Neighborhood Effects on Low-Performing First Graders' Mathematics Growth Trajectories

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CHAPTER 1

INTRODUCTION

A central goal of the formal education system is to provide each student with an opportunity to academically excel. Yet, the question of why certain students perform worse academically in mathematics during their first three years (kindergarten through to the second grade) of schooling remains unanswered. The need to identify causes of deficiencies in mathematics achievement is of critical importance given the significant role such insights have in shaping public policies designed to promote student achievement.

The primary objective of this dissertation is to investigate and understand the impact neighborhood contexts may have on low-performing first-grade students' mathematics achievements. An empirical investigation is possible because this study uses data from a two-year, randomized field experiment that contains information on students, neighborhoods, longitudinal mathematics achievement data, and a myriad of relevant student-level covariates (e.g., race, ethnicity, gender, and socioeconomic status).

The rest of this chapter is organized as follows: Section One discusses the problems associated with low achievement in mathematics. Section Two provides a brief overview of the relevant literature concerning neighborhood effects and identifies the existing knowledge gap in the contextual neighborhood effects research field. Section Three presents the purpose of this study and the research questions. Section Four establishes the limitations of this study and outlines the remaining chapters.

Problems Associated with Low Mathematics Achievement Scores

Identifying potential sources of low mathematics achievement is important because mathematics achievement relates to future educational attainment, career choices, and advancement (National Mathematics Advisory Panel, 2008). The pervasive lack of basic mathematics competency is well documented. For example, the 2003 cycle of the National Assessment of Educational Progress (NAEP) reported that 32% of fourth-graders performed at or above the proficiency level. Results from the 2005–2019 cycles of the NAEP produced slightly higher results for fourth-graders performing at or above the proficiency level (i.e., 35–41%). Over the last decade, there have been noticeable differences in NAEP performance levels by subgroups. For example, from 2007– 2019, 51– 52% of White 4^{th} graders performed at or above the proficiency level. In contrast, from 2007–2019, 15–20% of Black 4^{th} graders performed at or above the proficiency level. During the same time period, there were noticeable differences related to gender (Male: 41–44% vs. Female: 37–41%), free or reduced lunch eligibility (Eligible: 22–26% vs. Not Eligible: 53–59%) and status as English learners (English learners: 12–16% vs. not English learners: 42–25%).

Economists Murnane and Levy (1996) highlighted the importance of mathematical knowledge:

> Close to half of all seventeen-year old's cannot read nor do math at the level needed to get a job at a modern automobile plant. Barring some other special knowledge or talent that would allow them to earn a living as, say, a plumber or artist, they lack the skills to earn a middle-class paycheck in today's economy. (p. 23)

The National Science Board predicts that jobs with mathematics-related skills are outpacing overall job growth by a 3:1 ratio (National Science Board, 2008).

Although few would question the importance of school-age children achieving early success in mathematics, children enter kindergarten with a vast range of mathematical knowledge, skills, and abilities (Alexander et al., 1994; Baroody, 1987; Byrnes & Wasik, 2009;

Denton & West, 2002; Gross, 1993; Houssart, 2001). For example, results from the United States (U.S.) Department of Education's nationally representative Early Childhood Longitudinal Study (ECLS) revealed that approximately 35% of the four-year-olds tested were classified below the proficiency level of recognizing numbers and shapes, and 40% of the four-year-old study participants could not count 20 objects.

Unfortunately, the mathematics achievement gap observed in early grades continues to widen during subsequent years of schooling. Kowaleski-Jones and Duncan (1999) found, using data from the nationally representative Children of the National Longitudinal Survey of Youth (NLSY), that correlations between children aged six to seven years and 12–13 years were 0.46 for the Peabody Individual Achievement Test (PIAT) mathematics assessment. Likewise, Claessens et al.'s (2009) analysis of ECLS-K found that pre-k mathematics ability was predictive of mathematics achievement in the first grade and that "the most powerful pre-school avenue for boosting fifth-grade achievement appears to be improving the basic academic skills of low-achieving children prior to kindergarten entry" (p. 1). Princiotta et al.'s (2006) analysis of the ECLS report found that a student's mathematical achievement in kindergarten was associated with their fifth-grade mathematics achievement scores. For example, 67% of the kindergarteners who scored in the highest third of the distribution in a mathematics assessment did this once more in the fifth grade. Similarly, kindergartners who scored in the lowest third scored lower than their peers six years later in the fifth grade.

The observed mathematics achievement gap is particularly persistent for certain subgroups. For example, the U.S. Department of Education's ECLS-K report shows that only 11% of African-American kindergartners scored in the highest third of the mathematics assessment distribution, while approximately 62% scored in the lowest third (Claessens et al., 2009). Similarly, Fryer and Levitt (2004) used the ECLS-K dataset to explore the observed Black-White test-score gap during the first two years of formal schooling. The researchers reported, after controlling for various covariates, that there was no statistically meaningful difference between incoming African-American and White kindergartners' mathematics achievement scores.[1] However, the researchers observed, after controlling for a set of available covariates, that during the first four years of schooling, African-American children lost approximately 0.10 standard deviations per school year when compared to children of other races (Fryer & Levitt, 2004). In another study that reported results from the ECLS-K, it was shown that African-American and Hispanic kindergartners scored approximately two-thirds of a standard deviation below White kindergarteners in mathematics (Magnuson & Duncan, 2006). Denton and West (2002) further reported that, on average, first graders belonging to racial minority groups scored below average in mathematics skills.

The possible determinants associated with students' low mathematical achievement scores include differences in their families' socioeconomic statuses and wealth (Brooks-Gunn et al., 1997; Entwisle & Alexander, 1992; Jencks & Mayer, 1990a; Wilson, 1987), differences in the quality of their schooling (Caldas & Bankston, 1998; Cook & Evans, 2000; Rivkin et al., 2005); differences in access to high-quality teaching of mathematics (Anyon, 1981; Ladson-Billings, 1997; Means & Knapp, 1991); and differences in perceptions of socialization, behavior, and culture (Cook & Ludwig, 1998; Fordham & Ogbu, 1986; Lareau, 2002; Steele & Aronson, 1998). All of these factors likely contribute to the persistent educational inequalities and the different achievement levels in mathematics observed between economically advantaged and disadvantaged students and

[1] Fryer and Levitt (2004) used the following covariates in their analysis: a series of race dummy variables (i.e., White, Black, Hispanic, Asian, Other); gender; age (in months); SES composite measure; mother's age at time of first birth; number of children's books present in home; WIC (women, infants, and children) participation.

minority and majority students. The research in this section supports the theory that once a student falls below the standard level of mathematics achievement for their grade level, in the absence of an intervention, it is difficult for that student to "catch up" with their peers who perform at the standard level for their grade.

Relevant Literature on Neighborhood Studies

Although many hypotheses explain observable differences in students' academic achievements, few explore the notion that certain differences in students' academic achievements are attributable to differences in neighborhood contexts. In general, empirical research has suggested that neighborhood contexts have a degree of influence on students' academic outcomes.

The majority of the literature regarding neighborhood contexts has assumed that growing up in an affluent (i.e., advantaged) neighborhood enables children to learn more in school, graduate from college, and seek high-income jobs. Furthermore, a majority of theoretical models predict that children from more affluent families and neighborhoods outperform children from disadvantaged families and neighborhoods (Brooks-Gunn et al., 1993; Chase-Lansdale et al., 1997; Ginter et al., 2000; Leventhal & Brook-Gunn, 2001). The classic and influential review of neighborhood effects conducted by Jencks and Meyer (1990b) identified three models that assessed the influence adults and peers had on school-age children: firstly, the collective socialization model examines how adults living within a neighborhood influence children and serve as role models for children who are not theirs. Secondly, the epidemic model assumes that "like begets like" and highlights the manner in which peers influence one another. Thirdly, the relative deprivation model focuses on how students evaluate their accomplishments by comparing themselves to others in their environments (e.g., school and neighborhood).

In Leventhal and Brooks-Gunn's (2000) review of neighborhood research, they reported that, across all studies, neighborhood effects on student outcomes were small to moderate in magnitude. The researchers found that the statistical results varied by age group. For example, the researchers reported that, after controlling for multiple individual and family characteristics, the presence of high socioeconomic status (SES) neighbors had a positive effect on the achievement outcomes of children aged zero to 10 years of age.

The datasets of studies of neighborhood effects show consistent characteristics. Firstly, neighborhood contextual studies frequently rely on national datasets (e.g., the National Longitudinal Survey of Children and Youth, the Panel Study of Income Dynamics, and the ECLS) to examine the relationship between neighborhood contexts and student outcomes. These national datasets are then linked to data from the U.S. Census Bureau because census data provides information relating to structural neighborhood characteristics (e.g., median household income, percentage of residents with a high-school diploma, and percentage of the population living below the poverty line). In studies that have utilized national datasets, the researchers have additionally included information about a neighborhood's racial-ethnic composition. Several studies have been able to include a robust list of parent-focused characteristics, such as parental income, mother's education level, and race or ethnicity. This dissertation adds family characteristics to the analytical model to control for and minimize selection bias given the possibility that unmeasured family characteristics, among other characteristics, may account for certain observed neighborhood effects.

To address issues related to potential selection bias in estimating neighborhood effects, researchers have analyzed data from the Moving to Opportunity (MTO) Program; this is a well-known, federally funded program that aims to help "very low income families move from povertystricken urban areas to low-poverty neighborhoods." In 1994, the MTO program was implemented in five metropolitan U.S. cities. Approximately 5,000 families were randomly assigned vouchers to assist them in moving out of high-poverty public-housing neighborhoods into private housing located in low-poverty neighborhoods or neighborhoods of their choice. The results of the MTO program indicated that children whose families moved to low-poverty neighborhoods had, among other measures, higher academic achievement than their peers who remained in high-poverty neighborhoods (Katz et al., 2001; Leventhal & Brooks-Gunn, 2001). In both the experimental and non-experimental studies of neighborhood effects, the samples rarely included first- and second-grade students. Instead, the studies focused on students in the sixth through 12^{th} grades.

Purpose of the Study

The lack of robust analysis of the determinants associated with neighborhood effects on first graders is a critical knowledge gap because this is a period that encompasses two major transitional phases of a child's life: starting school and gaining cognitive growth. When children enter the U.S. public school system, their exposure to others extends beyond their parents to include teachers, classmates, friends, and their friends' families. Additionally, at this age, children begin to interpret the social relationships that are present within their environment. Entrance into the school system further coincides with the age at which children begin to develop beliefs about what is deemed acceptable and normal, through their interactions with and observations of peers and adults.

In addition, kindergarteners and first graders have noticeable and substantial differences. For example, the first grade generally represents a child's first exposure to the formal learning process, which includes an array of norms and rituals and a structured learning environment. First graders attend school for a full day and are asked to remain focused on academic subjects, such as reading and mathematics, for longer durations. As a result, young children may experience challenges during the transition from kindergarten to the first grade (Fox et al., 2002; Sink et al., 2007).

Furthermore, the early years of school include a mathematics skills curriculum based on step-by-step cumulative learning. Thus, high performance in a preceding year should help a child have relatively greater success the following year (Fox et al., 2002). Unfortunately, as a child matriculates through the early years of formal schooling, the curriculum further magnifies earlier inadequate performance. As previously noted in this chapter, it is important to identify and address inadequate performance early, as academic achievement scores gained from the first, second, and third grades impact future achievement (Alexander et al., 1994; McCelland & Cameron, 2011; Mathews et al., 2009; Hughes et al., 2001).

Although academic performance is individually assessed, there is a relationship between what a child learns in school versus non-school environments because schools are frequently viewed as neighborhood institutions. Students participate in numerous group-learning activities that take place inside and outside of the school environment (Entwisle et al., 2001; Manski, 1993). The environment of the school captures the interactions between peers and displays the influence that teachers and administrators have on children

There are plausible reasons to suspect that elementary-aged children's neighborhood environments may affect their academic achievements and development; yet few studies have been conducted to formally verify this proposition. A majority of the existing research literature on neighborhood contexts has focused on the academic achievements of middle and high-school students (Behnke et al., 2011; Leventhal & Brooks-Gunn, 2001). Another body of literature on neighborhood effects has focused on non-academic student outcomes (e.g., health, violence, teenage pregnancy rates, and arrests). There is, therefore, a knowledge gap regarding the extent to which young children's academic performances are influenced by their neighborhood environments.

The education research community has yielded minimal information about how neighborhood contexts influence children starting formal schooling. This dissertation expands the investigation of the effects of neighborhood on students' academic achievement in four key areas. Firstly, this study analyzed how neighborhood contexts influence children who enter the first grade with low levels of mathematical knowledge and whether these students' mathematical capabilities improve over time, remain the same, or fall further behind their peers. Secondly, this study exclusively focused on the mathematics achievement levels of low-performing first graders. Thirdly, the dataset contained multiple repeated measures of mathematics achievement scores, allowing the researcher to construct mathematics growth trajectories for all participating students. Fourthly, the dataset contained unique elements that had traditionally been unavailable for neighborhood context studies:

- The dataset contained multiple mathematics achievement scores of first graders. The achievement data in this dissertation was unique because states typically do not assess first-grade students using state exams.
- The dataset could be used to simultaneously assess (1) family SES, measured via participation in schools' free or reduced lunch programs, and (2) neighborhood effects on students' mathematics achievements.
- The dataset demonstrated extensive student-level demographics (e.g., gender, race, and ethnicity, families' SES) variability and neighborhood variability. This created an opportunity to study how the mathematics growth trajectories of poor

children living in advantaged neighborhood contexts might differ from poor children living in less-advantaged neighborhood contexts and vice versa.

Research Question

The current study examined how, in terms of first graders, neighborhood contexts influence children's mathematics achievements. More specifically, this study was guided by the following research questions:

1. How do growth rates vary across different types of students?
2. On average, to what extent do differences in neighborhood contexts affect children's mathematics growth trajectories when controlling for gender, race, ethnicity, English as a second language, and SES?

This study focused on low-performing first-grade students in 20 schools located in five districts across two states. The data for this study came from a Goal 2 Institute of Education Sciences (IES)-funded randomized control trial to evaluate math recovery (MR), which is a one-on-one tutoring intervention. For each participating student, there were many student-level data (e.g., mathematics achievement scores, gender, race-ethnicity, families' SES, and postal zip codes). The dataset additionally included demographic data from the U.S. Census Bureau to measure neighborhood contextual factors.

Limitations and Outline for Remaining Chapters

There were several important limitations relating to this study. Firstly, because the dataset included students' five-digit postal zip codes, this study only focused on the effects of macro-level neighborhood contexts. Secondly, it was plausible that neighborhood environments might not affect all children and their families to the same extent. For example, certain children and their families could have access to beneficial resources (e.g., tutoring or positive role models) that extended beyond their neighborhood contexts. In an attempt to account for the potential bias associated with examining neighborhood effects, the analytical models included a proxy variable for family-background characteristics. In addition, as in previous empirical work, a student's SES was measured by their participation in a free or reduced-cost lunch program.

The inclusion of a more robust set of family-background characteristics would have been ideal; however, it was impossible to include all of the relevant variables in an analytic model, and, therefore, a certain degree of bias from omitted variables was unavoidable. As a result, the inclusion of additional control variables would not have guaranteed that the bias attributed to omitted variables would be eliminated (Clarke, 2005). Finally, although the decennial census definition of neighborhoods has been widely used in the literature regarding neighborhood effects, one frequently cited critique is that census data is geographically excessively large or small.

The dissertation is divided into four remaining chapters: Chapter II critically reviews the relevant literature on neighborhood effects on student outcomes to illustrate how the proposed study contributes to existing knowledge. Chapter III describes the methodology, including information on the research design, participants, and quantitative data. Chapter IV presents the results, and Chapter V presents the discussion section.

CHAPTER 2

LITERATURE REVIEW

Within the last quarter of a century, research has increasingly focused on how different neighborhood contexts influence children and adolescents. A majority of the research has focused on how low-income neighbors and neighborhoods impact the cognitive, behavioral, and social development of children and adolescents. Wilson's seminal 1987 book titled *The Truly Disadvantaged* is frequently cited as the catalyst for research on neighborhood effects. Jenks and Mayer's influential review in 1990 has additionally provided evidence to support the theory that neighborhood contexts are related to students' outcomes. For example, Sampson et al. (2002) identified and reviewed 40 studies of neighborhood effects that appeared in peer-reviewed journals from the 1990s through to 2001.

This chapter examines the relevant literature discussing the neighborhood effects on students' academic outcomes. The first section of this chapter introduces a definition for SES and neighborhoods. The second section of this chapter reviews the relevant theoretical frameworks that focus on the mechanisms through which neighborhoods influence student outcomes. The third section of this chapter analyzes previous quantitative studies of neighborhood effects on student outcomes. This chapter does not report qualitative or descriptive evidence or outcomes other than student achievements. The fourth section of this chapter summarizes what is currently known about knowledge in the literature concerning neighborhood effects and describes what this study adds to the field.

Key Terms and Definitions

Socioeconomic Status

SES is a widely used contextual variable in education and sociological research. Researchers have chosen to measure SES by using either an individual student's SES (e.g., participation in free or reduced-cost lunch programs or parents' income) or an aggregated SES measure, such as the demographic composition of the school the student attends (i.e., the proportion of students at a school who are eligible for a reduced-price or free lunch program) or the neighborhood in which the student resides. Throughout this dissertation, the following terms are used interchangeably: "advantaged", "affluent", and "high SES." Likewise, "disadvantaged", "poor", and "low-SES" are used synonymously. The terms are to be interpreted as relative measures and not as absolutes (Brooks-Gunn et al., 1997). For example, "affluent neighborhoods" refers to all neighborhoods that are more affluent than disadvantaged neighborhoods; this is as opposed to neighborhoods that are more affluent than national averages. When the term "high-SES student" appears, it refers to a student whose family's SES is higher than that of low-SES students. Thus, in a practical sense, high-SES families may not include families whose parents are high-earning professionals (e.g., doctors, lawyers, professors). Instead, high-SES families may include only families whose parents are mid-earning professionals (e.g., teachers, police officers).

Neighborhoods

Although the term "neighborhood" is conceptualized in various ways, in general, neighborhoods represent some form of geographical space or region. This study used the following definition, provided by Gephart (1997):

> Conceptually, neighborhoods and communities are the immediate social context in which individuals and families interact and engage with the institutions and societal agents that regulate and control access to community opportunity structures and resources. (p. 9)

Neighborhoods and communities represent the geographical places where residents interact with one another and both individual and collective norms and behaviors are observed and established. As individuals reside in neighborhoods, several environmental factors are shared by individuals within a given neighborhood. The level of human, social, and economic capital within a neighborhood additionally varies considerably.

Neighborhood Theoretical Models

Several theoretical frameworks have been developed to explain the influence neighborhoods may have on the children that live within them. This study, however, focused on the following four models: ecological, epidemic, collective socialization, and relative deprivation. The four models discussed below have guided a substantial portion of the theoretical dialogue concerning how neighborhoods influence children's outcomes.

Ecological Model

Urie Bronfenbrenner's ecological systems theory identifies and differentiates the contextual influences on child development. The ecological systems theory posits that the interrelated and reciprocal relationship between the various contextual environments in which development occurs is important (Bronfenbrenner, 1977, 1979). The theory identifies three subsystems within a child's environment: the microsystem, mesosystem, and exosystem. Each subsystem influences a child's development and contains physical features and agents that interact with one another and assume particular roles. The linchpin of ecological theory is the observed behaviors and interactions of structures (e.g., community, family, and school) both within and between the four subsystems.

The microsystem is the most direct level of a child's environment because it includes the structures, activities, and interactions that occur in the child's immediate surroundings. The microsystem environment represents the structures and interactions that have direct contact with a child for a substantial period of time. The most common and visible features in an infant's microsystem are their parents, siblings, or caregivers at a daycare. As a child grows to school age (i.e., the first grade), the microsystem is likely to expand to include the elementary school, teachers, peers, and their peers' parents because children spend a substantial amount of the day in this environment (Berk, 2003). Bronfenbrenner states that children are frequently exposed to bi-directional influences. For example, although a child's mother may affect and mold the child's behavior, the child may simultaneously affect the mother's behavior. Over time, this bi-directional interaction may have a profound impact on the child's development.

The second aspect of Bronfenbrenner's model refers to the mesosystem, which includes the connections between a child's microsystems. Bronfenbrenner's model suggests that a child's academic progress is influenced by activities that occur outside the classroom. To assess these interactions, the mesosystem is defined with reference to a child's engagement in activities within more than one setting. For example, a mesosystem is created when a child spends time both at home and at school. Due to the amount of time children spend in school, conventional wisdom suggests that the relationships developed within this context have at least a degree of influence on a child's development.

In the mesosystem, the child is identified as the primary link, and other people who participate in the same two or more settings are identified as supplementary links (Brofenbrenner, 1977, 1979). Thus, a child's transition from kindergarten to the first grade can be characterized as a mesosystem because the child enters a new setting for the first time. The early primary grades (kindergarten to the second grade) may further serve as the first time a child fosters a relationship with adults outside their immediate family. This relationship process is referred to as an ecological transition (Brofenbrenner, 1979).

The exosystem represents the third layer of Brofenbrenner's model. This layer contains formal and informal contexts but does not directly refer to the developing child. The exosystem still has a meaningful effect on the experiences and development that take place within the child's microsystem. The exosystem is comprised of three main components: the parents' workplaces, the parents' social networks, and the neighborhood's influence on the behavior of both the family and the child. The larger exosystem in which a child lives may not have a direct effect on their development, but a child is nevertheless influenced either positively or negatively by the interactions that occur within this layer.

In summary, Brofenbrenner (1977) states that early childhood development occurs within an array of contexts situated in the neighborhood, home, and school. He goes on to acknowledge that although a substantial part of a child's development takes place in the family context; there are other "layers" whereby a child's developmental process may occur and that the developmental processes occurring throughout the various contexts are not mutually exclusive. Thus, his theory posits that the interaction between biological, family, school, and neighborhood, and overarching societal norms ultimately shapes and molds a child's development because, as Brofenbrenner (1977) explains, the ecological environment "is conceived topologically as a nested arrangement of structures, each contained with the next" (p. 3). Brofenbrenner (1974).

Epidemic Theory Model

The epidemic theory model likens the diffusion of ideas to the spread of an infectious disease (Goffman & Newill, 1964). The model is premised on the notion that the communication process involves the transmission of information within a population using social contacts (Goffman & Newill, 1965). Although a member of a defined population may be more susceptible to certain ideas (and resistant to others), when that member is "infected" with an idea, he or she may then transmit the idea to other members of the community. The theory additionally implies that while certain ideas may be extremely contagious within a certain population, others are less transmittable (Goffman & Newill, 1964). Furthermore, Small and Newman (2001) state that epidemic models are examples of socialization mechanisms:

> [s]ocialization mechanisms tend to conceive of individuals as (relatively passive) recipients of powerful socializing forces, suggesting that neighborhoods mold those who grow up in them into certain behavioral patterns. For this reason, these mechanisms tend to focus on children and adolescents. (p. 33)

Jencks and Mayer (1990a) have applied the epidemic theory model to neighborhood contexts. They conclude that individual behavior is linked to the behavior of other members living in the neighborhood and use the model, in turn, to describe how a neighborhood effect manifests itself in members of a particular neighborhood. More specifically, the model assumes that "like begets like:" a child who is continuously exposed to positive or negative individual behavior will emulate the observed behavior. For example, if a child lives in a neighborhood where a majority of his or her peers value education and excel academically, then the child will additionally feel compelled to perform well academically. Negative actions by others in the neighborhood are equally influential. Thus, a child who observes several of his or her peer neighbors committing crimes will be more likely to engage in criminal activity.

Collective Socialization Theory

Collective socialization is another theoretical model used to explain neighborhood effects on children's outcomes. Children learn a substantial amount about what behaviors are acceptable from the adults they interact with in their neighborhoods. Collective socialization models focus on the manner in which neighborhood adults influence and monitor children's behavior (Jencks & Mayer, 1990b; Newman, 1999; Wilson, 1987). The model assumes that the level of social organization observed within a neighborhood influences children. It has been observed that neighborhoods with low levels of social organization are frequently plagued by high unemployment rates and few adult mentors. As a result, children are unable to observe the adult social norms associated with work. The collective socialization model posits that a neighborhood with a relatively high level of social organization will yield positive outcomes for the neighborhood's children. Conversely, a neighborhood with a low level of social organization will have a negative impact on the neighborhood's children.

It has been argued that poor children living in disproportionately poor neighborhoods are likely to find it harder to escape from poverty than poor children living in more affluent neighborhoods (Wilson, 1987). Wilson (1987) observed the following:

> in a neighborhood with a paucity of regularly employed families and with the overwhelming majority of families having spells of long term joblessness, people experience a social isolation that excludes them from the job network system that permeates other neighborhoods and that is so important in learning about or being recommended for jobs. Thus, in such neighborhoods the chances are overwhelming that

> children will seldom interact on a sustained basis with people who are employed or with families that have a sustained breadwinner. The net effect is that joblessness, as a way of life, takes on a different social meaning: the relationship between schooling and post-school employment takes on a different meaning. The development of cognitive, linguistic and other education and job-related skills necessary for the world of work in the mainstream economy is thereby relatively adversely affected. In such neighborhoods, therefore, teachers become frustrated and do not teach and children do not learn. A vicious cycle is perpetuated through the family, through the community, and through the schools. (p. 57)

The collective socialization model posits that more advantaged neighborhoods are filled with positive adult role models who serve as "enforcers" and are able to collectively communicate the importance of work and civility. The model further hypothesizes that neighborhood adults play an integral role in the socialization and maturation processes necessary for children to become law-abiding, successful adults.

Relative Deprivation Model

Relative deprivation is the fourth model reviewed in this chapter. Runciman (1966), one of the first researchers to introduce the relative deprivation concept, defines relative deprivation as follows:

> We can roughly say that [a person] is relatively deprived of X when (i) he does not have X, (ii) he sees some other person or persons, which may include himself at some previous or expected time, as having X (whether or not this is or will be in fact the case), (iii) he wants X, and (iv) he sees it as feasible that he should have X. (p. 10)

Runciman concluded that individuals identify with a defined reference group, and that reference group establishes standards and provides the opportunity for individuals to compare and evaluate themselves with and against others. According to Jencks and Mayer (1990b), relative deprivation models posit that individuals evaluate their accomplishments by comparing themselves to others in their environment (e.g., school, work, the neighborhood). For instance, the model assumes that poor children judge and compare their families' economic status to that of their more affluent classmates or neighbors. This comparison process negatively affects poor children because they feel poorer when judged against their more affluent peers. Similarly, the model argues that when children who are low academic performers compare their academic achievements to that of their high-performing classmates, the low-performing children develop unfavorable opinions of themselves. Therefore, despite what several social scientists have assumed, academically advantaged classmates may not positively influence disadvantaged students (Davis, 1966). However, if low-performing students believe that their academic performance is equal to, or higher than that of their fellow classmates, the low-performing students judge themselves more favorably.

The theoretical models discussed above suggest that neighborhoods are geographical areas in which children and their families are exposed to certain types of people; collective norms and behaviors; and places in which residents can build a sense of ownership, togetherness, and control. All four models argue that there is a relationship between contextual neighborhood factors and student outcomes (i.e., academic achievement).

In general, the four theoretical theories presented in this chapter support one of the two following contrasting notions: advantaged neighbors (adults or peers) positively impact student outcomes or, in certain cases, advantaged neighbors negatively impact student outcomes. There are several noteworthy similarities and differences across the four models. For example, the epidemic model focuses on the manner in which peers influence one another, whereas the collective socialization model identifies the extent to which adults in a neighborhood influence children other than their own. More specifically, the epidemic and collective socialization theoretical models argue that growing in an advantaged neighborhood encourages children to achieve more academically and avoid getting into trouble with the law. The epidemic and collective socialization models additionally contend that children from more affluent families and neighborhoods outperform their peers from disadvantaged families and neighborhoods. In contrast, the relative deprivation theory predicts the potential for these positive neighborhood factors to harm student outcomes. Table 1 includes a summary of the four theoretical models discussed in this chapter.

Table 1

Neighborhood Theoretical Models

THEORY	DEFINITION	KEY ASSUMPTIONS	IMPACT ON STUDENT OUTCOMES
Collective Socialization	The framework focuses on how neighborhood adults influence and monitor children's behavior (Newman, 1999; Wilson, 1987).	The framework assumes that the level of social organization observed within a neighborhood influences children.	A neighborhood with a relatively high level of social organization will yield positive outcomes for neighborhood children. Conversely, a neighborhood with a low level of social organization will harm neighborhood children.
Ecological	The model posits that the interrelated and reciprocal relationship between the various contextual environments in which development occurs is important (Bronfenbrenner, 1977, 1979).	Contains five subsystems: microsystem, mesosystem, exosystem, macrosystem. Each subsystem influences a child's development and contains physical features and agents that interact and assume particular roles.	A child's environment is unique, ever-changing, and defined by "ecological transitions." This model aims to capture the contextual influences relating to a child's development.
Epidemic	Individual behavior is linked to the behavior of other members living in the neighborhood (Jencks & Mayer, 1990b).	The model assumes that "like begets like:" a child who is continuously exposed to positive or negative individual behavior will emulate the observed behavior.	If a child lives in a neighborhood where most of his or her peers value education and excel academically, then the child will also feel compelled to perform well academically. Negative actions by others in the neighborhood are equally influential.

Relative Deprivation	Individuals identify with a defined reference group, and that reference group establishes standards and provides the opportunity for individuals to compare and evaluate themselves with and against others (Runciman, 1966).	The model posits that individuals evaluate their accomplishments by comparing themselves to others in their environment (e.g., neighborhoods, schools).	When children who are low academic performers compare their academic achievements to their high-performing classmates, the low-performing children develop unfavorable opinions of themselves.

Neighborhood Effects on Students' Academic Outcomes

Previous empirical studies have produced myriad results regarding the impact various neighborhood contexts have on a child's wellbeing. The role of living in a disadvantaged neighborhood and the effects of poverty on a child's development are well documented in the social science literature (Aaronson, 1997; Ainsworth, 2002; Brooks-Gunn et al., 1997; Jencks & Mayer, 1990a; Sampson, et al., 2002). Attempts to identify and quantify which specific neighborhood characteristics have the most influence on student outcomes have yielded inconclusive results. During the 1990s, the neighborhood research literature shifted its focus from concentrated poverty and residential segregation to measuring how the role of neighborhoods impacts the behaviors and academic outcomes of children and adolescents (Sampson et al., 2002). The remainder of this chapter is dedicated to a review of commonly cited studies of neighborhood effects on students' academic outcomes.

To date, the majority of studies of neighborhood effects on student outcomes have focused on middle- and high-school students (Burton & Jarrett, 2000; Ellen & Turner, 1997; Ginter et al., 2000; Kohen et al., 2002). In the few instances in which a study included first- and second-grade students (i.e., five and six-year-olds), the measured outcomes were not consistently related to mathematics achievement. As a result, this chapter only references studies that used quantitative techniques, academic outcomes (i.e., mathematics, reading, or IQ measures), and student subjects between the ages of three and 12 years old. All of the quantitative studies reviewed in this chapter include, at a minimum, information relating to the following: research design (e.g., data-collection processes, sampling, and statistical techniques), descriptions of neighborhood variables, academic or cognitive outcome measures or both, and key findings. The studies that were reviewed in preparation for this study identified links between neighborhood effects and students' academic achievement.

Quantitative Studies

Chase-Lansdale and Gordon (1996) analyzed data from the NLSY, a longitudinal study funded by the U.S. Department of Labor that aimed to more comprehensively understand the causes and consequences of employment patterns. The NLSY study additionally collected data from the children born to the female study participants. For this study, Chase-Lansdale and Gordon restricted their sample to children aged five or six years old who primarily lived with their mothers (n = 673) in four regions (Northeast, Midwest, West, and South). The researchers used census data to create the following five neighborhood variables: neighborhood SES (a composite variable that included educational level, income level, and occupational status of residents within a specific neighborhood), male joblessness (a composite of the average of a standardized measure of male underemployment and men not in the civilian labor force), adult presence for monitoring and supervision (the ratio of adults aged 25–64 years to children aged 0–17 years), concentration of people (the ratio of persons to occupied dwelling units within a neighborhood), and racial similarity of neighbors to the child (the percentage of people in a neighborhood who shared the same race as the child included in the study). The primary cognitive outcome measures used in this study were the Peabody Picture Vocabulary Test (PPVT-

R) and the PIAT.[2] Chase-Lansdale and Gordon used a series of multivariate regression models to conclude that neighborhoods with higher SES were associated with children scoring higher on both the PPVT-R and PIAT. Similarly, higher levels of male joblessness were associated with lower PPVT-R scores.

Using the same dataset, Chase-Lansdale et al. (1997) investigated neighborhood and family influences on the intellectual and behavioral development of pre-school age (three- and four-year-olds) and early school age (five- and six-year-olds) children. The primary academic outcome measures were the PPVT-R and the Stanford-Binet Intelligence Scale, Form L-M. The researchers reported that having high-SES neighbors was positively associated with five- and six-year-old boys' PPVT reading achievements and negatively associated with girls' mathematics achievements. Their study further indicated that high levels of male joblessness had a negative effect on boys' reading achievements and that ethnically diverse neighborhoods had a negative effect on White children but not their Black peers.

Research by Brooks-Gunn et al. (1993) investigated the impact of neighborhood characteristics on the development of children and adolescents.[3] The research team used data from the Infant Health and Development Program (IHDP).[4] The IHDP research design randomly assigned newborns into two groups: one-third to an intervention group and the remaining two-thirds to a follow-up group. Over the child's first 36 months of life (i.e., up to three years old),

[2] The PPVT-R measures a child's verbal ability, and the PIAT measures a child's word recognition and pronunciation ability.

[3] For the purpose of this review, the author only reviewed the portion of the study linked to children and not the portion linked to adolescents.

[4] The IHDP is an eight site randomized clinical trial designed to improve the cognitive and health status of low birth weight and premature infants.

the intervention group received home visits, child-care with an educational component, and parent-focused seminars. The explicit goal of the original IDHP study was to capture any differences between intervention and follow-up groups concerning cognitive development, behavioral development, and quality of health.

The subject pool included 895 three-year-olds in eight medical centers across the U.S.. The researchers used the following neighborhood measures for their analysis: the fraction of families in a 1980 census tract with incomes below $10,000 (low-income); the fraction of families in a 1980 census tract with incomes above $30,000 (affluent); two dichotomous variables (a neighborhood with 40% or more of the residents being poor and less than 10% of the residents having incomes above $30,000); the fraction of males working in professional or managerial roles; the fraction of families with children living in mother-led, single-parent households; and the fraction of men who had not worked during the previous year. The Stanford-Binet Intelligence Scale, Form L-M, third edition, was the major outcome measure used in this study.

Brooks-Gunn et al. (1993) used a series of multiple regression models to support the theory that, including after controlling for family characteristics, three-year-olds living in more affluent neighborhoods outperformed their peers living in low-income neighborhoods. More specifically, they reported that a one-standard-deviation increase in the proportion of affluent neighbors yielded an increase of one-quarter of a standard deviation in a child's IQ test score. The study additionally found that the presence of affluent neighbors had a larger effect on White, affluent children.

Using the same large IDHP dataset, Brooks-Gunn et al. (1993) additionally investigated the impact of neighborhood contexts on child development. The sample for this study included

895 five-year-olds in eight medical centers throughout the U.S.. The Wechsler Pre-School and Primary Scale of Intelligence was the major outcome measure used in this study.[5] The research team used 1980 census data to construct the same neighborhood variables as in the Brooks-Gunn et al. (1993) study. Participants in the IDHP study were administered an income-focused questionnaire, and the researchers used parental responses to create a continuous variable to measure family-level poverty. Brooks-Gunn et al. (1993) used a series of multiple linear regression models to explore the relationship between neighborhood and family income and cognitive development. Their study revealed that having high-SES neighbors was positively associated with higher IQ's for five-year-olds.

In a subsequent study using IDHP data, Klebanov et al. (1998) wanted to quantify when neighborhood effects first appear. The study by Klebanov et al. (1998) included children (n = 347) aged one through to three years old. The Bayley Scale of Mental Development was used for all one- and two-year-olds, and the Stanford-Binet Intelligence Scale, Form L-M, was administered to all children (i.e., one- to three-year-olds). The researchers used a series of multiple linear regression models to conclude that neither high nor low neighborhood income was associated with one- and two-year-olds' IQ levels. In contrast, neighborhood affluence was associated with higher IQ scores at three years old. Overall, the studies using IDHP data support the idea that neighborhoods play a role in the intellectual development of very young children, and, more specifically, the presence of affluent neighborhoods appears to be a more impactful neighborhood characteristic when compared to the presence of poor neighbors.

Shumow et al. (1999) used census tracts to study children from working-class and low-income families in Milwaukee, Wisconsin. They aimed to study the relationship between

[5] The WPPSI included the following components: verbal IQ, performance IQ, and full-scale IQ.

neighborhood risk and academic achievement. The study tracked the academic performance of students from the third to the fifth grade (n = 168). The neighborhood risk measure included the following neighborhood descriptors: income, educational level, female-headed households, and violent crimes. In the third grade, the academic measure used was a reading test, and, in the fifth-grade, results from a mathematics and reading test were averaged to create a standardized achievement indicator.[6] The researchers used a series of hierarchical linear models (HLMs) to report that, although neighborhood economic risk factors were not associated with the academic performance of third-graders, neighborhood economic risk factors had an impact on the academic performance of children by the time they entered the fifth grade.

Halpern-Felsher et al. (1997), using data from the 1980 census tract, conducted a study that exclusively focused on neighborhood effects on elementary students' outcomes. Their dataset was comprised of White and African-American students aged eight to 11 years old in four elementary schools (grades three through to five) in an upstate New York urban school district. Their dataset included a total of 1,040 students. To analyze the potential impact of neighborhood characteristics, the researchers used the following five neighborhood characteristics: percentage of neighbors with low SES, percentage of neighbors with high SES, ethnic diversity, family composition, and the percentage of unemployed males. To control for individual family characteristics, the eligibility of students for the free or reduced-price lunch program served as a proxy for families' economic risk. The researchers used a version of the Five-Flag Identification System that included a flag for the following elements: annual attendance below 82%; national percentile scores on standardized tests below 38% for mathematics and 37% for reading;

[6] In the third grade, the only exam available was a reading comprehension score on the Wisconsin Third Grade Reading Test. In the fifth grade, the researchers use scores form the Iowa Test of Basic Skills.

suspensions greater than two instructional days; for each grade, a student one or more years older than the average student; and the number of parents or teachers who requested child services in each grade. A series of linear regression models were used to investigate the relationship between neighborhood and family factors with attainment. The results suggested that, for White males, having high-SES neighbors minimized educational risks. The researchers concluded that neighborhood contexts had a small effect on elementary students' outcomes. These results should be interpreted with caution: this was a small-scale study that only included four schools, and the researchers did not directly measure academic achievement.

Entwisle et al. (1994) investigated the possible relationship between gender-specific mathematics scores and neighborhood contextual factors. The researchers' data came from the Beginning School Study (BSS), a study in Baltimore City that used various stratification techniques to obtain an equal number of African-American and White students living in socioeconomically diverse environments. The BSS included 20 randomly selected schools. The research team restricted the dataset to include only first graders with complete mathematics test data who remained in the same school through to the completion of the third grade. Entwisle et al. (2001) used the California Achievement Test (CAT). The CAT was administered to Baltimore City children in October and May of each academic year.[7] The researchers used census data to create a variable that measured the median household income. The analysis further included many other contextual variables (i.e., the average number of years of schooling for parents, measured at the school level, and the school-level racial composition). The results from a series

[7] The CAT assessedassesses students' mathematical reasoning, and, for this study, the researchers used Form C, Level 11 in the first grade, and Levels 12 or 13 were used during third grade.

of HLMs found a negative relationship between the gender-related gap in mathematics achievement and neighborhood household incomes.

In another study, Greenberg et al. (1999) followed 337 parents and their children who participated in a longitudinal, multisite (Durham, NC; Nashville, TN; Seattle, WA; Central Pennsylvania) study designed to identify the relationship between risk factors and the developmental (e.g., psychological and academic) outcomes of kindergarteners and first graders.[8] The research team included a diverse set of variables (e.g., number of years of schooling obtained by the head of the household, psychosocial family factors, marital distress, and social support) in their analytical models to operationalize risk factors. A neighborhood questionnaire was developed and used for this study, which was a 13-item survey that aimed to assess the quality of each family's neighborhood regarding safety, violence, the presence of drugs, overall satisfaction, and stability. To measure students' verbal and non-verbal academic development, T scores on the Letter-Word Recognition of the Woodcock-Johnson Psycho-Educational Battery (WJ-R) were used. A series of ordinary least squares regression models and path analyses were used to assess the relationship between a child's academic development and risk factors. Greenberg et al. (1999) reported that neighborhood risks significantly predicted lower reading achievement for the children who participated in the study.

Duncan and Raudenbush (1999) exploited the neighborhood design to include multi-level modeling. A multi-leveling analytical technique was deemed preferable by the authors because it considered the nested nature of neighborhood-based designs: the multi-leveling framework recognizes that students are nested within neighborhoods (Bryk & Raudenbush, 1992; Duncan &

[8] Due to the focus of this dissertation, the author only reviews results associated with academic outcomes.

Raudenbush, 1999). The results from using HLMs suggest that neighborhoods tend to have more variability within neighborhoods and are internally heterogeneous (Cook et al., 1997; Elliot et al., 1996). Furthermore, although neighborhood effects are noticeable during a child's pre-school years, the impact is more persistent with respect to school-age children. Their research additionally suggests that studies of neighborhood effects have shown that White children appear to be more affected by neighborhood conditions than African-American children.

Gaps in Previous Research

Previous studies in the literature about the relationship between neighborhood contexts and students' academic outcomes have used a range of designs (e.g., quasi-experimental, experimental, and observational) and analytical techniques (e.g., hierarchical linear modeling, and multiple regressions). The datasets used to conduct prior neighborhood context studies have ranged from surveys collected from nationally representative samples (Brewster, 1994; Chase-Lansdale et al., 1997) to city or regional studies (Elliot et al., 1996). The national and multisite studies have typically included a range of incomes across varying neighborhoods and families (Leventhal & Brooks-Gunn, 2000). Furthermore, the data has frequently been culled from the IDHP, NLSY-CS, PSID or the NLS (Baker & Mott, 1989; Gross et al., 1997).

The majority of neighborhood studies have additionally used census tracts or postal zip code data to operationalize neighborhood indicators (e.g., the percentage of individuals within a neighborhood who are poor, jobless, or who have received a college degree). The U.S. Census tracts typically represent geographical areas that include 4,000 to 6,000 individuals, whereas metropolitan areas, county lines, and postal zip codes identify geographical areas that include 10,000 to 45,000 individuals. Several of the proxies used to represent neighborhood contexts are as follows: economic conditions (e.g., the average family income level, percentage of residents with at least a high-school diploma, and the percentage of adults with professional or managerial jobs); racial and ethnic characteristics; poverty rates; and median salaries or demographic characteristics (e.g., female-headed families). The family characteristics have frequently included, at a minimum, race and ethnicity, the parents' education level, the size of the family, or a proxy to identify the family's economic level.

A majority of the empirical research related to the association between neighborhood effects and students' academic outcomes has relied on non-experimental data and has typically involved the linking of child-focused developmental studies to U.S. Census data and postal zip codes. The studies that have used national and regional datasets have yielded stronger neighborhood effects. However, regional and city-based data have frequently yielded inconclusive results because the neighborhoods in the smaller datasets have frequently been more homogenous. Additionally, from a methodological standpoint, the analytical models that have included multiple neighborhood measures have frequently suffered from multi-collinearity (Leventhal & Brooks-Gunn, 2000) because several of the independent neighborhood variables in the statistical models are highly correlated. Although the presence of multi-collinearity does not bias the estimates, it potentially makes it difficult to interpret the estimates and reduces the power of the models. The neighborhood-based approach has been more advantageous than the national or regional design because the sampling design specifically includes a variety of neighborhoods.

The majority of the neighborhood studies reviewed in this chapter included a multitude of social-demographic factors and characteristics linked to census and other government-sponsored data statistics. Overall, the most consistent finding documented in the neighborhood contextliterature is that the presence of affluent neighbors is positively associated with school readiness and achievement outcomes. More specifically, several studies have suggested that a child's academic performance is more heavily influenced by the presence of affluent neighbors than the presence of disadvantaged neighbors (Brooks-Gunn et al., 1997; Duncan & Raudenbush, 1999; Sampson et al., 2002).

In conclusion, while previous studies have concluded that neighborhood factors influence children's academic experiences and successes, the association between neighborhood factors and academic achievement measured during the first few years of school has received less of an empirical inquiry. A majority of research has focused on how different neighborhood factors influence the academic achievement of students in secondary school. However, there is a reason to posit that children's social and environmental contexts may matter more in the early stages of life: the observed academic-growth trajectories for children in the primary grades are both stable and persistent throughout a child's matriculation.

CHAPTER 3

METHODS

The extent to which neighborhood and school contexts influence the mathematical growth trajectories of low-performing students is a relevant policy issue because of the persistent educational inequalities between advantaged and disadvantaged students and between subgroups of majority and minority students. This chapter details the methodological steps used to answer the dissertation's research questions. More specifically, it describes the study's participants and settings, measurements, and analytic techniques.

This study addresses the following research questions:

1. How do growth rates vary across different types of students?
2. On average, to what extent do differences in neighborhood contexts affect students' mathematical growth trajectories when controlling for gender, race, ethnicity, English as a second language, and SES?

Research Settings

During the first month of the 2007–08 and 2008–09 academic school year, MR tutors in each participating school conducted screening interviews with all first graders to identify a pool of eligible students. The goal of the screening interview process was to identify first graders with mathematical deficiencies. After the MR tutor identified the pool of eligible students, they conducted a video-recorded assessment interview. Then, eligible students were randomly assigned to one of three cohorts set to receive the MR tutoring intervention or be placed on the waitlist. The waitlist was used if a student selected to receive MR tutoring intervention exited the study. The research team additionally collected mathematical achievement data from children with scores above the MR eligibility threshold, and, therefore, there was a sub-sample of students that was not classified as low-achieving. This sub-sample of students was originally collected as a contingency plan if the student waitlist strategy was unsuccessful. Using the sub-sample of students who were not classified as low-achieving is a sophisticated statistical technique (i.e., regression discontinuity) that could be used to investigate the causal effect of the MR intervention. Students were classified as low-performing or achieving in mathematics using, primarily, their performance on the various MR assessments administered at the beginning of the 2007–08 and 2008–09 academic school years. If the necessary variables (i.e., multiple test scores, postal zip code, and other previously described covariates) were available, this study further included the sub-sample of students that scored above the MR eligibility threshold (referenced above).

Table 2 below illustrates the characteristics of participating school districts. The five districts vary ranged in size and student characteristics. Approximately three-quarters of first graders in this study were from the two largest participating districts (i.e., Districts D and E). Approximately 40,000 students were enrolled in the largest district and roughly 6,000 in the smallest district. The percentage of Black or Hispanic students served by the districts ranged from 3% to 57%. The percentage of students who participated in their district's free or reduced lunch (FRL) program ranged from 29% to 67%.

Table 2

Characteristics of Participating School Districts[9]

[9] Common Core of Data (2007–2008) formed the primary source for district-level data. In some cases, it was necessary to gather district-level data from state and district reports. In an effort to protect the identity of

State	District	Total Number of Students	Percentage of Black or Hispanic Students	Percentage of FRL	Urbanicity
	A	7,000	33%	63%	Rural
1	B	7,000	22%	67%	Rural
	C	6,000	3%	29%	Rural
	D	36,000	57%	64%	Urban
2	E	40,000	14%	33%	Suburban

Student Demographics

For participating school districts, the sample overrepresents the district enrollment of students eligible for FRL (see Table 3 below). For example, in District E, the district enrollment in FRL across all schools equals approximately 33%; meanwhile, 51% of this sample is FRL. Similar results were observed in every district (i.e., 79% vs. 63%, 80 % vs. 67%, 58% vs. 29%, 77% vs. 64%). A potential reason for this data artifact is that, on average, students eligible to participate in a district's FRL program may have obtained lower achievement scores. Due to the nature of the over-arching IES-funded evaluation study, the sample primarily included students with low mathematical achievement scores. Therefore, when reviewing the interpretation of how FRL status influences mathematical achievement, it is worth mentioning that the purpose of this variable is to indicate a student's poverty status.

Table 3

Characteristics of Sample and Participating School District

State	District	Number of First Graders in Study	Number of Schools in Study	Number of Schools	Percent FRL of Sample at	Percent FRL at District Level

participant districts, the number of schools in a district was rounded to the nearest 10, and the number of students was rounded to the nearest thousand.

				in District	District Level	
1	A	110	2	10	79%	63%
	B	108	2	10	80%	67%
	C	55	1	20	58%	29%
2	D	272	5	90	77%	64%
	E	465	10	50	51%	33%

The data in this dissertation covers two academic school years (2007–08 and 2008–09). The overall number of study participants comprises 509 first graders in Year 1 (2007–08 academic year) and 501 first graders in Year 2 (2008–09 academic year), yielding a total sample of 1,010 students. Complete student background characteristics are presented below in Table 4. In total, this dissertation's sample of first graders consists of approximately 44% minority students, 47% males, and 53% females. Furthermore, 14% of the first graders are classified as limited English proficiency (LEP), and approximately 65% of the sampled first graders participated in their district's FRL. Additionally, 14% were identified as overage at the start of the academic year. The variable "overage" is defined as any student who was 93 months (i.e., 7.75 years) or older at the start of testing time 0.

In Table 4, for the 2007–08 academic year, approximately 50% of participants are male, 42% are minority students, 71% received FRL, 16% are classified as English learners, and 10% are classified as being overage. For the 2008–09 academic year, 44% of participants are male, 47% are minority students, 58% participated in their district's FRL program, 14% are classified as English learners, and 14% are classified as overage. Although the sample in both years came from the same 20 schools, the percentage of students who participated in their district's FRL noticeably differed (i.e., 71% vs. 58%). No additional data or information was available to the researcher to explain the change in FRL. As a result, the researcher included a *Year* dummy variable within all analytical models, the reason for which is explained later in this chapter.

Table 4

Sample Student Background Characteristics by Year

Characteristics	Study Participants
Academic Year 2007–08	n = 509
Male	50%
Minority[10]	42%
FRL	71%
LEP	16%
Overage	10%
Academic Year 2008–09	n = 501
Male	44%
Minority	47%
FRL	58%
LEP	13%
Overage	15%
Total Sample: Both Academic Years	n = 1,010
Male	47%
Minority	44%
FRL	65%
LEP	14%
Overage	14%

Table 5 identifies the sample student background characteristics at the school level. Here, considerable variability can be observed across and within schools. The distribution of minority students at the school level ranges from 5% (School E) to 100% (School F). The percentage of students participating in their district's FRL program at the school level ranges from 36% (School T) to 100% (School H).

Table *5*

Total Student Background Characteristics by School

School	Percentage of Minority Students	Percentage of FRL
A (n = 57)	46%	81%
B (n = 53)	55%	77%

[10] All non-White students appear in the Minority student variable. More specifically, this variable includes African American, Hispanic, Asian, and all other races/ethnicities.

C (n = 51)	25%	94%
D (n = 57)	5%	67%
E (n = 55)	5%	58%
F (n = 49)	100%	52%
G (n = 57)	98%	53%
H (n = 45)	93%	100%
I (n = 65)	98%	97%
J (n = 60)	81%	83%
K (n = 48)	31%	38%
L (n = 46)	37%	63%
M (n = 49)	51%	66%
N (n = 42)	33%	45%
O (n = 46)	22%	41%
P (n = 49)	22%	53%
Q (n = 50)	42%	48%
R (n = 45)	27%	53%
S (n = 51)	35%	61%
T (n = 44)	30%	36%

Neighborhood Contextual Variables

Previous studies have operationally defined neighborhood measures in several ways; this study utilizes U.S. Census Bureau data. Census data have been employed frequently in the literature on neighborhood effects. Furthermore, the U.S. Census Bureau data contain several neighborhood-level indicators related to poverty, which represents an essential parameter in this study.

Because the dataset includes the postal zip code for each participating student's family, this study links the U.S. Census Bureau data to each student's postal zip code. The following census-level data for each geographical area were considered for use: median household income, mean household income, percentage of families living at or below the poverty line, percentage of female-led households living at or below the poverty line, unemployment rate, percentage of families who receive food stamps, percentage of single-parent households, and proportion of neighbors aged 25 years or older possessing less than a high-school diploma.

For this sample, each school features a range of students living in 1 (School C) to 13 (School G) neighborhood contexts with an average of five neighborhood contexts per school (see Table 6 below).

Table 6

Sample Zip Codes by School

School	Number of Zip Codes
A (n = 57)	3
B (n = 53)	4
C (n = 51)	1
D (n = 57)	2
E (n = 55)	2
F (n = 49)	5
G (n = 57)	13
H (n = 45)	5
I (n = 65)	10
J (n = 60)	6
K (n = 48)	7
L (n = 46)	3
M (n = 49)	3
N (n = 42)	3
O (n = 46)	5
P (n = 49)	3
Q (n = 50)	10
R (n = 45)	7
S (n = 51)	6
T (n = 44)	7

As expected, a noticeable degree of variability can be observed within and across the six neighborhood variables included in this study. For example, in Table 7, although the median household income for this sample equals approximately $52,397, the minimum value for median household income for some students' zip codes equals $22,846, and the maximum value for median household income for some students equals $106,355. Similarly, in some neighborhood contexts, the percentage of families who receive food stamps equals approximately 1%, whereas in other neighborhood contexts, the percentage of families who receive food stamps equals approximately 37%. Additionally, some students live in neighborhoods with little to no unemployment (1.8%) while some of their peers live in neighborhoods where almost a third (30%) of adults are unemployed.

Table 7

Descriptive Statistics of the Six Neighborhood Contextual Variables Included in the ND Variable

Variable	Mean	St. Dev.	Min	Max
Median Household Income	\$52,397	\$15,632	\$22,846	\$106,355
Pct. Poverty	12.7%	10.6%	1.4%	40.0%
Unemployment Rate	7.33%	4.0%	1.8%	30.0%
Pct. Food Stamps	13.4%	10.2%	1.0%	37.2%
Pct. Single Parent Households	13.3%	6.5%	1.5%	29%
Pct. Less than HS	13.2%	7.7%	1.9%	33.4%

Originally, the researcher sought to investigate the independent effects of these neighborhood indicators on students' math growth trajectories. However, this strategy was not optimal, as a high degree of collinearity existed across the six indicators. For this reason, the researcher conducted a series of statistical tests to measure the extent to which the proposed individual neighborhood contextual variables are correlated.

The neighborhood contextual variables collected from the census data yielded a high degree of collinearity (see Table 8 below). More specifically, all of the neighborhood contextual variables yielded a strong (e.g., $|r| = > 0.5$) relationship. The relationship between all neighborhood contextual variables was statistically significant at the $p < 0.05$ level.[11]

[11] The researcher included the Bonferroni multiple comparison procedure to adjust for estimating several correlations.

Next, the researcher conduced an exploratory factor principal analysis and Cronbach's alpha test on the six census indicators found to reflect neighborhood disadvantages (NDs)[12] Where needed, the researcher recoded individual indicators so that the interpretation of the combined ND variable implies that a higher score reflects higher levels of disadvantage and a lower score reflects lower levels of disadvantage. This approach is similar to what is often cited in prior neighborhood effects research. Results from these tests yielded a Cronbach's alpha of 0.94, and all neighborhood contextual variables scored highly on the first component, which accounted for 84% of the cumulative variance (see Table 8 below). Therefore, the six neighborhood contextual variables chosen for this analysis are statistically appropriate.

Following this, the researcher then combined the aforementioned six variables (i.e., median income, percentage of families living at or below the poverty line, unemployment rate, percentage of families who receive food stamps, percentage of single-parent households, and proportion of neighbors aged 25 years or older possessing less than a high-school diploma) into a single measure to represent neighborhood characteristics with a mean of 0 and a standard deviation of 1. For interpretation, this single measure variable *ND* represents the extent to which a neighborhood is comparatively disadvantaged. If the *ND* variable increases, the reader should assume that the student's neighborhood is more disadvantaged. The *ND* variable is included in various statistical models discussed throughout this dissertation.

[12] During the Cronbach's alpha test, the researcher recoded the median income variable.

Table 8

Neighborhood Contextual Variables Correlation Matrix[13]

	A	B	C	D	E	F
A	1.0					
B	-0.85	1.0				
C	-0.36	0.66	1.0			
D	-0.86	0.99	0.64	1.0		
E	-0.71	0.91	0.67	0.94	1.0	
F	-0.75	0.76	0.32	0.73	0.67	1.0

Table 9

Factor Analysis for Neighborhood Contextual Variables

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor 1	4.921	4.248	0.840	0.840
Factor 2	0.674	0.407	0.115	0.955
Factor 3	0.266	0.258	0.045	1.000
Factor 4	0.008	0.008	0.001	1.001
Factor 5	-0.00024	0.0077	0	1.001
Factor 6	-0.0079		-0.0014	1.000

It is plausible that both family and individual attributes may influence where an individual chooses to live. As such, neighborhood contextual studies must adequately control for the influence of family and individual characteristics. Failure to do so may lead to misidentification or overestimation of neighborhood effects. To account for family characteristics, a student's participation in their school's FRL program serves as a proxy for their family's SES status.

Next, the researcher assessed the variability of students' neighborhood contexts and their families' characteristics (see Figures 1 and 2 below). The goal of this exercise was to ensure that

[13] For readability, the researcher assigned letters A–F to each of the neighborhood contextual variables. This process yielded the following assignment: A = Median Income, B = Pct. Below Pov, C = Pct. Unemployment, D = Pct. Food Stamps, E = Pct. Single Parent, F = Pct. Less than HS.

the dataset possessed sufficient variability across key variables. In this study, among the students who participate in their schools' FRL program, 51% live in relatively high-poverty neighborhoods, and approximately a quarter live in medium- and low-poverty neighborhoods. In contrast, among the students who do not participate in their schools' FRL program, 46% live in relatively low-poverty neighborhoods, 33% live in high-poverty neighborhoods, and 21% live in medium-poverty neighborhoods. In both cases, variability exists throughout the various neighborhood contexts (high, medium, and low levels of poverty).

Figure 1

Percentage of FRL Participation by Neighborhood Context[14]

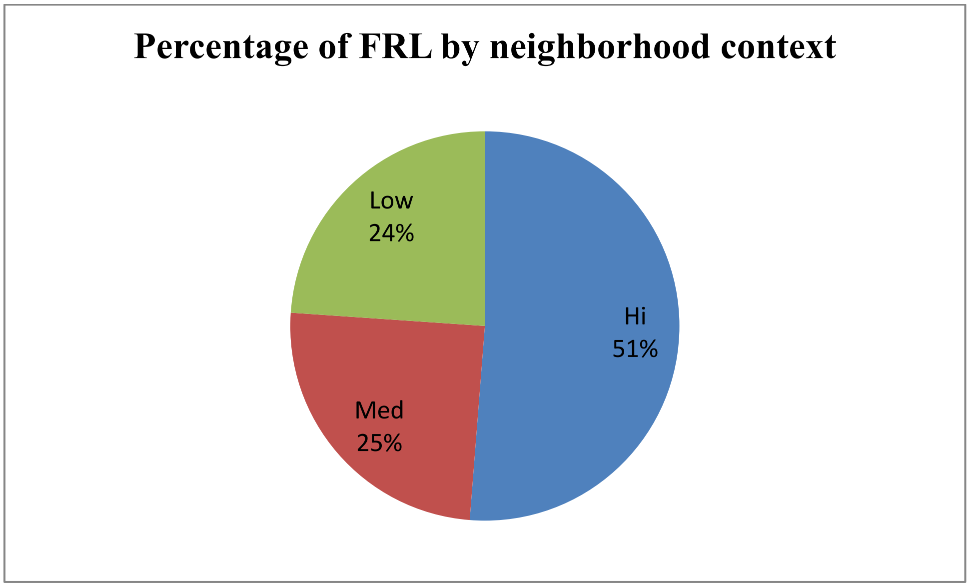
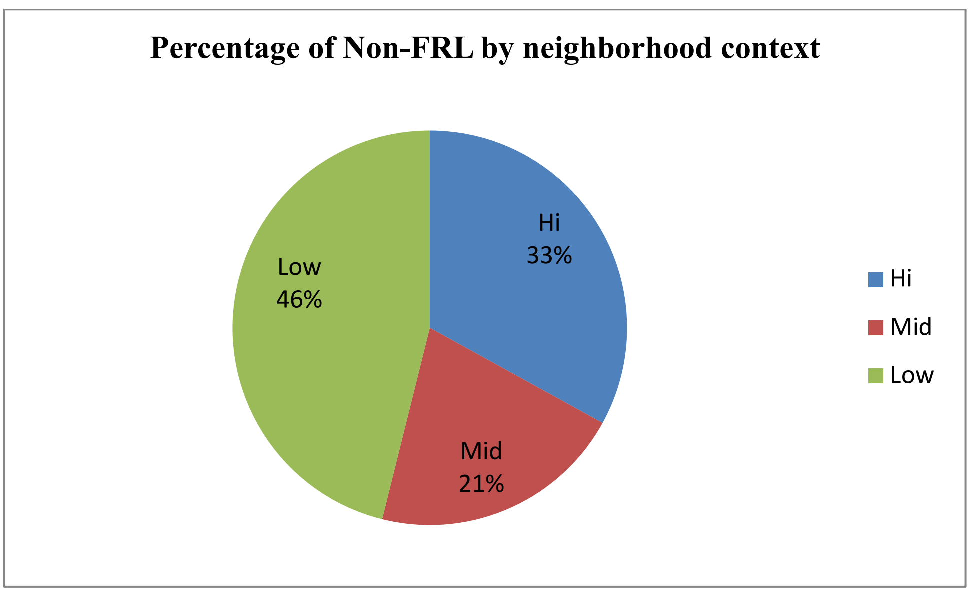


Figure 2

Percentage of Non-FRL Participation by Neighborhood Context



[14] For simplicity, the distinction made between high, medium, and low poverty that appear in for Figures 2 and 3 was generated solely using the percentage of families living below the poverty line for each available zip code.

Measures

The larger IES evaluation study employed a delayed treatment design. As such, for each participating school and during each academic year, eligible first graders (17–36 students) were randomly assigned to one of three MR tutoring cohorts or the waitlist. For both academic years (2007–08 and 2008–09), each school possesses three cohorts (Cohort A, Cohort B, and Cohort C), and each MR tutoring cohort consists of three students. At the start of the academic year and directly before each cohort entered or exited MR tutoring, each first grader who received MR tutoring was administered alternating forms of the following instruments: applied problems (AP), mathematical fluency (MF), and quantitative concepts (QC) subtests of the Woodcock-Johnson (WJ) III achievement test and the MR proximal instrument.[15] The students on the waitlist were administered the MF subtest when a cohort began MR tutoring, and they were only administered the other WJ subtests (AP and QC) and the MR proximal instrument at the beginning and end of the academic school year. Below, Table 10 provides a graphical representation of the testing cycles.

[15] The MR proximal instrument was internally designed by MR developers and, as a result, does not appear in the analysis reported in this study.

Table 10

MR Treatment and Assessment Cycles for Each School[16]

	Pre-Test	T_xA	Assessment	T_xB	Assessment	T_xC	Post-Test
Cohort A (n = 3)	MR 1.1 WJ	T_x	MR 1.1 WJ		WJmf		MR 1.1 WJ
Cohort A (n = 3)	MR 1.1 WJ		MR 1.1 WJ	T_x	MR 1.1 WJ		MR 1.1 WJ
Cohort A (n = 3)	MR 1.1 WJ		WJmf		MR 1.1 WJ	T_x	MR 1.1 WJ
WL ($7 \leq n \leq 16$)	MR 1.1 WJ		WJmf		WJmf		MR 1.1 WJ

The AP test assesses a student's ability to construct the mental models required to solve problems and demonstrate quantitative reasoning. The MF test measures a student's ability to calculate single-digit addition, subtraction, and multiplication in three minutes. The QC test captures a student's ability to orally apply mathematical concepts and analyze numerical relationships. The WJ III achievement test constitutes an age-appropriate assessment because (i) each subtest (i.e., AP, MF, and QC) features alternating forms such that no student is administered the same items in consecutive time points; (ii) at a minimum, all tests possess a reliability coefficient alpha of 0.80 or higher, and several tests have a coefficient of 0.90 or higher; and (iii) ample evidence supports the construct validity of all tests (Woodcock et al., 2001).

Tables 11–13 represent the range of WJ III subtest scores by school over the combined academic school years (i.e., 2007–08 and 2008–09). The MF mean for all schools equals 94.2,

16 Each cycle is approximately 11 weeks long and takes place five5 days per week. There are a total of three cycles each year for two years. WL = Waitlist students, Tx = MR tutoring treatment, WJ = Full Woodcock Johnson III Achievement Assessment (AP, MF, and QC), WJmf = Woodcock Johnson III Achievement Assessment subtest (MF), MR1.1 = Proximal Math Recovery Assessment.

the AP mean is 101.5, and the QC mean equals 100.3. For the MF subtest, School J achieved the highest mean of 97.4, and School H presented the lowest mean of 89.9. For the AP subtest, Schools O and P achieved the highest mean of 107.4, and School A possessed the lowest mean of 94.9. For the QC subtest, School L achieved the highest mean of 105.4, and School B demonstrated the lowest mean of 92.1.

Table 11

WJ III Math Fluency Subtest by School (Combining Both Academic School Years)

School	Mean	Std. Dev.	Min	Max
A	95.3	13.3	64	133
B	95.2	11.7	72	190
C	92.4	9.9	70	119
D	93.9	9.0	71	113
E	95.0	12.1	64	129
F	94.9	10.1	72	119
G	91.7	10.7	72	128
H	89.9	7.9	70	109
I	95.1	10.8	74	133
J	97.4	9.4	75	123
K	95.2	11.1	67	132
L	95.4	9.2	70	120
M	93.1	9.8	71	119
N	91.1	8.1	69	111
O	96.9	10.7	66	123
P	95.4	10.8	76	121
Q	90.0	8.4	62	117
R	96.2	8.2	74	119
S	93.8	8.8	74	123
T	96.9	9.9	75	120
All Schools	**94.2**	**10.4**	**62**	**190**

Table 12

WJ III Applied Problems Subtest by School (Combining Both Academic School Years)

School	Mean	Std. Dev.	Min	Max
A	94.9	9.2	73	116
B	96.3	9.6	78	129
C	96.3	10.1	69	117
D	100.7	9.2	79	122
E	97.8	11.9	71	135
F	99.2	11.9	64	128
G	99.5	13.5	57	139
H	97.0	10.8	72	127
I	98.5	11.1	70	128
J	104.2	12.5	71	142
K	105.3	12.6	72	140
L	105.6	10.9	85	130
M	102.8	12.6	64	131
N	104.5	11.1	73	126
O	107.4	11.6	81	139
P	107.4	13.8	73	138
Q	101.6	13.0	52	131
R	106.4	13.0	42	137
S	103.7	10.6	76	131
T	103.6	10.6	82	127
All Schools	**101.5**	**12.1**	**42**	**142**

Table 13

WJ III Quantitative Concepts Subtest by School (Combining Both Academic School Years)

School	Mean	Std. Dev.	Min	Max
A	95.1	11.6	71	130
B	92.1	9.4	71	114
C	95.0	11.0	67	123
D	101.3	9.8	76	123
E	95.5	12.7	68	133
F	101.5	11.6	67	129
G	97.4	14.0	56	127
H	98.7	11.9	68	125
I	100.6	11.8	62	133
J	103.6	13.3	70	134
K	103.7	12.5	68	128
L	105.4	10.3	81	125
M	100.9	13.7	55	131
N	100.9	10.5	66	125
O	105.0	13.4	72	135
P	103.7	13.4	76	135
Q	97.7	13.2	67	152
R	105.2	11.4	69	127
S	102.5	12.6	70	136
T	102.3	11.7	68	127
All Schools	**100.3**	**12.6**	**55**	**152**

Data Analysis Methods

This dissertation's sample is not nationally representative, nor was the district and school selection process random. Instead, the research design utilized districts and elementary schools that had implemented the MR intervention for the first time. Although this process virtually eliminates the generalizability of results, the districts and schools selected for this dissertation produced sufficient variation regarding student, school, and neighborhood characteristics.

The randomization process does not hinder this study's ability to assess the research questions, as the temporal nature of the testing cycle (see Table 10 above) presents periods where all study participants were provided at least one mathematics assessment. Therefore, it is possible to construct individual growth models. Furthermore, one inherent benefit of the individual growth modeling technique is that the timing of the assessments does not have to be identical. This allows students with missing data to remain in the analysis.

The research design adequately addresses the potential unmeasured effects using careful sample stratification and a random assignment of students to the control or treatment groups. Additionally, the sample presents a unique research opportunity into neighborhood effects because (i) the sample consists of diverse geographical, SES, and neighborhood characteristics and, (ii) unlike the majority of pre-existing data, this dataset contains a significant amount of mathematical achievement data for low-performing first graders at multiple time points throughout two different academic years across 20 schools.

Studying observable growth in students' achievement scores and how school and neighborhood contexts relate to differences in student progression is of considerable importance to the educational research community. Much can be learned by conducting an analysis that extends beyond student achievement data collected at a single point in time to an analysis that includes repeated measures. This allows the study to explore the relationship between a student's initial achievement status and their rate of progression.

The growth modeling technique provides a useful framework for examining students' change patterns. Growth modeling strategies enable assessing the extent to which, on average, students in a given context and academic subject (e.g., mathematics, reading, etc.) are progressing; in turn, this captures the differences between rates of progress among various demographic groups (Bryk & Raudenbush, 1987; Willett & Sayer, 1994).

A series of three-level hierarchical linear growth models were employed to estimate each student's growth trajectory. The three-level HLM is important because it estimates and interprets how higher level predictors influence Level 1 outcomes and calculates cross-level interaction effects of the predictors in the model. Furthermore, it is important to incorporate three-level structures in the various models because the higher level clusters (e.g., schools) differ substantially from one another on the WJ III subtests (see Tables 11–13 above).

Level 1 models individual student WJ III subtest scores over time. Consider the following Level 1 model:

(1) $Y_{tij=}\pi_{0\,ij} + \pi_{1\mathrm{ij}}Time_{\mathrm{t}ij} + e_{tij}$

Where Y_{tij} represents the mathematics achievement score on the WJ III subtest at time t for student i in school j. The term $Time_{tij}$ comprises a variable that captures time as the number of weeks since each student started the first grade and indexes when the mathematics test was taken. In this framework, the intercept, π_{0ij}, represents the average baseline mathematical achievement for student i at time t = 0. The coefficient, π_{1ij}, estimates each student's growth rate over the 2007–08 or 2008–09 academic school year and represents the expected change in mathematics scores during the fixed unit of time (Raudenbush & Byrk, 2002). These estimates are employed to generate predicted achievement from the actual date of testing at other times. Due to the delayed treatment design of the larger evaluation study, the number of mathematical assessments varies across students (see Table 10). It is assumed that the mathematical growth parameters vary across students. Assuming that the growth parameter is linear, the e_{tij} term represents the measurement error in a student's mathematics score that deviates from their true observed mathematical achievement level. It is assumed that the term e_{tij} is normally distributed and possesses a mean of 0 and variance of σ^2.

The purpose of Level 2 of the model is to estimate the extent to which mathematics baseline and growth varies as a function of student time-invariant characteristics such as race or ethnicity, SES, and neighborhood contexts. Consider the following Level 2 equation:

$$(2)\ \pi_{0ij} = \beta_{00j} + \beta_{10j}Treatment_{ij} + \boldsymbol{S}_{ij}\beta_{q0ij} + r_{0ij}$$

$$\pi_{1ij} = \beta_{10j} + \beta_{11j}Treatment_{ij} + \boldsymbol{S}_{ij}\beta_{q1ij} + r_{1ij}$$

$\boldsymbol{S}$ is a vector of q student characteristics such as Male, Free Lunch, English Learner, Minority, Overage, Year, and Neighborhood.

Level 2 includes time-invariant student-level characteristics that are believed to be related to student achievement and are supported by previous student achievement research as covariates on both the level (intercept) and slope (growth). More specifically, the following time-invariant student-level covariates are included at Level 2: FL, a dichotomous variable indicating whether or not a student is eligible for their district's FRL program (1 = eligible, 0 = ineligible); Male, a dichotomous gender variable (male = 1, female = 0); Minority, a dichotomous variable representing the student's race or ethnicity (all race/ethnic groups = 1, and White students are identified as the omitted reference group = 0); EL, a dichotomous variable to identify whether or not a student is classified as "English Learner" (1 = yes, 0 = no); and Overage, a dichotomous age variable (1 = yes, 0 = no). Because the dataset in this dissertation employs data from two different academic years, the researcher included Year as a dichotomous variable (2007–08 academic year = 1, 2008–09 academic year = 0) to account for any unobservable differences (e.g., change in the district's mathematics curriculum or change in a school's student attendance boundary map).

Neighborhood membership was determined using the home address zip code recorded in administrative records for all first graders in the sample, and this was assumed to remain constant over the study period. In these data, schools enroll students from different neighborhoods, and students in the same neighborhoods are also found to be enrolled in different schools. Accordingly, this study treats ND as a time-invariant student-level characteristic. The ND variable was created from the 2010 five-year estimates of the American Community Survey. The complete list of Level 2 neighborhood contextual variables represented in the ND variable is included in Table 7 (listed above). For this study, the ND variable is treated as a time-invariant student characteristic. As previously stated and illustrated, the schools in this sample feature students who come from several neighborhoods (e.g., measured by postal zip codes) within and across schools. The researcher opted not to specify a Time in Student in Neighborhood in School 4-level model, as the data available for this study were not rich enough (e.g., sample was not large enough) to support this type of model. As such, neighborhoods are treated as a student characteristic that does not vary with time.

The term β_{00j} describes the estimated mean baseline mathematics level of students in school j, and β_{10j} provides the estimated mean mathematical growth across students within school j. The Level 2 equation includes two random effects: r_{0ij}, which models individual deviations from the school mean baseline level, and r_{1ij}, which represents the individual deviations from the school mean growth rate. Both errors are modeled as possessing a mean of 0, variance of σ^2, and covariance of ${\sigma^2}_{0-1.}$

Level 3 of the modeling strategy seeks to capture the variation in mathematics achievement across schools. By design, Level 3 accounts for the fact that students are clustered within schools. Consider the following Level 3 equation, where school-to-school variation in the first-grade students' baseline and growth trajectories are defined as follows:

(3) $\beta_{00j} = \gamma_{000} + \mu_{00j}$

$\beta_{10j} = \gamma_{100} + \mu_{10j}$

Where γ_{000} represents the mean school baseline performance, and γ_{100} represents the mean school mathematics growth rate across all schools in the dataset. The random parameters μ_{00j} and μ_{10j} represent how school j differs from the school adjusted mean baseline and growth rate, and they are assumed to possess a mean of 0 and variance of .

CHAPTER 4

RESULTS

This chapter presents the results of the analyses discussed in detail in the previous Methods chapter. The following analysis utilizes data from a randomized control trial funded by the IES to evaluate MR, a one-on-one tutoring intervention. This study's participants consist of first graders from 20 elementary schools (five urban, five rural, and 10 suburban) located in five districts across two states. The study data cover two academic school years (2007–08 and 2008–09). The MR data are supplemented with school- and neighborhood-level data from the U.S. Census Bureau database. This dataset offers a unique opportunity for research concerning neighborhood effects by enabling the utilization of an analytic sample that includes the following qualities: A diverse set of student and school characteristics, diverse geographical and socioeconomic neighborhood factors, and a significant amount of mathematics achievement data from low-performing first graders observed at multiple time points throughout two different academic school years. Due to the delayed treatment design of the larger evaluation study, the number of mathematics assessments varies by student.

The first section provides a review of the primary dependent variables of interest, which consist of the following WJ III subtests: Math Fluency (MF), Applied Problems (AP), and Quantitative Concepts (QC). Subsequently, each WJ III subtest is analyzed individually.

Analysis

The extent to which neighborhood contexts influence low-performing students' mathematical growth trajectories represents a relevant policy issue due to the persistent educational inequalities between advantaged and disadvantaged students as well as between subgroups of majority and minority students. All the models considered below possess a three-level structure where test events are nested within students and students are nested within neighborhoods within and across schools. The researchers who conducted the overarching IES-funded MR evaluation study employed a delayed treatment design. Consequently, the observations vary within and across the three WJ III subtests of interest (i.e., MF, AP, and QC).

WJ III Subtest Overview

The students in this dissertation's sample were administered the MF, AP, and QC WJ III subtests. The MF subtest measures the extent to which a student can solve simple addition, subtraction, and multiplication facts over a short time period (Shrank et al., 2001; Wendling et al., 2007). The AP subtest measures the extent to which a student can analyze and solve math problems (Shrank et al., 2001; Wendling et al., 2007). Most of the AP questions require students to listen to the math problem, identify the required mathematical procedure, and then perform the correct mathematical calculation. Finally, the QC subtest measures a student's knowledge of mathematical vocabulary, symbols, and concepts. This subtest also measures a student's ability to recognize number patterns (Shrank et al., 2001; Wendling et al., 2007).

The WJ III subtest standard scores (SS) were utilized for the analysis below. The average SS equals 100 with a standard deviation of 15. Table 14 presents a concordance between SS ranges, percentile rank ranges, and a qualitative classification of each range for the respective MF, AP, and QC subtests (Washington Center for Cognitive Therapy, 2011). For example, a student with an SS of 80 on the MF subtest would be classified as performing in a "Low Average" range. The percentile rank refers to the percentage of scores equal to or less than the score referenced. Similar to percentages, percentile ranks fall within a range of 0 to 100. For instance, a percentile rank of 40 would indicate that 40% of the distribution of scores for a similar age and education level would fall at or below the score at the 40th percentile.

The observed mathematics scores for first graders examined in this study are below the national average (see Tables 14–16 below). For this sample, the majority students' MF scores were in the "Low Average" (45.7%) and "Low" (9.2%) classifications. Of these MF scores, almost 40% fell within the "Average" classification. In contrast, approximately 69% of the sample managed an AP SS in the range of 90 to 110 (i.e., "Average" classification). Approximately 60% of students' QC SS results fell in the "Average" classification. In addition, nearly a third of students' QC SS results fell within the "low average" or lower classifications.

Table 14

Standard Score, Percentile Rank, and Classification

Score Range	Percentile Rank Range	Classification
131 and above	98–99.9	Very Superior
121–130	92–97	Superior
111–120	76–91	High Average
90–110	25–75	Average
80–89	9–24	Low Average
70–79	3–8	Low
69 and below	0.1–2	Very Low

Table 15

Sample WJ III Subtests Standard Scores at Time Zero

Standard Score	Math Fluency	Applied Problems	Quantitative Concepts
Above 131			0.30%
121–130		1.31%	1.31%
111–120	0.13%	6.33%	7.73%
100–110	6.8%	28.51%	22.49%
90–99	37.73%	40.56%	38.45%
80–89	45.73%	18.37%	21.18%
70–79	9.20%	4.12%	7.23%
Below 70	0.40%	0.80%	1.31%

Table 16

Sample Descriptive Statistics for WJ III Subtests by Testing Cycle

WJ III Subtest	Obs.	Mean	Std. Dev.	Min	Max
		Math Fluency (MF)			
MF 0	770	88.5	7.2	64	111
MF 1	909	93.9	9.8	67	190
MF 2	897	96.4	10.6	65	133
MF 3	885	97.3	10.9	62	133
		Applied Problems (AP)			
AP 0	996	96.4	10.4	52	127
AP 1	231	103.0	11.5	42	134
AP 2	236	104.6	11.4	77	139
AP 3	883	106.3	12.0	71	142
		Quantitative Concepts (QC)			
QC 0	996	95.1	11.6	55	136
QC 1	231	104.4	12.1	69	134
QC 2	236	104.6	12.4	74	131
QC 3	883	104.3	11.6	64	152

Woodcock-Johnson III Math Fluency Results

The first model includes the Level 1 growth specification described above and only the treatment variable predicting the level on the intercept and slope at Level 2 (see Table 17 below). The initial score represents the baseline score for the control group at time zero. The coefficient for the initial score equals 89.3. The treatment variable represents the pre-intervention stage at time zero and identifies the difference between the treatment and control groups. The estimate of the treatment implies that, on average, the treatment group scored 0.51 higher than the control group. However, this observed difference was not statistically significant. For each additional unit of time (one week), the average increase in WJ III MF SS equaled 0.21. The Time variable represents the additional unit of growth for the control group for each additional week of school. The primary interaction term of interest would be the Treatment x Time variable, which represents the additional benefit of being in the treatment group over time. The 0.51 coefficient on the Treatment x Time variable is statistically significant.

Model 2 builds on Model 1 by including the student fixed characteristics, as described above. After controlling for student covariates, the growth per time unit equals 0.22 and remains statistically significant (see Table 17). However, the estimated treatment effect is still not statistically significant. As stated earlier, the additional student covariates are broken down into the following two components: baseline and mathematical growth over time. The baseline component interpretation is the first to appear, followed by the growth component.

None of the student characteristics provided statistically significant predictors of baseline mathematical achievement. However, it is worth noting that the Overage, EL, and FRL coefficients are noticeably large. Overage students achieved an initial score almost 6 points lower than their peers. English language learners, meanwhile, scored 1 point higher than their peers. Next, students who participate in their district's FRL program scored 1 point lower than those who do not participate in such a program.

Over time, the EL, Year, and Treatment coefficients are all positive and statistically significant. English language learners gained 0.06 points per week and 2.4 cumulative points over the course of the academic year compared to their peers. Similarly, students who participated in Year 2 of the study (i.e., 2008–09) gained 0.06 points per week of schooling and 2.4 points over the course of the year compared to students who participated in Year 1 of the study (i.e., 2007–08). Additionally, the treatment group gained approximately 0.03 points per week and an additional 1.2 points over the school year compared to the control group. Conversely, minority students are estimated to lose approximately 0.05 points per week compared to their non-minority peers. This implies a cumulative loss of 2 points for minority compared to non-minority students.

Model 3 builds on Model 2 by including the student neighborhood characteristics at Level 2, as described above. Therefore, within this sample and data, after controlling for student demographic characteristics, neighborhood contextual variables (i.e., ND) possess no additional explanatory power for student mathematical baseline achievement or growth over time.

Table 17

Neighborhood Effects on Mathematics (Math Fluency) Growth Trajectories

	Model 1		Model 2		Model 3	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Level 1: Scores						
Initial Score	89.3***	.47	89.9***	.71	89.9***	.73
Time	0.21***	.02	0.22***	.03	0.22***	.03
Level 2: Students						
Treatment	0.51	.59	0.57	.59	0.56	.59
Treatment x Time	0.04~	.25	0.03~	.02	0.03~	.02
Male			-0.52	.59	-0.52	.59
Male x Time			-0.03	.02	-0.03	.02
Minority			-0.26	.68	-0.22	.76
Minority x Time			-0.05*	.02	-0.05*	.02
EL			1.03	.90	1.03	.90
EL x Time			0.06~	.03	0.06~	.03
FRL			-1.00	.66	-0.91	.66
FRL x Time			0.01	.02	0.10	.27
Overage			-5.60	3.20	-5.59	3.4
Overage x Time			0.02	0.09	0.02	0.09
Year			0.13	.60	0.13	.60
Year x Time			0.06**	.02	0.06**	.02
ND					-0.06	.51
ND x Time					-0.0005	.02

*** for $p < .001$, ** for $p < .01$, * for $p < .05$, ~ for $p < .10$

Woodcock-Johnson III Applied Problems Results

The first model includes the Level 1 growth specification described in the previous section, and it contains only the treatment variable predicting the level on the intercept and slope at Level 2 and a null model at Level 3. The intercept and time slope are allowed to vary across Levels 2 and 3. The initial score represents the baseline score (intercept) for the control group at time zero. The coefficient for the initial score equals 95.6 (see Table 18). The treatment variable identifies the difference between the treatment and control groups represented at the baseline or pre-intervention stage at time zero. The estimated coefficient on treatment implies that, on average, the treatment group scored 1.5 points higher than the control group at the baseline, producing a statistically significant difference. For each additional unit of time (1 week), the average increase in AP SS equaled 0.25 scale score points per week for students in the control group, and this coefficient is statistically significant. The primary interaction term of interest is the Treatment x Time variable, which represents the additional benefit of being in the treatment group according to growth over time. The benefit of treatment in terms of score growth was estimated at 0.06 SS points per week and was statistically significant.

Model 2 builds on Model 1 by including student characteristics, as described above. After controlling for student covariates, the estimated growth per time unit equaled 0.02, which is statistically significant (see Table 18). As stated previously, the additional student covariates were added to both the intercept (baseline performance) and growth slope. The student characteristics for the intercept are examined first, followed by a discussion of the growth component characteristics.

Some student characteristics (i.e., Minority, EL, and Year) offer statistically significant predictors of baseline mathematical achievement. The EL and Minority coefficients are both statistically significant and substantively large. English language learners (i.e., EL) are estimated to possess a 6.6-point lower baseline score compared to their peers. Similarly, non-White students score 2.2 points lower compared to White students. Furthermore, students who participated in Year 2 of this study achieved a score 1.4 points lower than students from Year 1. It is also worth noting that the FRL and Overage coefficients are both negative and substantively large, but statistically insignificant.

Over time, the EL, Male, Minority, Year, and Treatment coefficients exhibit higher growth rates and are statistically significant. The growth rate for English language learners is estimated to be 0.11 points per week higher compared to their non-ELL peers. This suggests that English language learner students gain 4.4 points over the course of the academic year compared to their appropriate peers. Additionally, over time, minority students are estimated to gain 0.04 points for each unit of time compared to their non-minority peers, translating into an increase of 1.6 points over the academic year. Male students' growth rate was estimated to be 0.03 points per week higher than female students. Over time, the students in Year 2 of this study were estimated to gain approximately 0.02 points for each unit of time compared to their peers in Year 1, translating into a cumulative annual growth that is nearly 1 point higher. In contrast, the FRL coefficient growth rate was 0.02 points lower over time, but it was not statistically significant.

Model 3 builds on Model 2 by including the student neighborhood characteristics at Level 2, as described above. Similar to Model 2, several of the estimated student characteristic coefficients in Model 3 remain statistically significant predictors of student baseline mathematics achievement and mathematics growth over time. For example, English language learners were still estimated to possess lower scores at a baseline of almost 6.5 points while minority students scored approximately 2 points lower than their White peers.

For student mathematical baseline achievement, neighborhood contextual factors provide no additional explanatory power, as the estimate is not statistically significant. Therefore, after controlling for student demographic characteristics, neighborhood context does not appear to condition student baseline performance, at least within the current sample. However, neighborhood contexts do appear to condition growth rates over time even after controlling for student demographic characteristics. A standard deviation increase of one in neighborhood factors (i.e., a more distressed neighborhood) was estimated to decrease a student's mathematical achievement by 0.06 points per week and by 2.4 points over the course of the year compared to students at the mean of the neighborhood contextual variable. This result is statistically significant.

Table 18

Neighborhood Effects on Mathematics (Applied Problems) Growth Trajectories

	Model 1		Model 2		Model 3	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Level 1: Scores						
Initial Score	95.6***	.71	99.30***	.96	99.1***	.96
Time	0.25***	.03	0.21***	.03	0.20***	.03
Level 2: Students						
Treatment	1.50*	.71	1.38*	.69	1.34*	.69
Treatment x Time	0.06***	.02	0.06***	.02	0.06***	.02
Male			-1.04	.70	-1.05	.70
Male x Time			0.03~	.02	0.03~	.02
Minority			-2.21**	.85	-1.94*	.90
Minority x Time			0.04*	.02	0.05*	.02
EL			-6.59***	1.08	-6.62***	1.07
EL x Time			0.11***	.03	0.11***	.03
FRL			-1.19	.80	-1.18	.79
FRL x Time			-0.02	.02	-0.02	.02
Overage			-4.73	5.43	-4.78	5.43
Overage x Time			0.009	0.15	0.009	0.15
Year			-1.42*	.70	-1.42*	.70
Year x Time			0.02	.02	.02	.02
ND					-0.97	.75
ND x Time					-0.06**	.03

*** for $p < .001$, ** for $p < .01$, * for $p < .05$, ~ for $p < .10$

Woodcock-Johnson III Math Quantitative Concepts Results

The first model includes the Level 1 growth specification and only the treatment variable predicting the level on the intercept and slope at Level 2. The coefficient for initial score represents the baseline score for the control group at time zero. The coefficient for the initial score equals 94.3. The treatment variable represents the pre-intervention stage at time zero and identifies the difference between the treatment and control groups. The Treatment estimate implies that, on average, the treatment group scored 2.7 points higher than the control group. This observed difference was statistically significant and relatively large compared to the other WJ III subtests. For each additional unit of time (1 week), the average increase in WJ III QC SS equaled 0.23. The Time variable provides the additional unit of growth for the control group for each additional week of school. The primary interaction term of interest is the Treatment x Time variable. This term represents the additional benefit of being in the treatment group over time. The 0.04 coefficient on the Treatment x Time variable is statistically significant, indicating that the students in the treatment group gained an additional 0.04 points per week compared to those in the control group.

Model 2 builds on Model 1 by including student demographics, as described above. After controlling for student covariates, the growth per time unit increases to 0.25 and remains statistically significant (see Table 19). The student-level covariates were added to both the intercept (baseline performance) and growth slope. The researcher first presents the student characteristics for the intercept and then discusses the student characteristics associated with the growth component.

Most of the coefficients (i.e., Treatment, Male, EL, Overage, and Year) associated with student characteristics offer statistically significant and substantively large predictors of baseline mathematical achievement. For example, the EL estimate suggests that English language learners possess a baseline score almost 3 points lower than their peers. Overage first graders, meanwhile, possess a baseline score that is 10 points lower compared to their peers. Next, male students possess a baseline score that is nearly 2 points lower than female students. Furthermore, as with the previous models, those first graders who participated in the treatment group achieved a baseline score that is almost 3 points higher compared to the control group. In contrast, however, the Year 2 study participants achieved a baseline score that is 3 points lower than Year 1 participants.

Over time, the Treatment, EL, and Year coefficients exhibit higher growth rates and are statistically significant. The growth rate for English language learners is an estimated 0.07 points per week higher than for their non-English language learner peers. This difference suggests that, over the course of the academic year, English language learners possess a math growth trajectory that is nearly 3 points higher than non-English language learner students. Similarly, those students who participated in the treatment group are estimated to possess a growth rate 0.04 points higher than the control group. Students in Year 2 of this study, meanwhile, were estimated to gain approximately 0.05 points for each unit of time compared to their peers in Year 1. In contrast, the growth rate for non-White students is 0.05 points per week lower than for White students. This implies that non-White students possess a cumulative math growth trajectory that is 2 points lower than that of their White peers. Similarly, the coefficient associated with FRL program participation is 0.03 points lower for those who participate in this program compared to students who do not.

Model 3 builds on Model 2 by including student neighborhood characteristics at Level 2. Similar to Model 2, several of the estimated student demographic coefficients in Model 3 remain statistically significant and directionally consistent.

For student mathematical baseline achievement, neighborhood contextual factors do not add further explanatory power, as the estimate is not statistically significant. However, neighborhood contextual factors do appear to influence growth rates over time even after controlling for student demographic characteristics. A standard deviation increase of one in neighborhood factors (i.e., a more disadvantaged neighborhood) was estimated to decrease a student's mathematical achievement by 0.03 points per week, which translates to 1.2 points lower overall for the academic year compared to students at the mean of the neighborhood contextual variable.

Table 19

Neighborhood Effects on Mathematics (Quantitative Concepts) Growth Trajectories

	Model 1		Model 2		Model 3	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Level 1: Scores						
Initial Score	94.3***	.74	97.7***	1.03	97.7***	1.04
Time	0.23***	.02	0.25***	.03	0.24***	.03
Level 2: Students						
Treatment	2.65***	.76	2.70***	.74	2.72***	.74
Treatment x Time	0.04*	.02	0.04*	.02	0.04*	.02
Male			-1.79**	.74	-1.79**	.75
Male x Time			0.02	.02	0.02	.02
Minority			-0.47	.91	-0.69	.87
Minority x Time			-0.05*	.02	-0.04~	.03
EL			-2.63*	1.15	-2.60*	1.15
EL x Time			0.07*	.03	0.07*	.03
FRL			-1.21	.85	-1.21	.85
FRL x Time			-0.03	.02	-0.03	.02
Overage			-10.2~	5.96	-10.1~	5.96
Overage x Time			0.11	.17	0.11	.17
Year			-2.74***	.75	-2.74***	.75
Year x Time			0.05**	.02	.05**	.02
ND					0.22	.83
ND x Time					-0.03~	.02

*** for $p < .001$, ** for $p < .01$, * for $p < .05$, ~ for $p < .10$

CHAPTER 5

DISCUSSION

The primary objective of this dissertation was to investigate and understand how neighborhood contexts may influence low-performing first-grade students' mathematical achievement. This chapter summarizes this study's key findings, discusses study limitations and suggestions for further investigation, and elaborates on implications for practice and policy.

This study examined data gathered through an IES-funded evaluation study of Math Recovery (MR). Focusing primarily on the characteristics of the neighborhood in which participants resided enabled quantifying the impact neighborhoods may have on students' mathematics growth trajectories.

Study Limitations and Future Investigations

Although students' academic performance is assessed individually, all students participate in an array of group learning activities occurring within both the school and non-school environment (Entwisle et. al, 2001; Manski, 1993). Neighborhoods represent one of the pertinent non-school environments that children are exposed to daily.

With respect to geography, the neighborhood effects literature demonstrates no general consensus regarding how to define neighborhoods. As such, the researcher of this study used students' zip codes as a proxy for the neighborhood boundary in which they live. In turn, this allowed the researcher to estimate how neighborhoods influence mathematics achievement. This decision remains superior to the decision to use the zip code of the school's geographical location primarily because, for this dataset, students attend schools with peers who live in different neighborhoods (e.g., measured via zip codes).

This study features two major limitations: First, due to the nature of the overarching IES-Funded MR Evaluation Study data collection design, it was not possible to obtain participants' street addresses. These addresses would have enabled using the U.S. Census tracts as the geographical boundaries to define neighborhoods in the analysis. Instead, the mailing zip codes were obtained for all study participants.

In general, five-digit zip codes represent larger geographical boundaries and, thus, often include several census tracts within each five-digit zip code. Additionally, five-digit zip codes represent boundaries that are determined by physical size rather than population. In contrast, census tracts boundaries are defined by populations and include a population of approximately 4,000 individuals. However, census tracts represent a smaller geographical boundary than what many would consider a neighborhood.

Second, this study does not control for the duration of exposure to the observed neighborhood factors. For example, one can assume that living in a disadvantaged neighborhood for a relatively long period of time is more detrimental to children than living in a disadvantaged neighborhood for short time periods. Corcoran et al. (1992) accordingly found that the number of years adolescents with families lived below the poverty line offered a significant predictor of early career outcomes.

However, despite plausible reasons to suspect that elementary-aged children's neighborhood environment may influence their academic achievement and development, few studies have been conducted on the subject. Furthermore, most of the existing neighborhood research literature focuses on academic achievement in either adolescents (Cook et al., 2006; Plunkett et al, 2007) or middle-school students (Leventhal & Brooks-Gunn, 2003; Thompson, 2002). Therefore, more research is needed to investigate the extent to which young children are influenced by their neighborhood environment. In addition, a substantial amount of the neighborhood effects literature focuses on non-academic student outcomes (e.g., health, violence, teenage pregnancy rates, arrests, etc.). This study addresses the resultant gaps in neighborhood effects research by examining how neighborhood influences mathematics growth trajectories.

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