness variables and academic achievement through initial academic starting points and later growth, but this study cannot claim that one school-readiness variable is the most important predictor of academic achievement or that one variable causes academic achievement.

Discussion of Findings

As previously stated in this chapter, there are four major findings of this study. Before discussing these findings with more detail, it is necessary to discuss two general conclusions. First, the use of HLM growth modeling in this study, and second, the use of the ECLS data set to study school readiness. First, through the literature review, this study found that the research concerning children's school readiness and their academic achievement focused on one or two school-readiness categories and neglected to include a broad range of school-readiness categories. Therefore, this study set out to create a comprehensive definition of school readiness and include as many school-readiness variables as possible in the final HLM growth models, which was a definition that included six classes of school-readiness variables (13 variables). Ultimately only three classes were included (five variables), which was decided because a large number of explanatory variables in the HLM growth models would produce too many interaction terms, which would be too complicated to interpret. A simple correlation analysis of the 13 school-readiness variables with reading and mathematics achievement in fall kindergarten and spring fourth grade specified five school-readiness variables with correlations .200 and above. These five variables (from three classes) were concluded to have the strongest relationship to reading achievement and consequently included in the HLM growth models. These five variables were measures of the children's general academic knowledge, working memory, cognitive flexibility, behavior, and SES. The correlation analysis showed that some variables, such as coordination and BMI, have practically no relationship to academic achievement in the fall of kindergarten. Therefore, it was decided that variables like these would not benefit from being included in the HLM growth models.

The second general conclusion concerned the ECLS school-readiness variables used in this study versus previous school-readiness studies that used ECLS data sets. The 2011 ECLS data set used for this study had different school-readiness variables than the

1998 ECLS data set, which included fall kindergarten measures of the students' fine motor skills and a general knowledge assessment (called science assessment) administered by ECLS officials. In previous school-readiness studies, these variables were strong predictors of later academic achievement (Grissmer, Grimm, Aiyer, Murrah, & Steele, 2010; Hair et al., 2006). In the 2011 data set, children's physical coordination represented gross motor skills and general knowledge was based on a survey completed by the kindergarten teachers, not a cognitive assessment. If this study had been able to include the students' fine motor skills and a direct assessment of their general knowledge the final results might have been different.

Rank order of school-readiness variables

The first major finding of this study was the rank order of school-readiness variables. The results from the HLM growth modeling suggested an order of importance for the school-readiness variables, in terms of their coefficients, for reading and mathematics achievement. Estimates of the explanatory variables' intercepts helped to rank the variables by the amount of IRT points an above-average student would achieve. For the reading and mathematics HLM growth models there were three models each. Model 1 was the unconditional model, which included the two time variables EarlyGrades and LateGrades. Model 2 introduced four school-readiness variables: general knowledge, cognitive flexibility, working memory, and behavior. Model 3 introduced one more school-readiness variable: SES. The results of Model 2 of the reading and mathematics HLM growth models indicated the same rank order of the four school-readiness variables: (a) general knowledge, (b) working memory, (c) cognitive flexibility, and (d) behavior. After adding SES in Model 3 the rank order changed but it was still identical for reading and mathematics: (a) general knowledge, (b) working memory, (c) SES, (d) cognitive flexibility, and (e) students' behavior. The following paragraphs explain each of these variables.

The rank order of importance was based on the explanatory variables' coefficients, which represented the amount of IRT scale assessment points an above-average student on that variable would attain compared with a student on the mean of that variable. For example, this study found that general knowledge is the variable that contributed the most IRT scale assessment points to academic starting points in fall kindergarten for reading and mathematics. For this variable, students who scored one standard deviation above the mean have a mean fall kindergarten reading score of 4.20 IRT scale assessment points higher than students who are average on this variable (ES = 0.37). For mathematics, students who scored one standard deviation above the mean on this variable have a score of 3.24 IRT scale assessment points higher than students at the mean (ES = 0.28). The finding of the importance of general knowledge is similar to previous studies that used ECLS data sets to study general knowledge and academic achievement (Chatterji, 2006; Duncan et al., 2007; Grissmer et al., 2010; Linder, Ramey, & Zambak, 2013).

Perhaps one reason the general knowledge variable contributed the most IRT scale assessment points is that the general knowledge with which students start kindergarten (such as letter and number knowledge, writing their names, using strategies to solve math problems, etc.) are foundational early-education skills that kindergarten curriculum builds on. When students start kindergarten without basic early-education academic skills they have difficulty understanding grade-level lessons, which is reminiscent of the achievement gap and the school-readiness gap: the idea that children who start school academically behind have a harder time catching up to grade-level performing peers and are more likely to remain academically behind (Sadowski, 2006). Additionally, the questions on the teachers' survey used to create the general-knowledge variable might have been similar to the questions on the grade-level kindergarten reading and mathematics assessments, which possibly produced strong relationships. However, it is important to point out that the general knowledge construct in the first ECLS study was measured by a science achievement test not the ARS. The science achievement test would ostensibly be more similar to the reading and mathematics achievement tests.

A child's executive functioning skills (cognitive flexibility and working memory) also are important contributors to academic starting points in kindergarten. The working memory variable contributed a 2.64 IRT scale assessment point increase in reading (ES = 0.24) and a 3.23 IRT scale assessment point increase in mathematics (ES = 0.28). Additionally, for reading, working memory is about 1.5 IRT scale assessment points less than general knowledge, but for mathematics, working memory contributed almost the same number of points as general knowledge, which might be because of the strong relationship between working memory and mathematics (Bull & Scerif, 2001).

This study found that SES has a strong relationship with academic starting points. Based on the framework provided by Bronfenbrenner's (1979) ecological systems theory, this variable was the only variable categorized as distally developing, so it was entered fifth in the HLM growth models in SPSS. The other four variables were considered proximally developing. Even though the SES variable was entered last in the SPSS module during Model 3, it was found to be the third strongest influencer on academic achievement out of the five school-readiness variables. The change that SES made in the rank order shows the importance of this variable, suggesting that even variables that are a part of a child's farther-reaching ecological systems can have major consequences for their cognitive development. This finding is similar to the school-readiness research review by Linder et al. (2013), which showed that low SES was consistently found to be most detrimental to developing school readiness: children from low SES were twice as likely to have difficulty with school readiness compared with children from middle or high SES.

Finally, compared with previous studies, this study found that students' behavior has relatively little relationship to their academic starting points. Students with more positive behavior did not change their academic starting points by even half of one IRT scale assessment point for either reading or mathematics. These results are similar to DiPerna, Lei, and Reid (2007) and Duncan et al. (2007), who concluded that student behavior failed to predict reading or mathematical achievement, and Linder, Ramey, and Zambak (2013), who found that kindergarten students with high cognitive performance performed best on first-grade academic assessments regardless of their social skills. One reason for this weak relationship might be that social and emotional skills matter more for other school-related outcomes, not academic test scores (Duncan et al., 2007). For example, low attention spans may inhibit paying attention in the classroom but that does not necessarily mean low academic test scores (Georges, Brooks-Gunn, & Malone, 2012). Additionally, attention and behavior are not as easy to measure as achievement (Duncan & Magnuson, 2011). This means that the survey used to rate the students' behaviors may not have been as reliable as the cognitive assessments used to measure their working memory.

The correlation analysis performed to investigate which school-readiness variables would be included in the HLM growth models (the five variables outlined above) also determined that some school-readiness variables have little to no relationship to academic achievement; thus, these variables were not included in the HLM growth models. This conclusion about the lesser importance of some school-readiness variables is contrary to previous school-readiness studies that used ECLS data sets. For example, Reaney et al. (2002) found that children who participated in home educational activities, extracurricular activities, and frequented community resources had higher kindergarten reading and mathematics scores than children who did not. There are a few reasons why Reaney et al.'s (2002) study concluded this. First, Reaney et al. (2002) eliminated students who did not speak sufficient English to pass an oral screener for the reading and mathematics assessments, whereas this study excluded no children from the data set because one goal was to include all ECLS participants and thus enhance generalizability to the U.S. elementary-school population. Also, Reaney et al. (2002) used a series of linear regressions to examine only four school-readiness variables (home educational activities, extracurricular activities, access to community resources, and SES; none are cognitive measures). In contrast, this study used HLM growth modeling to examine five variables. These conflicting results show that different methodologies and different variables can lead to opposite conclusions about the same research interest.

In summary, the first major finding of this study is the rank order of school-readiness variables in terms of their contributions to students' academic starting points in fall kindergarten. This study's conclusion of the importance of a student's general academic knowledge to their academic achievement is similar to previous research (Chatterji, 2006; Duncan et al., 2007; Grissmer et al., 2010). Also, this study's conclusion that students' behavior is not as important to academic achievement as their general academic knowledge is similar to previous research (DiPerna et al., 2007; Duncan et al., 2007). Conversely, this study found that a child's home educational activities (their home environment), their extracurricular activities, and their use of community resources do not have a strong relationship to their academic achievement, which is different than previous research (Reaney et al., 2002).

Academic growth rates of school-readiness variables

The second major finding of this study is the contribution of the five school-readiness variables to academic growth in elementary school. Using HLM growth modeling as this study's methodology showed the students' academic growth in reading and mathematics from fall kindergarten to spring fourth grade. The academic growth rates are a product of the interaction between the school-readiness variables and the two time variables used in this study, EarlyGrades (fall kindergarten to spring first grade) and LateGrades (spring second grade to spring fourth grade). The academic growth rates show the IRT scale assessment points for students with above-average values on the different school-readiness variables compared with average students, either as more academic growth or less academic growth during both time periods. The coefficients were interpreted as the change in IRT scale assessment points per month.

In Model 3 of the HLM growth model for reading, three variables have a 0.10 IRT scale point increase per month during EarlyGrades: working memory, behavior, and SES. Cognitive flexibility is 0.07 and general knowledge shows no growth. For all five explanatory variables, there was no academic growth for above-average students during LateGrades (the coefficients are negative).

In Model 3 of the mathematics HLM growth model, during EarlyGrades, two variables have a 0.08 IRT scale assessment point increase per month for students above average on the variables: cognitive flexibility and SES. Working memory was 0.07, and general knowledge is 0.01. There is no academic growth during LateGrades for above-average students for any variable (the coefficients are negative).

The school-readiness variables' coefficients establish an initial order of importance for the school-readiness variables, which is the same for reading and mathematics, and the growth rates show how the school-readiness variables relate to students' academic growth over time. Working memory, behavior, and SES show the most academic growth for reading, whereas cognitive flexibility and SES show the most academic growth for mathematics. The growth rates also show that even though SES is third in order of importance for academic starting points, it is the largest contributor to academic growth for reading and mathematics. This means that students who are above the average on SES show more academic growth than students who are average SES or low SES. This conclusion is similar to Isaacs (2012) research, which showed that children from low-SES backgrounds suffer the negative effects of the school-readiness gap.

One of the goals of this study was to include academic growth to better understand how the relationships between school-readiness variables and academic achievement change over time. The research on this specific topic is sparse, perhaps because more emphasis is placed on student assessment scores (achievement at one point in time) instead of growth (achievement over time). Measuring student achievement at one point in time and ignoring academic growth raises some concerns (Anderman, Gimbert, O'Connell, & Riegel, 2014). First, it ignores students' prior knowledge and skills, and it unfairly holds different schools to the same standards (Anderman et al., 2014). One way to counteract the one-sidedness of student achievement measured by one point in time (e.g., one assessment score) is to show students' academic growth with multiple assessment scores. By using a longitudinal data set and six assessment scores (for reading and mathematics each), this study was able to show growth and how different school-readiness variables relate to it.

Using academic growth as a measure of student achievement has advantages. First, students in the early grades who show slow academic growth rates, or whose academic growth seems to stop, can receive academic interventions sooner and possibly be identified for special services like resource or special education (Shin & Lee, 2007). Second, academic growth in elementary school is less strongly related to SES than academic achievement measured at one point in time (e.g., as one assessment score; McCoach, Rambo, & Welsh, 2013). In other words, showing the academic growth of low-SES students is a better measure of their academic performance than one assessment score. Although this study did not focus on growth as a measurement of academic performance, it did conclude that there is a strong relationship between SES and students' initial academic achievement and growth. This study can be an example of the potential of using HLM growth modeling to understand how different explanatory variables relate to academic growth.

Rank order of school-readiness variables in reading and mathematics

The third major finding of this study was the comparison of rank order of the school-readiness variables in reading and mathematics. Originally, the third research question of this study sought to compare the explanatory variables' starting points (intercepts) and growth rates (slopes) of the HLM growth models for reading and mathematics, but this could not be accomplished because the ECLS reading and mathematics assessments are different assessments of different academic subjects. Instead, the rank order of the school-readiness variables was compared. Model 1 of the HLM growth models did not included any explanatory variables, only the time variables (EarlyGrades and LateGrades), which produced one mean intercept, one mean coefficient for EarlyGrades, and one mean coefficient for LateGrades. These values were different for reading and mathematics.

Four explanatory variables were introduced in Model 2: general knowledge, cognitive flexibility, working memory, and behavior. The rank order of the variables was the same for both reading and mathematics. General knowledge was the school-readiness variable with the strongest relationship with academic achievement, then working memory, cognitive flexibility, and behavior. When SES was introduced in Model 3 of the HLM growth models, the rank order changed, but it remained the same for reading and mathematics: general knowledge was the school-readiness variable with the strongest relationship to academic achievement, then working memory, SES, cognitive flexibility, and behavior.

This comparison shows two things. First, SES is an important contributor to academic achievement because even though it was added last in Model 3, it changed the rank order of the variables found in Model 2. Second, this comparison shows that school-readiness variables are not subject specific. Meaning, the rank order was not different for reading or mathematics, which suggests that school-readiness variables are equally important for both subjects.

Preschool analyses

The fourth major finding of this study is showing how adding explanatory variables to an HLM growth model changes the rank order of the variables, which was accomplished with the additional HLM growth models using the preschool variable. Research suggested that preschool educational programs help children achieve higher cognitive and academic assessment scores at the end of preschool and enhance initial readiness in kindergarten, but these effects fade out in later years of elementary school (Brooks-Gunn, 2011; Magnuson, Ruhm, & Waldfogel, 2007). This study found, however, that without a well-specified model, most of the mean score difference between students with preschool experience and students without preschool experience was not that pronounced at fall kindergarten so the fading is not surprising.

This additional analysis in Chapter IV, an HLM growth model using the CenterDummy variable for reading and mathematics, examined students' early educational experiences. The dummy variable used represented students who had center care (private or public preschool such as Head Start) before kindergarten versus students who had no center care (daycare, babysitters, or no nonparental care). Having a general definition in the form of a dummy variable took into account all early educational experiences of the children in the data set. Similar to the other HLM growth models, this analysis used three models as well: Model 1 with the two time variables, Model 2 with the preschool variable, and Model 3 with the five school-readiness variables (general knowledge, cognitive flexibility, working memory, behavior, and SES).

When the preschool variable was the only variable in the growth model (Model 2), results indicated that students with preschool experience before kindergarten scored 2.92 IRT scale assessment points higher on their fall kindergarten reading assessment compared with students without preschool experience. When the other five school-readiness variables were introduced in the growth model (Model 3), students with preschool experience had only 0.47 reading IRT scale assessment points more than students without preschool experience. This change may have occurred because when the other school-readiness variables were included in the HLM growth models, the effects were removed from the error term in Model 1 and instead were used as explanatory variables in Model 3 making Model 3 a better specified model, which means that studies that look at only one variable may not be accounting for the influence that other variables have on results. This additional analysis showed the importance of including as many variables as possible in a statistical model when studying something multivariate, such as school-readiness, and when the study is correlation rather than experimental.

Another possible reason for the change in the CenterDummy intercept estimate relates to Bronfenbrenner's (1979) ecological systems theory. Preschool is a distally developing variable, which may explain why it does not have as strong a relationship to students' academic starting points as cognitive abilities such as general knowledge, working memory, or cognitive flexibility. Another conceivable reason for the change in the CenterDummy intercept estimate might be the different racial demographics of the two CenterDummy groups, which are not equal. The different racial groups of the two

CenterDummy groups are listed in Table 29 (Chapter IV).

Conclusions

Children are not “blank slates” with no control over how their environments influence their personal growth; they are dynamic beings who can restructure their development depending on how they are treated and respond to treatment (Bronfenbrenner, 1979). This study’s results suggested that certain school-readiness variables, like cognitive knowledge and working memory, better prepare children to succeed academically in school. Resources need to be allocated to developing these school-readiness skills in children before kindergarten. For many children, a lack of support and resources increases their risk of school failure (West, Denton, & Germino-Hausken, 2000). Well-intentioned adults (families, friends, neighbors, educators, doctors, and government officials alike) are the key to helping children shift dynamically from ill prepared for school to well prepared for school. When educators know what interventions will be the most beneficial for academic success then children will succeed more. This will help address the school-readiness gap.

The first step in helping adults understand how to help children develop school readiness is to educate them about child development and show them ways to encourage children to develop readiness skills. For example, preschool directors must educate and train staff to address all areas of school readiness with their teaching, including nonacademic areas like working memory and behavior. Additionally, community centers, healthcare workers, and public places like the library must provide access to educational materials, counseling services, and information sessions geared toward helping adults support children’s development. Having more access to services that promote child development may raise school readiness in children.

Preparedness for school must include a checklist with ways to help children develop all aspects of school readiness, which can start with educating preschool and elementary school teachers about the components of school readiness. Teachers are at ground zero because they interact with students frequently during the school year, they can provide families with access to services, and educate children's caregivers about ways to develop school readiness. Including standards for teacher education in state preschool standards and Common Core Standards can ensure teachers are receiving trainings and staff development to educate them on new research. Educational videos, conferences, curriculum trainings, and other opportunities for professional development are all ways to promote teacher education.

A bigger issue beyond the classroom and what teachers can do continues to be the negative consequences of poverty on children's education. The influence that SES has on children's fall kindergarten academic starting points and their academic growth demonstrates what poverty can do to a child's educational career: a child with low SES has a disadvantage at the beginning of kindergarten that continues throughout elementary school. Even accounting for preschool experience did not change the strong relationship SES has to academic achievement, suggesting that a few years of early-childhood education cannot eliminate the persistent achievement gap between low-SES and high-SES children (Zigler, 2011). Intense early intervention, coupled with resources for families and home visits, may provide families with the resources and support they need to improve educational opportunities for children living in poverty (Zigler, 2011). To remedy the negative effects that poverty has on a child's education is a community effort.

The achievement gap has societal consequences. Children who fall behind in school are more likely to drop out, which causes problems for families, communities, the economy, and government agencies in general. If society is dedicated to closing the achievement gap, which seems to be confirmed by decades of attempts with initiatives such as Head Start and NCLB, then school readiness must be made an essential standard, not just in early education, but in all environments in which young children interact: their households or places of living, pediatricians' offices, public spaces, government services offices, and U.S. society in general. As Bronfenbrenner (1979) suggested, child development does not occur in a single environment, so all adults who interact with children must be thoughtful about ways to encourage children.

Implications for Research

The first implication for future research is the importance of the process of elimination when designing a research model for a broad topic such as school readiness. One goal of this study was to include six classes of school-readiness variables in the final HLM growth models. The purpose of creating inclusive models was to determine which variables are most influential in students' academic achievement, which had not been carried out by previous studies. However, through preliminary analyses, it was determined that not all school-readiness variables are equally important for academic achievement, which is why only three classes were ultimately examined. This study demonstrates why it is important to start with an inclusive model when studying a broad construct and specify the final model based on a process of elimination. Researchers should be aware of the problematic conclusions that can result from a misspecified model.

A second implication is the importance of general academic knowledge, working memory, and SES on a child's academic achievement. Investigations into how these three variables are related may reveal ways to help children progress academically or cope with the negative effects of low SES. Also, studies about how working memory can be developed to increase school readiness in children should be undertaken. Working memory is not a typical preschool standard, but the findings from this study suggest that it is a skill that can help achieve academic success. Working memory experiments with preschool children using treatment and comparison groups with academic assessment scores from elementary school as the dependent variable may lead to the development of preschool curriculum that teachers can use.

Finally, the last implication for future research is the importance of SES for school readiness. A child's SES is not a personal characteristic but a circumstantial variable. There have been many studies about the relationship between a child's SES and their academic preparedness for school (e.g., Isaacs, 2012; Linder et al., 2013), but there needs to be research about specific ways to help families combat the negative consequences of poverty so their children can be academically more prepared for school. Some circumstances of SES always will be harmful for children and their development but some resolutions can be offered. For example, providing books to children can help prepare them for school (Linder et al., 2013) although it will not eliminate their poverty. More empirical evidence is needed to help inform policy makers about the best course of action to improve educational outcomes for children living in poverty (Zigler, 2011).

Implications for Practice

Credential programs prepare teachers to enter the classroom and teach a variety of subjects. Student-teaching placements offer student teachers opportunities to work with a master teacher or team of teachers to develop their practice. When teachers graduate from credential programs and become solely responsible for their own students, however, support often ends. A new teacher might have a mentor for the first year of teaching, but once a teacher is tenured, support and observations typically become scarce or nonexistent. Even though the needs of students, curriculum, and society constantly are changing, teachers are sometimes left to their own devices to accommodate the changes. They are expected to adapt to these changes while also educating their students to the highest level to succeed in society.

One way to help teachers adapt to changes while maintaining their teaching practice is through classroom observations and assessments, which monitor teacher-student interactions and offer an evidence-based approach that can provide immediate feedback to teachers to inform them of pedagogical changes they can make to advance their students' learning. For example, the Classroom Assessment Scoring System (CLASS) was developed from a national study in early-childhood development as a way to hold teachers accountable for teacher-student interactions in the classroom (University of Virginia, Center for Advanced Study of Teaching and Learning, n.d.). CLASS is reliable and was validated in over 2,000 classrooms. It involves four 15-minute observations by a certified CLASS observer in three different areas: emotional support, instructional support, and classroom organization. These three areas address the five school-readiness variables that this study found to be most important: (a) emotional support to help teachers better understand their students' home environment (e.g., the negative effects low SES can have on a child's education), (b) instructional support to develop students' academic knowledge and skills (e.g., meeting grade-level standards and developing executive functioning skills like cognitive flexibility and working memory), and (c) classroom organization to help understand and manage student behavior. Having a common assessment tool provides a straightforward way of holding teachers accountable and helping them improve their teaching practice.

If teachers gain insight from observation assessments to improve their teaching and develop more caring relationships with their students, positive teacher-student interactions may occur, which will improve the educational experience for teachers and students. Improving instructional pedagogy based on student need puts the emphasis on student learning. In the end, few people have the privilege of changing positively the lives of children as teachers do, and preschool and elementary education needs to be focused on helping teachers accomplish this goal.

Summary

This study set out to develop a cohesive definition of school readiness and apply that definition to study school readiness. Specifically, this study examined the relationships between children's school-readiness variables and their academic achievement and growth from fall of kindergarten to spring of fourth grade. Based on research of associations interested in children's development (e.g., American Academy of Pediatrics, 2016; Head Start, 2015; National Association of the Education of Young Children, 2009), and definitions that previous authors used (e.g., Duncan et al., 2007; Mashburn & Pianta, 2006; Meisels, 1999), the definition of school readiness developed for this study included six classes of variables (13 variables). The intention of using a cohesive definition of school readiness for this study was based on a review of school-readiness literature and research, which showed that school-readiness skills and academic achievement had been studied in pieces and that no study attempted to look at six classes of school-readiness variables and how they related to students' academic achievement. Therefore, one of the purposes of this study was to establish an encompassing definition of school readiness and apply it to answer the research questions.

This study used a secondary data set to study school-readiness and academic achievement and growth. The ECLS-K:2011 data set, a nationally representative sample of more than 18,000 children, had measurements for all six classes of school-readiness variables and measurements of academic growth in reading and mathematics (assessments) from fall kindergarten to spring fourth grade. This study used variables from the ECLS data set to answer three research questions. First, how are the school-readiness variables related to academic achievement and growth in reading? Second, how are they related in mathematics? And third, how do they compare in reading and mathematics?

HLM growth modeling was used to answer the research questions. Ultimately, five school-readiness variables were included in the final models. The results of the HLM growth modeling indicated that the variable with the biggest relationship to students' academic starting points in reading and mathematics in fall kindergarten is their general knowledge. The variable with the second biggest relationship was working memory, third was SES, fourth was cognitive flexibility, and fifth was behavior. Growth rates (measured by assessment points) for each variable showed how each variable was related to changes in students' assessment scores in reading and mathematics. In general, the school-readiness variables contributed to more academic growth during kindergarten and first grade, and less academic growth during second, third, and fourth grades.

Limitations to the study include the use of a secondary data set, which meant that this study relied on accurate measurements and testing from the ECLS administrators, and limited the definitions of the variables in this study to the ECLS definitions. Another limitation is the nature of using a longitudinal survey study: no causal relationships were found, just indications of relationships between variables. The indication of the relationships between different school-readiness variables and children's academic achievement and growth give hope to the idea that adults can help children academically succeed by developing specific areas was one conclusion of this study. One way of accomplishing this goal is by educating teachers of the different school-readiness skills a child can have, and that some of these skills can be improved by effective teaching (e.g., students' general academic knowledge) and some are circumstantial, like SES, which are difficult or impossible for a teacher to remediate, but teachers can provide support and resources to help families.

Implications for future research include using process of elimination to choose variables when studying broad topics such as school readiness. Ignoring variables by not including them in data analyses can lead to misspecified models and incorrect results that can produce inaccurate conclusions. This implication was shown by an additional HLM growth analysis concerning preschool experience. A second implication is to study how general academic knowledge, working memory, and SES are related and how they interact to influence academic achievement. Implications for future practice include informing teachers of ways to improve their teaching, especially with classroom observations and professional development. Making teachers more aware of their students' educational, emotional, and physical needs may lead to more effective instruction, which, in turn, may help students gain more academic success.

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APPENDICES

APPENDIX A

Hierarchical Linear Growth Modeling Overview

Hierarchical linear growth modeling (HLM growth modeling) was chosen as the data analysis for this study several reasons. First, traditional approaches used to study longitudinal data, such as repeated measures techniques, are not as flexible. Unlike traditional methods such as ordinary least squares regressions (OLS regressions) that place constraints on the data, growth modeling is more flexible (Holt, 2008). For one thing, the points in time when the data were collected (e.g., assessment scores) can vary (Holt, 2008). Also, the number of assessments does not have to be the same for each student, so individuals do not have to be deleted if they are missing assessment scores, and the data set can keep its originally sampled population (Holt, 2008). A second reason for using HLM growth modeling is that it can be used to analyze nested data (Woltman, Feldstain, MacKay, & Rocchi, 2012). Each participant in this sample has six reading assessments scores and six mathematics assessment scores nested within six semesters of elementary school. Finally, HLM growth modeling is designed to handle multiple levels of data. This study had two levels: level 1 was multiple test scores nested in students and level 2 included the school-readiness variables.

The growth model used for this study has two levels. First, at level 1, there is a basic least squares OLS regression equation. OLS is a type of linear least squares method used for linear regression. Level 1 is represented by

$$Y = \pi_0 + \pi_1(time) + e_i$$

where Y represents the achievement outcome, π_0 is the intercept, π_1 is the slope or growth rate, *time* means time of testing, and e_i is the residual error. If this equation were estimating the fixed effect of achievement on time, it would produce a single regression to represent all students in the sample with one intercept and one slope. A graph for a basic OLS for a hypothetical group of five students is depicted in Figure A1..

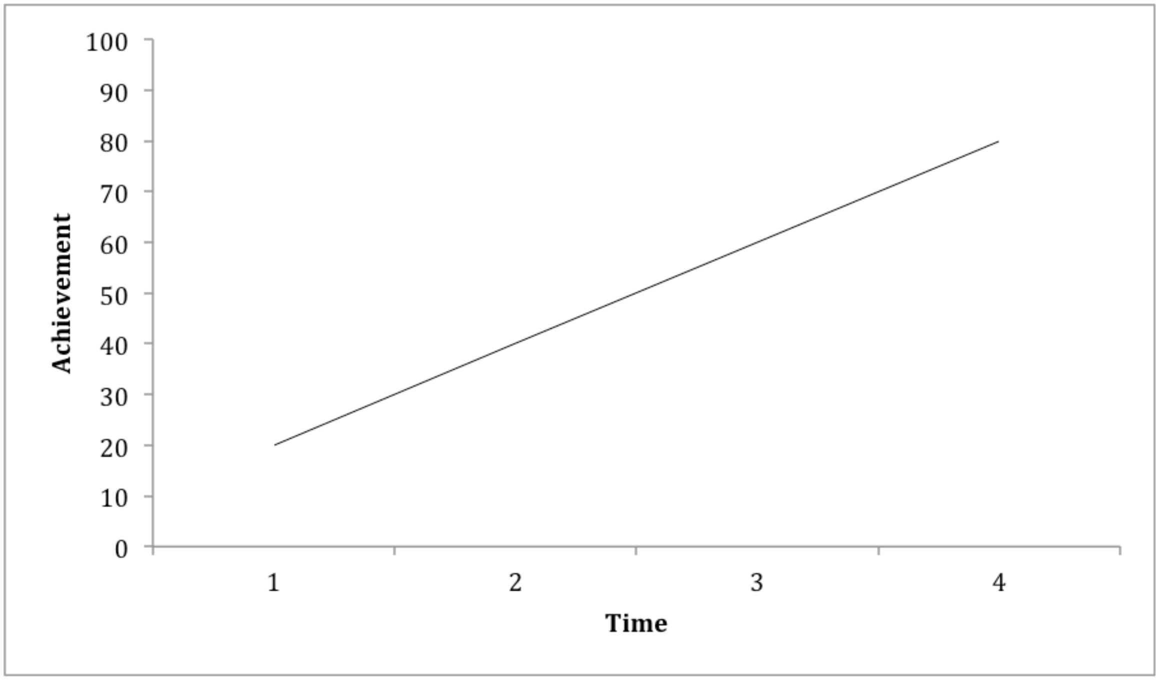

Figure A1. Fixed effects regression of achievement onto time.

One difference between OLS and HLM growth modeling is the addition of regression equations for the intercept and slope, which creates a regression line for each individual in a sample based on their unique data, which is especially important and useful for education research when the sample is a group of students. One concern with using OLS when studying academic growth is having one regression line represent all students in a sample, when in reality the rate of academic growth is usually not the same for all students. Some students start academically high and remain there, some start low and learn quickly, and some start low and remain low. A regression line may represent *most* students well, but it does not represent *all* students' growth well. Using growth modeling to create individual regression lines for a group of students is a more accurate way to model their academic growth, especially when working with assessment data.

The notation for HLM growth modeling is the basic OLS equation at level 1 with the addition of regression equations for individual intercepts and slopes at level 2. Also, the notation for the outcome variable now represents time (*t*) nested in individuals (*i*). The final notation is

$$Y_{ti} = \pi_{0i} + \pi_{1i}a_{ti} + e_{ti}$$

$$\pi_{0i} = \beta_{00} + r_{0i}$$

$$\pi_{1i} = \beta_{10} + r_{1i}$$

where *Y* represents the outcome score for time (*t*) nested in individuals (*i*), π_{0i} is the intercept or starting point at time zero ($t = 0$), π_{1i} is the slope or rate of change, a_{ti} is coded to represent the time of assessment, and e_{ti} is the residual error. A hypothetical graph for a sample of five students using this notation is displayed in Figure A2.

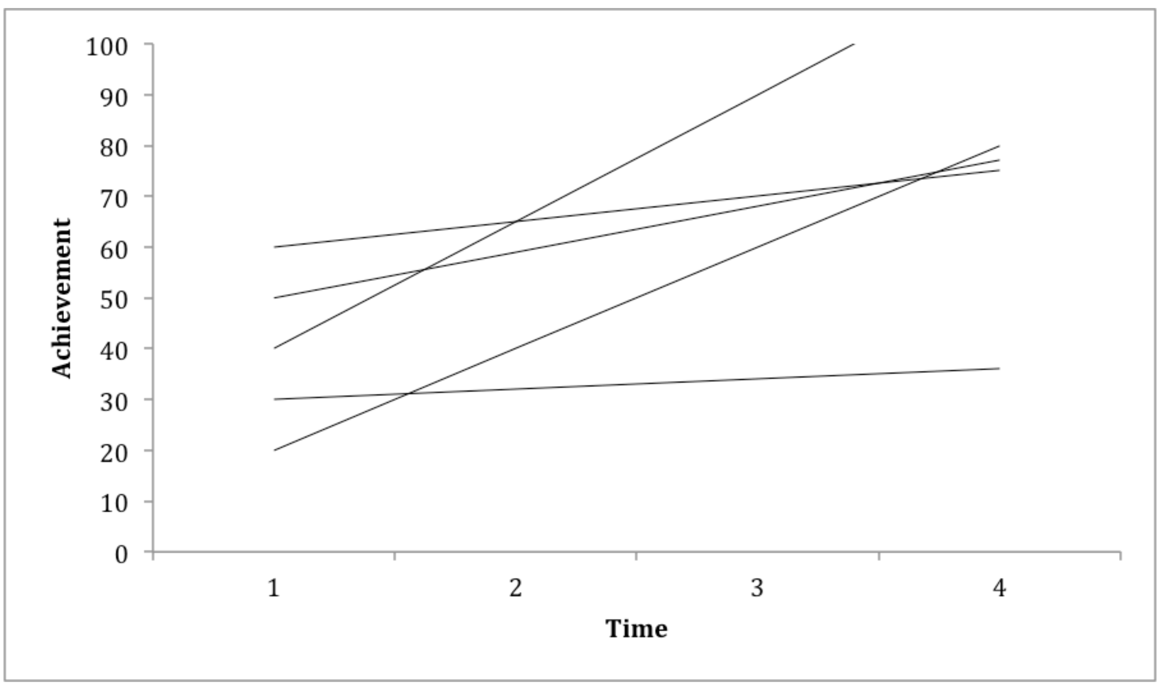

Figure A2. Level 2 HLM with random intercepts and slopes for five students.

To further illustrate how HLM growth modeling works, the subsequent notations and graphs show what happens to an individual regression line when the intercepts are fixed and then when the slopes are fixed. First is a level 2 model with random slopes (r_{1i})

and a fixed intercept. The residual (r_{0i}) has been removed, consequently fixing the intercept to a single value:

$$Y_{ti} = \pi_{0i} + \pi_{1i}a_{ti} + e_{ti}$$

$$\pi_{0i} = \beta_{00}$$

$$\pi_{1i} = \beta_{10} + r_{1i}.$$

This model estimates one intercept and individual slopes for the sample. Fixing the intercept changes the individual regressions as displayed in Figure A3.

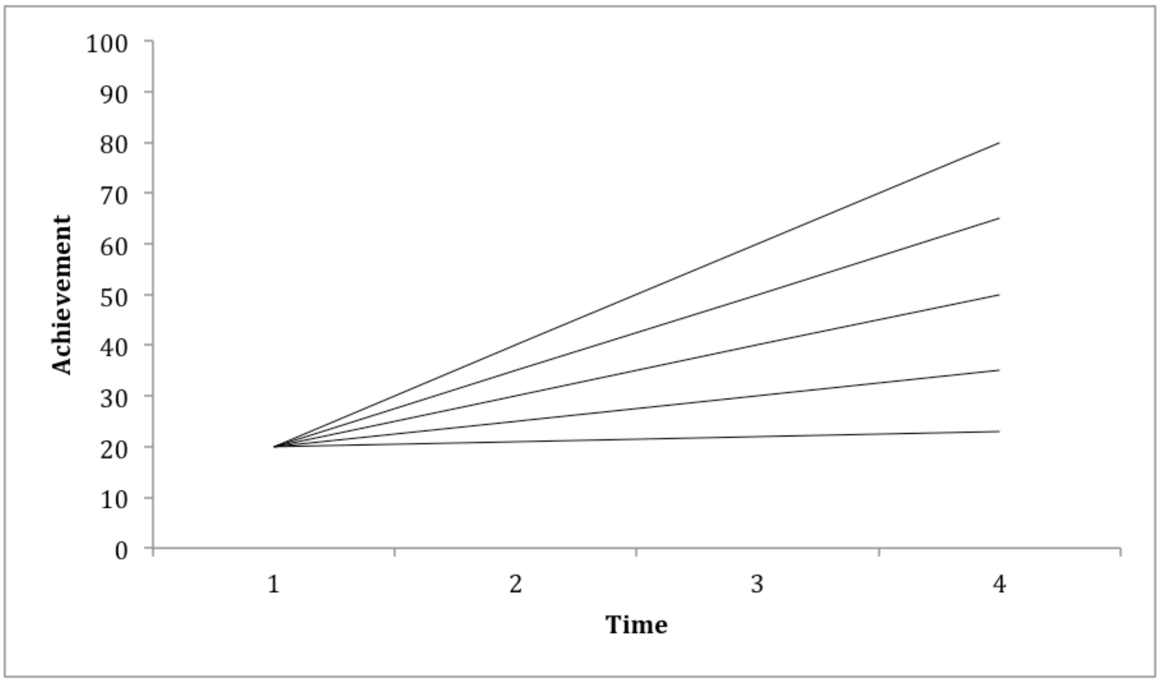

Figure A3. Level 2 HLM growth model with a fixed intercept for five students.

Although this model calculates the different rates of academic growth (displayed as different slopes), it does not account for the different academic starting points of the students. This model assumes the students are at the same academic starting point (intercept), even though it is rare for a group of students to be the same academically.

Next is the level 2 model including random intercepts (r_{0i}) and a fixed slope. The residual (r_{1i}) has been removed, thus removing the random effect and fixing the slopes to a single value:

$$Y_{ti} = \pi_{0i} + \pi_{1i}a_{ti} + e_{ti}$$

$$\pi_{0i} = \beta_{00} + r_{0i}$$

$$\pi_{1i} = \beta_{10}.$$

Adding the random intercepts term changes the starting point for each student is displayed in Figure A4.

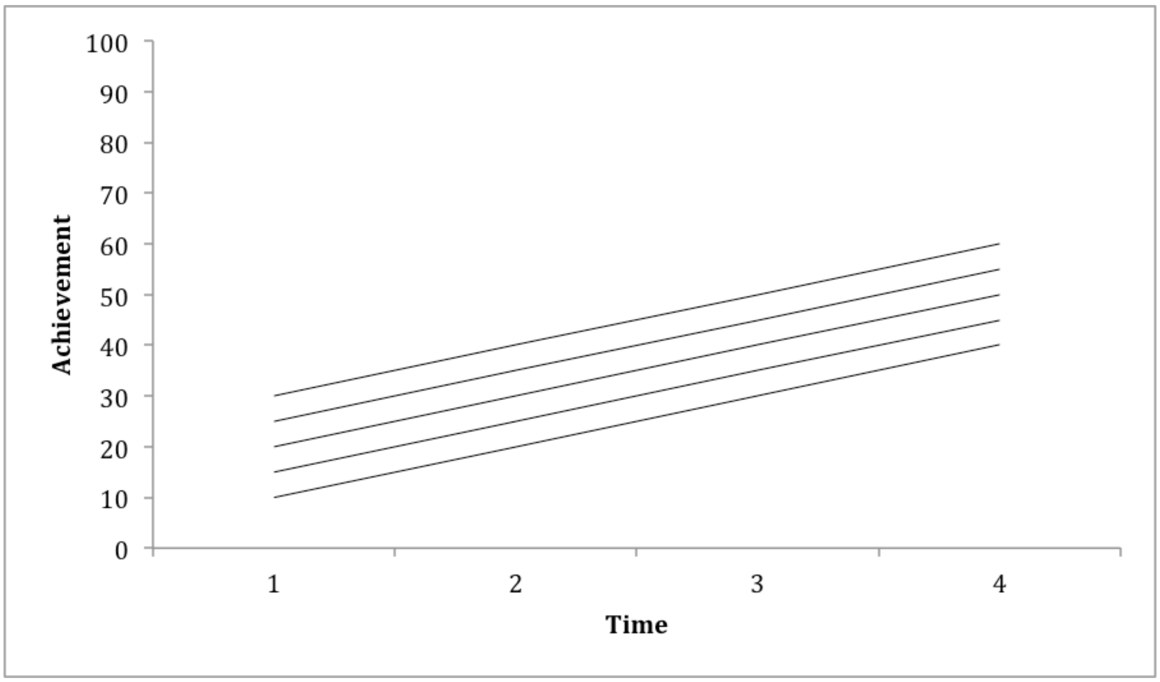

Figure A4. Level 2 HLM growth model with a fixed slope for five students.

Each student's unique academic starting point is represented in Figure A4, but this model assumes that all students learn at the same rate, as displayed by their equal slopes, which is unlikely in a group of students.

In summary, HLM growth modeling is a complex form of OLS that calculates a different intercept and slope for each student, whereas linear regression calculates only one intercept and slope for all students. The addition of the random intercepts (r_{0i}) and random slopes (r_{1i}) creates more accurate results because it uses each student's unique data to create individual regression lines, which leads to more precise interpretations of data. Also, it is often used in education to model student growth when the data are nested, such as in this study, which had two levels: six test scores (level 1) nested within each student over 5 years (level 2; Woltman et al., 2012). Because this study used nested data, it used a two-level model. Level 1 of the model represents time nested within each student to produce the repeated measures growth curve. The notation is

$$Y_{ti} = \pi_{0i} + \pi_{1i} a_{ti} + e_{ti}$$

where *Y* represents the outcome score for time (*t*) nested in individuals (*i*), π_{0i} is the intercept, *a* is the time point, and *e* is the residual error.

Level 2 of the model with an explanatory variable (*X*) is

$$\pi_{0i} = \beta_{00} + \beta_{01} X_1 + r_{0i}$$

$$\pi_{1i} = \beta_{10} + \beta_{11} X_1 + r_{1i}.$$

The final two-level model is

$$Y_{ti} = \pi_{0i} + \pi_{1i} \alpha_{ti} + e_{ti}$$

$$\pi_{0i} = \beta_{00} + \beta_{01} X_1 + r_{0i}$$

$$\pi_{1i} = \beta_{10} + \beta_{11} X_1 + r_{1i}.$$

As explained in Chapter III, the final model for this study was determined to be a two-piece linear model using the time variables EarlyGrades and LateGrades. The variance-covariance structure for the error term is AR(1): heterogeneous. The final two-level model with the six-classes of explanatory variables and time variables is

$$\Upsilon_{ti} = \pi_{0i} + \pi_{1i} EarlyGrades + \pi_{2i} LateGrades + e_{ti}$$

$$\pi_{0i} = \beta_{00} + \beta_{01}(\text{SR1}) + \beta_{02}(\text{SR2}) + \beta_{03}(\text{SR3}) + \beta_{04}(\text{SR4}) + \beta_{05}(\text{SR5}) + \beta_{06}(\text{SR6}) + r_{0i}$$

$$\pi_{1i} = \beta_{10} + \beta_{11}(\text{SR1}) + \beta_{12}(\text{SR2}) + \beta_{13}(\text{SR3}) + \beta_{14}(\text{SR4}) + \beta_{15}(\text{SR5}) + \beta_{16}(\text{SR6}) + r_{1i}$$

$$\pi_{2i} = \beta_{20} + \beta_{21}(\text{SR1}) + \beta_{22}(\text{SR2}) + \beta_{23}(\text{SR3}) + \beta_{24}(\text{SR4}) + \beta_{25}(\text{SR5}) + \beta_{26}(\text{SR6}) + r_{2i}.$$

Using IBM SPSS version 25, the correct time variables, error structures, school-readiness variables, and assessment variables were entered into the SPSS Mixed Models module to answer this study's research questions.

APPENDIX B

Descriptive Statistics for Explanatory Variables

Table B1
Descriptive Statistics for Teacher-Reported Academic Rating Scale (ARS) from ECLS-K:2011

Label	Description	Mean	*SD*	*N*
T1CMPSEN	Q1 Uses complex sentence structure	2.84	1.33	14,124
T1STORY	Q2 Interprets story read to him or her	2.86	1.21	14,192
T1LETTER	Q3 Names upper and lower case	3.19	1.41	14,383
T1PRDCT	Q4 Predicts what happens in stories	2.95	1.20	14,069
T1READS	Q5 Reads simple books independently	2.26	1.23	12,828
T1USESTR	Q6 Uses different strategies with unfamiliar words	2.13	1.16	11,630
T1WRITE	Q7 Shows early writing behaviors	2.28	1.18	12,654
T1CMPSTR	Q8 Composes simple stories	1.88	1.07	10,090
T1PRINT	Q9 Understands conventions of print	2.23	1.12	12,309
T1OBSRV	Q10 Uses senses to explore or observe	2.77	1.13	11,352
T1EXPLN	Q11 Bases explanation on observations	2.55	1.16	9,846
T1CLSSFY	Q12 Groups living and nonliving things	2.79	1.18	9,219
T1SCIPRD	Q13 Makes logical scientific predictions	2.60	1.13	9,604
T1COMSC	Q14 Communicates science information	2.39	1.12	9,153
T1PHYSCI	Q15 Understands physical science concepts	2.52	1.11	9,953
T1LIFSCI	Q16 Understands life science concepts	2.76	1.13	10,316
T1ERSPSC	Q17 Understands early or space science	2.34	1.14	6,602
T1SORTS	Q18 Sorts math materials by criteria	3.09	1.15	13,797
T1ORDER	Q19 Orders group of objects by criteria	2.91	1.20	11,222
T1RELAT	Q20 Understands quantity relationships	2.77	1.21	11,628
T1SOLVE	Q21 Solves problems with numbers or objects	2.41	1.17	9,428
T1GRAPH	Q22 Understands graphing activities	2.91	1.18	12,318
T1MEASU	Q23 Uses instruments for measuring	2.12	1.12	5,717
T1STRAT	Q24 Uses strategies for math problems	2.49	1.09	11,281
T1FRACTN	Q25 Models reads compares fractions	1.37	.84	2,958

Note: Min. and max. are 1 to 5 for all variables.

Table B2
Descriptive Statistics for ECLS-K:2011 Explanatory Variables

School-Readiness Class	Variable	Reliability Coefficient	Min	Max	Mean	*SD*	*N*
1. Cognitive knowledge and skills	25 ARS *See above						
	X1DCCSTOT		0.0	18.0	14.2	3.3	15,604
	X1NRWABL		393	581.0	433.0	30.2	15,598
2. Social and emotional skills	X1TCHCON	0.81	1.0	4.0	3.1	0.6	13,550
	X1TCHPER	0.86	1.0	4.0	3.0	0.6	13,708
	X1TCHEXT	0.88	1.0	4.0	1.6	0.6	14,385
	X1TCHINT	0.79	1.0	4.0	1.5	0.5	14,239
	X1ATTNFS	0.87	1.0	7.0	4.7	1.3	14,562
	X1INBCNT	0.87	1.0	7.0	4.9	1.3	14,556
	X1PRNCON	0.73	1.0	4.0	2.9	0.5	13,205
	X1PRNSOC	0.68	1.0	4.0	3.4	0.6	13,232
	X1PRNSAD	0.56	1.0	3.8	1.5	0.4	13,209
	X1PRNIMP		1.0	4.0	2.1	0.7	13,132
	X1TCHAPP	0.91	1.0	4.0	2.9	0.7	14,770
	X1PRNAPP	0.70	1.0	4.0	3.2	0.5	13,220
3. Family structure and home environment	X4SESL_I		-2.3	2.6	-0.05	0.8	16,005
	X12LANGST		1.0	3.0	1.8	0.4	16,045
	P1TELLST		1.0	4.0	3.1	1.0	13,380
	P1SINGSO		1.0	4.0	3.1	1.0	13,379
	P1HLPART		1.0	4.0	2.8	0.9	13,377
	P1CHORES		1.0	4.0	3.2	1.0	13,376
	P1GAMES		1.0	4.0	2.9	0.9	13,376
	P1NATURE		1.0	4.0	2.3	1.0	13,376
	P1BUILD		1.0	4.0	2.5	1.0	13,375
	P1SPORT		1.0	4.0	2.8	1.0	13,374
	P1NUMBRS		1.0	4.0	3.5	0.7	13,372
	P1READBK		1.0	4.0	3.3	0.9	13,370
4. Physical skills and health	P2COORD		1.0	4.0	1.7	0.5	13,011
	X1BMI		8.6	42.9	16.5	2.4	15,702
5. Access to community resources	P2LIBRAR		1.0	2.0	1.0	1.4	13,402
	P2BKSTOR		1.0	2.0	1.4	1.4	13,399
	P2CONCRT		1.0	2.0	1.6	1.4	13,396
	P2MUSEUM		1.0	2.0	1.6	1.5	13,393
	P2ZOO		1.0	2.0	1.5	1.4	13,393
	P2SPORT		1.0	2.0	1.5	1.5	13,392
6. Early school experiences	X12PRIMPK		0.0	8.0	4.7	3.0	15,020

Note: Reliability coefficients are provided for the variables if they were reported in the User's Manual (Tourangeau et al., 2015).

APPENDIX C

Descriptive Statistics and Correlation Matrix for Response Variables

Table C1
Descriptive Statistics for ECLS-K:2011 Response Variables

Variable	Reliability Coefficients	Range	Min.	Max.	Mean	*SD*	*N*
X1RSCALK4	.95	0-155	31.4	125.0	52.27	11.21	15,669
X1MSCALK4	.92	0-146	9.7	139.1	34.14	11.51	15,595
X2RSCALK4	.95	0-155	31.6	125.0	66.48	13.60	17,186
X2MSCALK4	.94	0-146	7.2	88.8	45.08	12.73	17,143
X4RSCALK4	.93	0-155	37.4	140.2	91.60	17.79	15,115
X4MSCALK4	.93	0-146	19.1	133.2	72.13	17.32	15,103
X6RSCALK4	.91	0-155	54.6	139.5	106.14	15.32	13,837
X6MSCALK4	.94	0-146	13.7	14.0	89.13	16.56	13,830
X7RSCALK4	.87	0-155	62.8	147.2	115.65	14.70	12,866
X7MSCALK4	.92	0-146	40.3	144.3	101.47	15.66	12,866
X8RSCALK4	.88	0-155	59.7	144.4	122.17	12.98	12,074
X8MSCALK4	.92	0-146	25.2	139.1	109.01	15.33	12,080

Note: All variables continuous.

Table C2
Correlation Matrix for Response Variables

	1	2	3	4	5	6	7	8	9	10	11
1 Fall K Rd	1.00										
2 Spr K Rd	.81	1.00									
3 Spr 1 Rd	.67	.79	1.00								
4 Spr 2 Rd	.59	.70	.86	1.00							
5 Spr 3 Rd	.55	.65	.78	.85	1.00						
6 Spr 4 Rd	.53	.63	.77	.84	.84	1.00					
7 Fall K Math	.76	.72	.68	.64	.63	.60	1.00				
8 Spr K Math	.66	.74	.71	.68	.67	.64	.82	1.00			
9 Spr 1 Math	.59	.66	.73	.71	.70	.68	.77	.82	1.00		
10 Spr 2 Math	.54	.62	.70	.73	.73	.72	.70	.78	.85	1.00	
11 Spr 3 Math	.51	.59	.67	.69	.72	.71	.68	.75	.82	.88	1.00
12 Spr 4 Math	.49	.57	.65	.69	.71	.73	.65	.72	.79	.87	.89

APPENDIX D

List of Missing Data for ECLS-K:2011 Explanatory and Response Variables

Table D1
Missing Data for ECLS-K:2011 Explanatory Variables

Variable	Valid	Missing
T1CMPSEN	14,824	3,350
T1STORY	14,800	3,374
T1LETTER	14,694	3,480
T1PRDCT	14,774	3,400
T1READS	14,775	3,399
T1USESTR	14,799	3,375
T1WRITE	14,802	3,372
T1PRINT	14,812	3,362
T1OBSRV	14,778	3,396
T1SORTS	14,785	3,389
T1ORDER	14,785	3,389
T1RELAT	14,783	3,391
T1GRAPH	14,800	3,374
T1STRAT	14,781	3,393
X1DCCSTOT	15,604	2,570
X1NRWABL	15,598	2,576
X1TCHCON	13,550	4,624
X1TCHPER	13,708	4,466
X1TCHEXT	14,385	3,789
X1TCHINT	14,239	3,935
X1ATTNFS	14,562	3,612
X1INBCNT	14,556	3,618
X1PRNCON	13,205	4,969
X1PRNSOC	13,232	4,942
X1PRNSAD	13,209	4,965
X1PRNIMP	13,132	5,042
X1TCHAPP	14,770	3,404
X1PRNAPP	13,220	4,954
P2COORD	13,060	5,114
X1BMI	15,702	2,472
X12SESL	16,005	2,169
X12LANGST	16,045	2,129
P1TELLST	13,380	4,794
P1SINGSO	13,379	4,795
P1HLPART	13,377	4,797
P1CHORES	13,376	4,798
P1GAMES	13,376	4,798
P1NATURE	13,376	4,798
P1BUILD	13,375	4,799
P1SPORT	13,374	4,800
P1NUMBRS	13,372	4,802
P1READBK	13,370	4,804
X12CAREPK	15,972	2,202

Table D1, Continued
Missing Data for ECLS-K:2011 Explanatory Variables

X12PRIMPK	15,020	3,154
P1HSPKCN	13,320	4,854
P1CTRSCH	13,317	4,857
P2LIBRAR	13,402	4,772
P2BKSTOR	13,399	4,775
P2CONCRT	13,396	4,778
P2MUSEUM	13,393	4,781
P2ZOO	13,393	4,781
P2SPORT	13,392	4,782

Note: N = 18,174 for all variables.

Table D2
Missing Data for ECLS-K:2011 Response Variables

Variable	Valid	Missing
X1RSCALK4	15,669	2,505
X1MSCALK4	15,595	2,579
X2RSCALK4	17,186	988
X2MSCALK4	17,143	1,031
X2SSCALK4	16,936	1,238
X4RSCALK4	15,115	3,059
X4MSCALK4	15,103	3,071
X4SSCALK4	15,072	3,102
X6RSCALK4	13,837	4,337
X6MSCALK4	13,830	4,344
X6SSCALK4	13,819	4,355
X7RSCALK4	12,866	5,308
X7MSCALK4	12,866	5,308
X7SSCALK4	12,856	5,318
X8RSCALK4	12,074	6,100
X8MSCALK4	12,080	6,094
X8SSCALK4	12,069	6,105

Note: N = 18,174 for all variables.

APPENDIX E

Correlation Matrices and Descriptive Statistics for 13 Explanatory Variables and 12 Response Variables

Table E1
Correlation Matrix for 13 Explanatory Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13
1 TAcadRating	1.000												
2 ZX1DCCSTOT	.234	1.000											
3 ZX1NRWABL	.311	.219	1.000										
4 TeacherSE	.341	.152	.174	1.000									
5 ParentSE1	.192	.130	.124	.177	1.000								
6 ParentSE2	-.101	-.054	-.086	-.246	-.279	1.000							
7 Coord	.067	.026	.058	.058	.163	-.058	1.000						
8 BMIDummy	.043	.031	.052	.043	.024	-.016	.045	1.000					
9 ZX12SESL	.289	.179	.228	.140	.182	-.127	.063	.101	1.000				
10 LangDummy	.147	.134	.061	.004	.233	-.032	.020	.056	.257	1.000			
11 HomeEnv	.079	.065	.049	.047	.342	-.113	.076	.002	.126	.221	1.000		
12 CommRes	-.108	-.050	-.066	-.059	-.177	.087	-.093	-.021	-.252	-.120	-.289	1.000	
13 CenterDummy	.124	.059	.073	.003	.067	-.020	.027	.025	.177	.061	.031	-.075	1.000

Table E2
Descriptive Statistics for 13 Explanatory Variables

Class	Variable	Min.	Max.	Mean	*SD*
1. Cognitive knowledge and skills	1. TAcadKnow	-2.66	2.97	0.00	1.00
	2. ZX1DCCSTOT	-4.27	3.38	0.00	1.00
	3. ZX1NRWABL	-2.09	6.16	0.00	1.00
2. Social and emotional skills	4. TRatingSE	-4.06	3.14	0.00	1.00
	5. PRatingSE1	-4.73	3.18	0.00	1.00
	6. PRatingSE2	-4.34	5.18	0.00	1.00
3. Physical skills and health	7. BMIDummy	0.00	1.00	0.50	0.50
	8. Coord	1.00	4.00	3.22	0.56
4. Family structure and home environment	9. ZX12SESL	-4.22	3.61	0.00	1.00
	10. LangDummy	0.00	1.00	0.81	0.39
	11. HomeEnv	-4.06	3.56	0.00	1.00
5. Access to community resources	12. CommRes	-3.51	3.64	0.00	1.00
6. Early school experiences	13. CenterDummy	0.00	1.00	0.50	0.50

Note: All variables *N* = 18,151 except X1NRWABL (*N* = 17,752).

Table E3
Correlation Matrix for Reading Assessments

	1	2	3	4	5	6
1 Fall K	1.000					
2 Spring K	.812	1.000				
3 Spring 1	.672	.791	1.000			
4 Spring 2	.595	.702	.856	1.000		
5 Spring 3	.553	.645	.776	.850	1.000	
6 Spring 4	.528	.629	.765	.835	.842	1.000

Note: All variables *N* = 18,151

Table E4
Correlation Matrix for Mathematics Assessments

	1	2	3	4	5	6
1 Fall K	1.000					
2 Spring K	.820	1.000				
3 Spring 1	.765	.822	1.000			
4 Spring 2	.704	.775	.850	1.000		
5 Spring 3	.676	.745	.816	.883	1.000	
6 Spring 4	.647	.719	.792	.867	.860	1.000

Note: All variables *N* = 18,151

Table E5
Descriptive Statistics for 12 Response Variables

Variable	Min.	Max	Mean	*SD*
Fall K Read	15.02	125.03	52.46	11.44
Spring K Read	24.80	125.03	66.59	13.86
Spring 1 Read	37.40	146.45	91.11	17.70
Spring 2 Read	49.20	151.31	105.71	15.32
Spring 3 Read	54.04	158.96	114.99	14.77
Spring 4 Read	59.72	162.65	121.32	13.44
Fall K Math	-11.32	139.16	34.38	11.63
Spring K Math	-3.00	98.29	48.31	12.71
Spring 1 Math	-0.17	133.20	71.55	17.42
Spring 2 Math	13.66	143.97	88.59	16.65
Spring 3 Math	24.05	152.88	100.73	15.76
Spring 4 Math	25.21	167.07	108.19	15.53

Note: N = 18,151 for all variables.