NEIGHBORHOOD CONDITIONS IN RELATION TO ACADEMIC ACHIEVEMENT OF ELEMENTARY SCHOOL STUDENTS

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ABSTRACT

HUIFANG ZUO. Neighborhood conditions in relation to academic achievement of elementary school students. (Under the direction of DR. CHUANG WANG)

In the United States, the academic achievement gap between European American and African American students has been identified as one of the major problems related to educational equity. Students' academic achievement has been largely examined from aspects related to student characteristics, student family background, teacher quality, parental involvement, and school features (Anderman & Anderman, 1999; Caprara, Barbaranelli, Steca, & Malone, 2006; Keith, Keith, Troutman, & Bickley, 1993; Meece & Holt, 1993; Paulson, 1994; Staub & Stern, 2002). However, the relationship between neighborhood and academic achievement has received inadequate attention overall. Furthermore, most neighborhood-academic achievement studies failed to consider the spatial properties of neighborhood attributes. The present study investigated relationships between neighborhood conditions and academic achievement of elementary school students with modeling spatial dependencies of neighborhood attributes. Measures of neighborhood conditions were developed through Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). Then a geodatabase was built to integrate neighborhood attributes and school characteristics. Exploratory Spatial Data Analysis (ESDA) was used to explore the spatial variations of neighborhood-based regional attributes present within Charlotte-Mecklenburg Schools (CMS) area. Finally, a transformed two-level Hierarchical Linear Modeling (HLM) with modeling spatial dependencies was used to investigate relationships between neighborhood conditions and academic achievement of elementary school students. One of the major findings from the current study is that school environments have a close association with mathematics achievement especially for students living in disadvantaged neighborhoods with more risk factors.

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CHAPTER 1: INTRODUCTION

1.1. Statement of the Problem

A body of the neighborhood literature emphasizes the exploration of neighborhood effects on youths' or adolescents' health outcomes, delinquent behavioral problems, or risk behaviors (Dubow, Edwards, & Ippolito, 1997; Kegler et al., 2005; Kohen, Brooks–Gunn, Leventhal, & Hertzman, 2002; Leventhal & Brooks-Gunn, 2000). However, the relationship between neighborhood conditions and academic achievement has received inadequate attention overall.

Students' academic achievement has been largely examined from aspects related to student characteristics, student family background, teacher quality, and school features, to name a few (Anderman & Anderman, 1999; Caprara et al., 2006; Keith et al., 1993; Meece & Holt, 1993; Paulson, 1994; Staub & Stern, 2002). The neighborhood conditions in relation to educational attainments have drawn researchers' attention since the 1980s (Johnson, 2010). The examination of neighborhood conditions offers an alternative perspective to explore educational performance of the youths and adolescents. Neighborhood conditions may play moderate or mediate roles between school settings and children's academic behaviors (Johnson, 2010; Kegler et al., 2005; Mullis, Dossey, Foertsch, Jones, & Gentile, 1991). The study of the neighborhood conditions is crucial for explaining variations of the educational outcomes in general and academic achievement in particular (Garner & Raudenbush, 1991; Johnson, 2010). The complex topic of the neighborhood conditions is difficult to define using single viewpoints. It covers a variety of resources, which provide important information to link neighborhoods to educational outcomes. In previous studies, structural factors, such as socioeconomic status (SES) are primarily used to represent levels of the neighborhood conditions (Kohen et al., 2002), while other studies also pay attention to neighborhood social process, including collective sense of the neighborhoods, non-parental and peer role models, and participation in neighborhood organizations (e.g., libraries, learning and community centers, parks, and churches) (Berg, Stewart, Stewart, & Simons, 2013; Garner & Raudenbush, 1991; Johnson, 2010; Kegler et al., 2005; Leventhal & Brooks-Gunn, 2000; Tate IV & Hogrebe, 2010). In addition, reports of the neighborhood conditions are primarily gained from surveys of parents, in which parents typically give their subjective perceptions and opinions. Direct measurement of neighborhood conditions for exploring educational outcomes is in its infancy. On the other hand, most neighborhood studies in educational fields only add variables related to neighborhood conditions without considering spatial properties of the neighborhood data (Crowder & South, 2011; Hogrebe, 2012; McMaken, 2014).

Although neighborhood conditions have become one of the prevailing factors to explain heterogeneities in educational performance between individuals (Berg et al., 2013; McCoy, Roy, & Sirkman, 2013), the specific processes and mechanisms of how neighborhoods affect the educational outcomes still remain unexamined (Johnson, 2010; McBride Murry, Berkel, Gaylord-Harden, Copeland-Linder, & Nation, 2011). Moreover, the spatial properties associated with educational outcomes (e.g., years of the schooling, graduation rate, school completion, dropout, and reading/math achievement) receive less attention in the field of the educational research (Crowder & South, 2011; McMaken, 2014). Therefore, it is necessary to not only propose methods and frameworks for mapping relationships between neighborhood conditions and academic achievement, but also explain the variations of academic achievement considering spatial properties of neighborhoods.

1.2. Academic Achievement Gap

Academic achievement is closely associated with race, family backgrounds, gender, school characteristics, and residential conditions (Barton & Coley, 2009; Coleman, 1990). In general, achievement gap is referred to as differences in grades, enrollment, drop-out rates, college or graduate school completion between African-American (or Hispanic) students and their European American counterparts, urban schools and schools in affluent suburbs, and males and females (Barton & Coley, 2009; Coleman, 1990; Ladson-Billings, 2006).

The achievement gap, caused primarily by educational inequality, has a long history. Attentions paid and trends observed related to achievement gap vary during different periods (Rothstein, 2004). During the 1960s, the federal government and academic researchers began focusing on closing the achievement gap by surveying educational inequalities and by signing the Elementary and Secondary Education Act into law (Kosters & Mast, 2003). These steps were taken to boost the academic achievement of students from low-income families. Responding to this action, the educational inequality surveys (called Equality of the Educational Opportunities) (Coleman et al., 1966) were published for guiding future research direction through reshaping inquiry perspectives and redefining evaluation stances, although this study was often questioned for its robustness of the methodology, validity of the procedures, and generality of the results (Coleman, 1990; Kosters & Mast, 2003). Later on, a series of the efforts were devoted by both the government and educational researchers, and these efforts seemed to have narrowed the achievement gap among different groups of students from the 1970s to the 1980s, especially through government-enforced desegregation. A large body of the studies focused on relationships between the achievement gap and desegregation emerged, a fair amount of which confirmed the effectiveness of desegregation on improving students' achievement (Bradley & Bradley, 1977) while others questioned its effectiveness (Carver, 1975; Hanushek & Kain, 1972).

Around the 1990s, government and researchers had to readjust and reform previous Acts and measures to fit new requirements. In 1994, Title I re-authorized its legislation of the related provisions (Kosters & Mast, 2003). The other highlighted event was the enactment of the No Child Left Behind Act (NCLB) in 2002, which further forwarded the Elementary and Secondary Education Act in 1965 and created visions of improving disadvantaged students' school performances by 2014. NCLB was a promising initiative in the beginning of the 21st century with sequences of the moves and plans-"target much-needed resources to our country's most disadvantaged students" (Rebell & Wolff, 2009, p. 1). Although a series of the legislations were reauthorized by the government, the achievement gap was widened from the 1990s to the 2000s (Barton & Coley, 2010). The effects of NCLB were not as large as expected reported by National Assessment of Educational Progress (NAEP) (Braun, Chapman, & Vezzu, 2010). The imbalance between efforts devoted and the sizeable achievement gap (e.g., African American-European American differences) raised questions for researchers and also inspired them for re-exploring and re-thinking factors and processes that might impact academic achievement. After that, numerous studies emerged to investigate issues related to the achievement gap with diverse perspectives (Ladson-Billings, 2006; J. Lee, 2002; Sirin, 2005), such as the detracting method adopted for evaluation of the disadvantaged students' academic achievement (Burris & Welner, 2005; Wells & Serna, 1996), exploring social-emotional factors (B. E. Becker & Luthar, 2002), and focusing on contextual factors (e.g., neighborhood conditions) (Ainsworth, 2002; Eamon, 2005; Jargowsky & El Komi, 2011). These studies broadened scopes and methods that were used to explore phenomena related to academic achievement.

1.3. Geospatial Properties

Most studies regarding academic achievement were conducted with non-spatial perspectives. Related educational data were measured and analyzed as aspatial (e.g., propensities of the individual students, teacher quality, school conditions, and family characteristics) (Crowder & South, 2011; Hogrebe, 2012). Some studies recognized "nested" attributes of the educational data (i.e., students nested with teachers while teachers grouped in schools) with the use of the multilevel models, such as Hierarchical Linear Models (HLM is apt at measuring individual data organized in hierarchical structures). Failing to recognize the hierarchical structure in data leads to inaccurate inferences (Corrado & Fingleton, 2011; Raudenbush & Bryk, 2002). However, most educational research with the use of the multilevel models did not take spatial properties into account in exploring educational phenomena in relation to neighborhood (Arcaya, Brewster, Zigler, & Subramanian, 2012; Garner & Raudenbush, 1991).

Around the1990s, researchers paid attention on relationships between geographic characteristics and health (Arcaya et al., 2012; Jones & Moon, 1993), bringing understandings and considerations on "place" and "space" in social theory (Arcaya et al., 2012; Kearns & Joseph, 1993). Arcaya et al. (2012) distinguished places between spaces. That is, the place "uses geographic information to form groups" while the space "defines each observation according to its proximity to all other observations, ignoring the potentially meaningful commonalities among observations that are generated by shared geographic or political boundaries" (p.824). Instead, the incorporation of places into education field emerged around the1990s with the prevalence of the HLM (Bock, 1989; Garner & Raudenbush, 1991; Hill & Rowe, 1996; Marsh & Rowe, 1996). The concept of the place informs educational researchers on how different geographic settings or locations shape educational behaviors. Proximate places share more commonalities than those far apart, which lead to homogeneities and heterogeneities of the variables by places (Hogrebe, 2012). Educational researchers contented that place plays critical roles in shaping educational outcomes by delineating shared contexts among individual students within dynamic ecological systems (Garner & Raudenbush, 1991). Studies holding on this perspective assume that students nested within similar environmental contexts perform similarly, leading to similar levels of the educational outcomes (Raudenbush & Bryk, 2002). In this sense, neighborhoods can be taken as one type of the places to form groups of people who share similar (or different) behavioral patterns related to academic achievement. Yet, only considering the concept of the place is inadequate. Space emphasizes interrelationships between observations. That is, the proximity of places in space forms spatial interrelationships, which affects how places can be manipulated. Individual students are nested within classrooms and schools, but for example, school are located in different neighborhoods, and there are spatial interrelationships among neighborhoods (which also affect interrelationships among individual students). Although educational researches with HLM take “nested attributes” of the educational data into account, they do not consider the geospatial properties in space (e.g., spatial dependency). Neighborhood studies considering space are one of the approaches that link spatial elements to educational outcomes, enabling those non-spatial educational variables vary by places and exploring their spatial interdependencies (Arcaya et al., 2012; Crowder & South, 2011; Hogrebe, 2012).

1.4. Neighborhood Conditions

In the social sciences, how to define neighborhoods is puzzling. In general, a neighborhood is “a collection of both people and institutions occupying a spatially defined area influenced by ecological, cultural, and sometimes political forces” with “geographic boundaries defined by Census Bureau or other administrative agencies (e.g., school districts, police districts) (Sampson, Morenoff, & Gannon-Rowley, 2002, p. 445). Investigating neighborhood contexts with geospatial viewpoints is one alternative way introduced to educational fields for characterizing educational variables that is typically measured in a non-spatial manner (Crowder & South, 2011; Hogrebe, 2012; McMaken, 2014).

Neighborhood studies revived with different streams around the1980s (Leventhal & Brooks-Gunn, 2000). Shaw and McKay (1942) was one of the earliest precursors that guided research on how different neighborhood conditions were linked to varied levels of the delinquent behaviors of young people. Subsequently, a lot of research was devoted to exploring neighborhood context in relation to youths' and children's outcomes in general and students' academic achievement in particular. Leventhal and Brooks-Gunn (2000) concluded different streams related to the neighborhood studies: The first stream was highlighted by Wilson (1987)'s poverty theory, which advocated that increased neighborhood-level poverty resulted in substantially adverse influences on individual socioeconomic outcomes. The disorganization theory was extended from the poverty theory, generating the second stream of discussions on neighborhood effect regarding crimes and others risky behaviors due to malfunction of the poor neighborhoods (Bursik, 1988). In light of the previous theories, Jencks and Mayer (1990) proposed relatively organized theoretical paradigms to study neighborhood influence on individual behaviors, which led to the third stream. These three major streams provided a theoretical basis for educational studies with a geospatial prospective at the neighborhood level.

In general, neighborhood effect can be regarded as social interactions between individuals and neighborhoods, leading to varied levels of the individual outcomes (Dietz, 2002). Based upon aforementioned theories, most neighborhood studies focused on one of the different areas: endogenous effects, correlated effects, and exogenous effects (G. Becker, 1974; Manski, 1993, 2000). Manski (1993) provided a great example for understanding the three types of effects: in relation to students' academic achievement, students within a same school embedded in same neighborhood or adjacent neighborhoods tend to perform similarly or have similar academic achievement due to shared institutional characteristics or resources (correlated effect). Yet, individual students' academic achievement varies with the average performance of their schools or ethnic groups (endogenous effect) or socio-economic statues (exogenous effect). Based on the example above, the three types of effects can be understood as: the endogenous effect emphasizes interacting influences among neighborhood members, which are referred to as the contagion or peer effect—the direct influence from one individual on behaviors of the other relevant individuals in the neighborhood (Dietz, 2002; Manski, 1993). Yet, individual outcomes vary within behaviors of groups under endogenous effect. In contrast, the correlated effect indicates the similar patterns of performances or behaviors among group members due to exposure to similar environmental contexts. Further, differences between individuals and the average behavior of groups are often caused by external factors such as socio-economic status (called exogenous effect) (Dietz, 2002; Manski, 1993).

In education, the neighborhood effect is mainly referred to as social interactions at the neighborhood level associated with the educational outcomes of individuals, such as the students' math/reading achievement, drop-school rate, and delinquent behaviors in school. Different individual-level academic outcomes may be related to neighborhood-level social disorders, which can be explained by varied levels of the neighborhood structural characteristics, such as neighborhood poverty, residential mobility, ethnic/race compositions, household structures, safety, and institutional resources (Ainsworth, 2002; Billings, Deming, & Rockoff, 2012; Bowen, Bowen, & Ware, 2002; Breen & Jonsson, 2005). For example, it was argued that neighborhood Socio-Economic Status (SES) is indicative of the academic achievement. Students from high SES neighborhoods tend to be associated with higher achievement, longer years of the schooling, and low rate of the drop out (Boyle, Georgiades, Racine, & Mustard, 2007; Fischer & Kmec, 2004; Johnson, 2010). Meanwhile, perspectives on how neighborhood conditions drive variations of the individual-level academic achievement are different. A group of the researchers focused on negative relationships between distressed neighborhood and students' academic achievement while other researchers have emphasized the importance of the presence of affluent neighbors, such as establishment of the role models and effective adult monitoring (Crowder & South, 2003). Further, detriments of the advantaged neighborhood on disadvantaged neighbors were also considered from relative deprivation models and competition models (Jencks & Mayer, 1990).

Meanwhile, neighborhood conditions can also be linked to school characteristics in shaping behaviors of the students and academic performances. The neighborhood-school link is important to explain academic outcomes (Eamon, 2005; Owens, 2010; Williams, Davis, Saunders, & Williams, 2002). Schools, as one important type of the institutional resources, are embedded in neighborhoods. Studies suggested that drawing neighborhoods in terms of the school locations are more helpful than from students' residential locations with respect to investigating neighborhood-achievement associations (McCoy et al., 2013; Welsh, Stokes, & Greene, 2000). McCoy et al. (2013) indicated that varied levels of the school social norms and academic attainments could be predicted by structural characteristics of the neighborhoods, such as violent crime, poverty level, and residential stability. Previous research contended that neighborhood disorders had a close association with school violence and malfunction of schools, which lead to poor academic performance (McCoy et al., 2013; Wacquant, 1996; Wilson, 1996). Overall, neighborhoods and schools have a tremendous influence on the development of students in general and academic achievement in particular (Crowder & South, 2003; Ennett, Flewelling, Lindrooth, & Norton, 1997).

The purpose of this study was to investigate the associations between neighborhood conditions and students' mathematics achievement in elementary schools. The following research questions guided this study:

1) What are the relationships between school factors and mathematics achievement of elementary school students?
2) What are the relationships between neighborhood contextual factors and mathematics achievement of elementary school students?

1.5. Delimitations

This study does not address growth of learning over time. Instead, it puts focuses on the spatial properties of neighborhood conditions in current stage of this study. The academic achievement is specified to mathematics and reading scores of fifth grade rather than, science, or other content area outside of mathematics and reading. The measurement of mathematics scores adopts the standardized End-Of-Grade (EOG) test scores. The study is only limited to Charlotte-Mecklenburg areas and results of this study can only be generalized to public elementary school students in Charlotte-Mecklenburg Schools (CMS) instead of charter, magnet, or other private schools.

1.6. Limitations

Due to the protection of the individual' information, no students' residential addresses would be located. Neighborhood information could not be linked to specific students. Neighborhood-level variables only link to school levels. This limitation may lower robustness for investigating associations between neighborhood conditions and individual students' academic achievement. The assumption for supporting this neighborhood-school link design was based upon previous studies that suggested that selecting neighborhoods based on school locations rather than students' residential locations may yield more predictive results for neighborhood-achievement study (McCoy et al., 2013; Welsh et al., 2000).

Students' academic achievement data were from the year of 2012 while neighborhood conditions data were from the year of 2014. The neighborhood conditions in 2014 may not reflect former neighborhood conditions for those students who were administrated with 2012 EOG test. Although there is only a two-year gap, the mismatch between the two sets of the data may influence its outcomes to some degree. Nevertheless, neighborhood conditions tend to stay relatively stable without dramatic changes within a short period.

1.7. Assumptions

The primary assumption of this study is that neighborhoods aggregated in school districts are similar in resources. Schools are embedded in neighborhoods. Meanwhile, based upon location of each school, there is a school attendance area encompassing several ambient neighborhoods, which forms a regional-level context. Students who are from similar regions (i.e., school attendance districts) share similar levels of the neighborhood conditions or resources. Another assumption is that CMS students represent large urban school district in the United States.

1.8. Definitions

In order to better study neighborhood-achievement associations, several variables are defined for the purpose of this study:

1) Achievement gap: differences of the academic achievements, such as grades, enrollment, drop-out rates, college or graduate school completion between

African-American (or Hispanic) students and their European American counterparts, urban schools and schools in affluent suburbs, students associated with low SES and those with high SES, and males and females in related subjects (Barton & Coley, 2009; Coleman, 1990).

2) Place and space: The place is an location defined by its geographic information while space was defined by proximity of the observations (i.e., spatial interrelationships) instead of focusing on shared geographic or political boundaries (Arcaya et al., 2012, p. 824).
3) Neighborhood: an area was spatially occupied by a group of people and institutions that are similar in ecological, cultural, and political resources with geographic boundaries defined by Census Bureau or other administrative agencies (e.g., school districts, police districts) (Sampson et al., 2002, p. 445)
4) Neighborhood conditions: a multidimensional condition for characterizing the overall desirability of the a neighborhood for both people and institutions, including availability of the institutional resources (e.g., school quality), environmental quality, employment accessibility, safety, walkability, and other facilities and amenities (Delmelle, 2012).
5) Geospatial perspectives: adding regional, community, or neighborhood context as a factor in exploring how much spatial variations of these contextual characteristics account for varied levels of the academic achievement.

1.9. Chapter Summery

The purpose of this study was to investigate neighborhood conditions in relation to academic achievement in mathematics of elementary school students. Past researchers have explored approaches to narrow achievement gap from such aspects as individual propensities, teacher traits, school qualities, and parental involvement (Caprara et al., 2006; Keith et al., 1993). Neighborhood-achievement link within the geospatial perspective was less considered. Most achievement studies related to neighborhoods solely treated neighborhood data as non-spatial. They failed in considering their spatial dependencies of the neighborhood attributes in accounting for variations of the academic achievement. However, considering the spatial dependencies of neighborhoods provides an alternative model for narrowing or closing the achievement gap. Studies of the neighborhood-achievement associations are rooted in several theories, such as poverty theory (Shaw & McKay, 1942; Wilson, 1987, 1996), social disorganization theory (Kornhauser, 1978; Sampson & Groves, 1989), and five neighborhood-level models integrated by Jencks and Mayer (1990). Neighborhoods, one important contextual factor linking students, parents, and schools, provide an alternative perspective for studying the achievement

CHAPTER 2: REVIEW OF THE LITERATURE

This chapter aimed at reviewing relevant literature regarding the exploration of the different facets regarding relationships between students' academic achievement and neighborhood conditions. First, historical trends of closing the achievement gap and related critical factors (e.g., race-based desegregation, SES, and school characteristics) were reviewed. Second, subsequent section explored neighborhood theories that supported the exploration of academic achievement. Third, the importance of spatial properties regarding neighborhood-achievement link was present. Then a detailed literature review on neighborhood-academic achievement studies was conducted.

2.1. Academic Achievement Gap

The African American-European American achievement gap has drawn substantial attention from policy makers and researchers. Since the study of Coleman et al. (1966), race/ethnicity-related academic achievement gap has been the focal point, especially the gap between African American and European American students (Bradley & Bradley, 1977) Although intensive efforts were made to narrow the achievement gap during different periods, setbacks existed (Bradley & Bradley, 1977; J. Lee, 2002). One of the significant setbacks was the widened achievement gap from the 1990s to recent after its reduction from the 1970s to the 1980s (Kosters & Mast, 2003; J. Lee, 2002; Reardon, 2011). A myriad of policy makers and researchers has investigated that why such setbacks occurred, what factors it was attributed to, and what lessons were learned in order to reduce the achievement gap. For example, J. Lee (2002) analyzed several factors that might affect the achievement gap: 1) socioeconomic and family conditions, 2) youth culture and student behaviors, and 3) schooling conditions and practices. Among these three factors, socioeconomic and family conditions demonstrated closer associations with African American- and Hispanic-European American achievement gap. Numerous studies suggest that closing the achievement gap has practical significance to help disadvantaged students improve academic achievement and employment condition.

2.1.1. Race/Ethnicity-Based Desegregation on Closing the Achievement Gap

A number of studies have investigated racial/ethnic achievement gap based upon different theoretical backgrounds (Fryer & Levitt, 2006; Jencks & Phillips, 2011; V. E. Lee & Bryk, 1989; Rampey, Dion, & Donahue, 2008; Stevenson, Chen, & Uttal, 1990). Theories, such as Stereotype Threat (Steele, 1997), the Attitude-Achievement Paradox (Mickelson, 1990), peer Pressures (Ogbu, 1987), social capital (Bourdieu & Passeron, 1990), and the Secondary Resistance theory (Ogbu, 1987), were used to explain race/ethnicity-based academic performance. The primary assumption of these theories is that African Americans are hesitated to devote real efforts due to a lack of the adequate life returns and a fear of being sneered to act like White (Steele, 1997). For example, although African Americans admitted the importance of education (Mickelson, 1990), the stereotype depredated their desires and inspirations to achieve good performance in school (Steele, 1997).

Those who supported school desegregation hypothesized that African American students absorbed positive values from European American students, which helped improve academic achievement and close the achievement gap (Bradley & Bradley, 1977; Coleman et al., 1966). That is, values that emphasize learning and beliefs that support to make academic accomplishments could be transformed to African American students (Bradley & Bradley, 1977).This hypothesis was called lateral transmission of the values proposed by Equality of the Educational Opportunity report (Bradley & Bradley, 1977; Crain & Mahard, 1978).

Far beyond an educational reform to close the achievement gap, race/ethnicity-based school desegregation was taken as a type of the social movements, leading to profound implications (Coleman, 1990). The first wave desegregation started from the Supreme Court decision regarding the Brown v. Board of Education in 1954. School desegregation became a turning point for raising a social force to exclude racial discrimination in school (Bradley & Bradley, 1977; Coleman, 1990). Nevertheless, the initial efforts to eliminate school desegregation did not gain quick success as expected. In response to the failure in the south and requirements to terminate de jure segregation in the North, Title VI of the 1964 Civil Rights Act emerged to further strengthen earlier attempts regarding the suspension of the funds for maintaining segregation (Bradley & Bradley, 1977). Then, the national school desegregation movement was ignited by Supreme Court's decision on busing case of the Swann v. Charlotte-Mecklenburg Board of Education at Charlotte, North Carolina (Mickelson, 2001; Orfield, Bachmeier, James, & Eitle, 1997).

Since the 1950s, a myriad of the studies has been conducted to examine effectiveness of the different means regarding school desegregation on closing the achievement gap, such as open enrollment, central schools, school closing, and busing (Bradley & Bradley, 1977). The report of the Equality of Educational Opportunity was one of these early studies, which shaped perspectives and inspired critical thinking to re-evaluate the school desegregation for later research. The report attributed the improvement of African American students' verbal achievement to the presence of larger proportion of the European American students in class. This propensity in favor of the school desegregation and ignoring other factors induced criticizes due to a lack of the strong support regarding methods and analyses (Bradley & Bradley, 1977; Carver, 1975; Hanushek & Kain, 1972). Replica of the report around the 1960s and the 1970s sprang up (Armor, 1972; Bradley & Bradley, 1977). Bradley and Bradley (1977) concluded that with the same data yet different methods, most studies confirmed similar results with Coleman et al. (1966): larger proportions of the European American students in schools had a positive influence on the academic achievement of African Americans (Crain & Mahard, 1978). During this period, positive relationships between school desegregation and African American students' academic achievements were favored by most studies.

Around the 1990s, the second wave desegregation switched the focus from solely racial-based to a compound standard, including economic class, family income, and neighborhood features (Orfield et al., 1997). In 1994, the U.S. Supreme Court declared that only racial-based desegregation was not reasonable enough. Many districts responded to this call with re-evaluation of the desegregation process and standards. For example, Wake County in North Carolina took family income into account in the school desegregation practice in 2000, while Charlotte Mecklenburg Schools (CMS) leveraged a neighborhood-based standard to re-divide school attendance area for student assignment at the end of 2001. Since the 1990s, it has gone through a decline of the desegregation (Rivkin, 2000). The relationship between school desegregation and academic achievement was examined through a more diverse perspective, including the lenses of economic class, family background, and neighborhood attributes (Orfield et al., 1997). Meanwhile, the downsides of school desegregation were re-evaluated. For example, a group of studies suggested that the involuntary reassignment of students suppressed academic attainments of African Americans. On the other hand, the effects of reclassification of the school service boundaries on narrowing the achievement gap were examined by Billings et al. (2012). This study contended that high proportion of the minority students was detrimental to improve academic achievement of European Americans and African Americans in high school, leading to the widened achievement gap in mathematics.

2.1.2. School Characteristics in Relation to Teacher Quality

There has been a long-standing debate on whether school characteristics are related to academic achievement (Bradley & Bradley, 1977; Coleman et al., 1966; Dobbie & Fryer Jr, 2011). A myriad of the attention has been paid to academic achievement through the lenses of the race and ethnicity as well as family background; however, school characteristics have been neglected, especially during the prevalence of the school desegregation in the 1960s (Bradley & Bradley, 1977; Coleman et al., 1966).

School is a dynamic environment in which diverse factors interplay to affect school outcomes, including student/teacher ratio, length of the stay in schools, school SES, teachers' professional levels, degrees obtained, teaching experiences, students' propensities, and parental involvements. All of these make the overall school capital (Ehrenberg & Brewer, 1994). Along with the argument of little or no obviously perceivable effect of the school characteristics on closing the achievement gap (Coleman et al., 1966), a group of researchers continued to devote efforts to investigating relationships between school factors and academic achievement. They argued that placing a high value on education and practices related to school settings achieves high results. This was exemplified by students of the lower demographics who achieved beyond average results due to studying in high quality school (Chenoweth, 2009).

Boozer, Krueger, and Wolkon (1992) suggested that school quality (especially computer use and application of the computer-aided instruction) might exert a heavy influence on the positive relationship between academic achievement and the proportion of European Americans in school. Other studies suggested that a higher percentage of the free/reduced-price lunch and minority status were associated with high rates of drop-outs, discipline incidents, and a reduction in 10th-grade science scores (Caldas & Bankston, 1997; Hogrebe & TATE IV, 2010). Dobbie and Fryer Jr (2011) contended that high quality schools helped close the African American-European American achievement gap in middle and elementary school mathematics and English language arts at Promise Academy charter schools at Harlem Children’s Zone (HCZ). HCZ, as a designated 97-block area, linked community programs (ensuring a healthy and supportive contextual environment for providing various community services to children from birth to college graduation) with charter schools in order to improve minorities’ educational conditions (see Dobbie & Fryer Jr, 2011). These children were then compared with their siblings who received the same community programs (e.g., early childhood programs, after-school tutoring, and health programs) yet living out of the HCZ. Their study concluded that the increases in minorities’ academic achievement were attributed to the quality of schools as well as high quality teachers and good school polices. Rivkin (2000) indicated that school quality was one of the critical indicators which might affect relationships between peer effect and academic achievement. This study further argued boosting school quality, especially the teacher quality instead of the mandatory student assignment, was critical to improve the academic achievement of African Americans.

Teacher quality has been recognized as a key factor that influences students' school outcomes in general and academic achievement in particular. Wayne and Youngs (2003) reviewed 21 studies related to teacher characteristics which highlight the following: gains of academic achievement were related to ratings of the teachers' undergraduate institutions, examination scores for licensing teachers and testing their professional skills (e.g., teacher licensure examination, and verbal skills), degrees and coursework, and certification status. It was concluded that the ratings of teachers' undergraduate institutions were a worthwhile consideration although it seemed to have an indirect relationship with student academic achievement. While the positive relationship could be observed in general between academic achievement and teachers' test scores, this review work suggested that types of the licensure tests and tested knowledge might affect the relationship. Regarding degrees, coursework, as well as certificate status, studies lack consensus findings. Yet, the more efforts teachers put on mathematical-related degrees, coursework, and certifications, the higher results, in regards to mathematics, there will be. Although based upon 21 studies from 1984 to 2001, it seems inadequate to draw any definite conclusions. Wayne and Youngs (2003) still offered valuable insights for subsequent studies. Later on, Harris and Sass (2011) indicated that a teacher's amount of the experience closely related to academic achievement, while formal pre-service and in-service training showed fewer associations (that might be due to context-related characteristics of teaching). In consistence with Wayne and Youngs (2003), advanced degrees and specific undergraduate coursework in education showed little support for increasing teachers' capabilities linking to academic achievement.

Regarding teacher/pupil ratio (i.e., class size) and school enrollment, there is also no consistent agreement. Although teacher/pupil ratio has been a critical consideration to improve academic achievement, it has been argued that reductions in class size were unnecessary to narrow the achievement gap (Hogrebe & TATE IV, 2010).

2.1.3. Family Socio-Economic Status (SES)

Family SES, as a pivotal factor, has been largely used in the educational field to explain school outcomes (Davis-Kean, 2005; Rothstein, 2004; White, 1982). Yet, there is no solid consensus on how SES can be defined. In general, SES characterizes, "a social system (usually a society or community) in which individuals, families, or groups are ranked on certain hierarchies or dimensions according to their access to or control over valued commodities such as wealth, power, and status" (Mueller & Parcel, 1981, p. 14). Moreover, low SES were characterized as "a collection of the occupational, psychological, personality, health, and economic traits that interact predicting performance not only in schools but in other institutions as well that, on average, differs from the performance of the families from higher social classes" (Rothstein, 2004, p. 4). The core idea of family SES is the social stratification based on owned commodities primarily supported by conflict (Marxist and neo-Marxist) or functionalist theories (Mueller & Parcel, 1981). The conflict theory claims that the privileged class tends to exploit less powered groups by controlling more material and non-material resources.

Instead, functionalist theory believes that social stratification sustains the stability of entire society (Connell, 1994; Mueller & Parcel, 1981; Rothstein, 2004).

The way of linking SES to educational outcomes was varied from the 1960s to recent years; more SES indicators were added into educational research in recent years, such as family structure, family income, the mother's education, neighborhood or school-level SES. This change may result from social movements. There are three critical indicators of the family SES which draw extensive attention in the educational field: parental income, education, and occupation (Davis-Kean, 2005; Dubow, Boxer, & Huesmann, 2009). In general, students from a low-income class did not receive the same educational opportunities as those (especially non-minorities) from middle- and upper-income classes. It was observed that low income class students (or families) performed worse than those that were a part of a higher income class (Desimone, 1999; Rothstein, 2004).

Family SES is an important consideration in the investigation of the academic achievement gap. Family SES at school level is a strong predictor for the academic achievement gap whereas at a student level it shows a medium correlation (Sirin, 2005). Meanwhile, various factors mediate this relationship, including students' grade levels, minority status, school locations, and ages (Sirin, 2005). Sirin (2005) indicated that the strengthens of relationship between SES and academic achievement increased from elementary to middle school, yet high school stayed the same as elementary school. SES shows more predicting power for European American students than for minority students. In addition, locations also impact relationships between SES and achievement. Family SES is a weaker predictor of academic achievement at urban school in comparison to non-urban school (Sirin, 2005). Meanwhile, the processes of how SES impacts academic achievement were also examined. With Structural Equation Modeling, Davis-Kean (2005) observed that family SES (parental education and family income in particular) was indirectly associated with academic achievement of students (8-12 years old) through parents' beliefs and behaviors. Meanwhile, racial groups mediated these relationships. This study also indicated that parental education is a more important factor than income in predicting academic achievement. Caro (2009) suggested that SES-achievement relationship was influenced by student age through exploring Canadian students from childhood to adolescence. With the use of the Hierarchical Linear Models, Caro's study concluded that the academic achievement gap between high- and low- SES was neither widened nor narrowed in the age range between 7 and 11 years, while from 11 to 15 years old the gap was increasingly widened. In light of the difference-deficit debate in learning language. Hoff (2013) identified several possible causes accounting for the achievement gap. One possible reason was that students from lower-SES had more difficulties in mastering English proficiently. Both SES and English proficiency were related to academic achievement, yet English skills might affect relationships between SES and academic achievement.

2.2. Neighborhood Context with Spatial Attributes

Most academic achievement studies to address educational issues are related to students' characteristics, family backgrounds, teachers' qualities, and school characteristics. The emergence of Hierarchical Linear Modeling (HLM) provides possibilities for decomposing variance into different levels to explain the heterogeneity of educational data. This method adopts a relative comprehensive perspective to explore the nested structures of students' data which are aggregated by classroom and school (Raudenbush & Bryk, 2002). Neighborhood attributes can be one level of HLM to explore the academic achievement gap (Berg et al., 2013; Catsambis & Beveridge, 2001). Yet neighborhood-achievement studies are still limited, and there is a lack of conclusive and consistent agreements on how neighborhood conditions are linked to academic achievement under the scope of spatial properties.

A body of studies has observed that neighborhood conditions were important resources which might shape residents' educational expectations and affect academic achievement (Fischer & Kmec, 2004). While some researchers focus on neighborhood disadvantages, other researchers emphasized neighborhood affluence in exploring neighborhood-achievement relationships. It was argued that neighborhood affluence had a positive effect on academic achievement, which raised calls to investigate the protective factors of affluent neighborhoods, instead of the neighborhood deprivation (Sampson et al., 2002). For example, with exposure to positive social networks and role models, students obtained a higher level of educational attainments (Bowen et al., 2002).

However, a large portion of past studies on academic achievement that were related to neighborhood conditions is less likely to consider the spatial properties (Hogrebe, 2012). Regarding the specific definition of the geospatial perspectives in relation to education, no firm agreements are reached. Hogrebe (2012) defined geospatial perspectives as "introducing regional, community, or neighborhood context as a factor that potentially moderates the relationships between the non-spatial education variables that are typically studied" (p. 151). Through a geospatial perspective, places (or locations) cannot be treated independently without considering their spatial autocorrelation. Spatial autocorrelation is “the correlation among values of a single variable strictly attributable to the proximity of those values in geographic space, introducing a deviation from the independent observations assumption of classical statistics” (Griffith, 2013, p. 3). Considering neighborhood-level (or regional) attributes and their spatial relationships with educational variables, is a way of exploring educational outcomes spatially. Locations and their spatial autocorrelations exert influence on educational outcomes in general and academic achievement in particular. This viewpoint may help explain heterogeneities in the academic achievement (Crowder & South, 2011; Hogrebe, 2012; McMaken, 2014).

As spatially located units, neighborhoods represent contextual attributes with spatial properties. It has been suggested that “the outcome at one location is partially affected by events at other locations” (Páez & Scott, 2005, p. 54). That is, spatial locations of the neighborhoods within regions, and their spatial proximity to adjacent neighborhoods play roles in driving spatial process. Past studies have argued that there are several types of spatial processes that may be related to varied levels of academic achievement (Crowder & South, 2011; Delmelle, 2012; McMaken, 2014). These spatial processes include spatial diffusions, spatial interactions, spatial spillovers, and spatial dependence (Delmelle, 2012; Páez & Scott, 2005). Spatial diffusion represents that a fixed population possesses new properties which are gradually obtained from previous adopters, and are affected by distance between them. Spatial interactions refer to the physical movement of commodities, people, and information at spatially interconnected locations, whereas spatial spillovers indicate ideas or knowledge that can be transferred and exchanged through invisible borders (in a seemingly unrelated context, yet spatially interconnected). Spatial dependence characterizes spatial association or autocorrelation (e.g., sharing similar characteristics or attributes) among locations due to their close spatial proximity (Crowder & South, 2011; Delmelle, 2012; Páez & Scott, 2005). These spatial processes may play a role in shaping educational outcomes directly and indirectly, which help explain differences of academic achievement in general.

2.3. Theoretical Framework

Dating back to the 1940s, neighborhood studies caught researchers' eyes, and its renaissance was from the 1980s. In decades, neighborhood studies are mainly rooted in poverty theory (Wilson, 1987), social disorganization theory, social capital theory (Leventhal & Brooks-Gunn, 2000), and Jencks and Mayer (1990)'s theoretical paradigms of neighborhood influence on individual behaviors. These fundamental theories support our understanding about to what degree and in which process neighborhood characteristics that associates with academic achievements (Ainsworth, 2002). Understanding relationships between educational achievement and neighborhood context may provide an alternative perspective for improving quality of the education and bring positive outcomes in social equality (Ainsworth, 2002). This section presents different theoretical frameworks in relation to neighborhood context for explaining educational phenomena in general and academic achievement in particular,

2.3.1. Poverty Theory

Since the 1970s, poverty has been through up and down due to economic changes. (Jargowsky, 1996, 1997, 2013; Wilson, 1996). Around the 1970s to the 1990s, the severity of concentrated poverty in urban areas regained attentions in the social science field in particular at the neighborhood level. A myriad of the studies in different times emerged to investigate the phenomena concentrated poverty. Concentrated poverty can be defined based upon different perspectives. In general, concentrated poverty represents spatially dense areas with high socio-economic deprivation. Bureau of the Census (1970) defined areas where the poverty rate exceeded the federal poverty threshold with 40 percent as concentrated poverty. After a decline in poverty through the 1990s to the 2000s, there has been a profound rise of the population in high-poverty neighborhoods since the 2000s (Jargowsky, 2013; Johnson, 2010). Small and Newman (2001) presented three major prevailing models for explaining causes of forcing poor individuals to cluster in extreme-poverty neighborhoods: 1) Black flight models—migration of the African American middle-class from inner-city; 2) residential segregation; 3) joblessness in inner-city neighborhoods.

Wilson (1987) argued that deindustrialization and technological advances had catalyzed socioeconomic transformation, which moved job opportunities and led economic growth from urban to suburbs. Middle-and upper-class residents migrated from center urban area to suburbs, which influenced the structures of opportunities and the availabilities of resources at inner-city neighborhoods. These changes aggregated urban poverty and social isolation of the poor neighborhoods from mainstream values. In such a process, those who were less able to move tended to be affected more by socioeconomic transformations and inner-city concentrated poverty with a high rate of the unemployment and negative educational outcomes (Wilson, 1987). Inner-city residents further disparaged the importance of education, which in turn aggregated their adversities: exposure to higher level of maltreatment, crimes, drug use, unemployment, and diverse social and school delinquencies (Dubow et al., 1997; Ensminger, Lamkin, & Jacobson, 1996; Johnson, 2010).

Neighborhood-level poverty and isolation aggregated adversities related youth and adolescent especially from the 1970s to the 1980s, which renewed interests in the investigation of academic achievement through the lenses of neighborhood. Researchers argued that students who lived in deprived neighborhoods were associated with poor educational performance with exposure to inferior or inadequate neighborhood-based educational resources (Ensminger et al., 1996; Vartanian & Gleason, 1999). These low educational performances involved low grades, high dropout rate, hard to teach, behavioral delinquency of the students, low enrolment, and graduation rate in schools. It has been long argued that low academic achievement is more of these observed in distressed neighborhoods, and school dropout rates in poor neighborhoods are three times higher than affluent ones (Ainsworth, 2002; Kegler et al., 2005). Moreover, the related jobless rate in these distressed neighborhoods reaches as high as 80% (Johnson, 2010; Kasarda, 1993). The lack of a high school degree made life especially disadvantaged, which in turn pushed them to live in neighborhoods with higher poverty. The trend of less educated living in more distressed neighborhoods has been increasing since the 1970s (Kasarda, 1993; Kegler et al., 2005).

Residential segregation may explain concentrated poverty from cross-sections of the neighborhoods (Quillian, 1999; Small & Newman, 2001). Residential segregation generally refers to racial and economic segregation (Jargowsky, 1997; Jargowsky & El Komi, 2011). Changes of the residential segregation are not always consistent with ebbs and flows of the poverty. For example, an increase of poverty was accompanied with a slight decline of segregations from the 1970s to the 1980s (although there is an increasing trend between 1970 to 1990s) (Small & Newman, 2001; Yang & Jargowsky, 2006). After numerous studies focusing on racial segregation, economic segregation has emerged as another topic in exploring related phenomena of the residential segregation since the 1970s. Spatial segregation of the households by income (or other measures of the socio-economic status) typically represents as economic segregation (Jargowsky, 1996; Yang & Jargowsky, 2006). Economic segregation not only affects certain groups, but also widely spreads across all racial or ethnic groups: becoming one of the primary factors that generate increasing geographic concentration of the poverty (Massey & Fischer, 2000; Mayer, 2002; Yang & Jargowsky, 2006). Yet, the economic segregation may influence African Americans with more severe adverseness due to their highly race-based segregation (Massey & Fischer, 2000).

Issues regarding measurement of the economic segregation and its consequences (e.g., concentration of the poverty) sparked debates of the neighborhood-related studies especially around the 1990s, such as multicollinearity, and omitted variable bias (Massey & Fischer, 2000). Jargowsky (1996) developed the Neighborhood Sorting Index (NSI) to evaluate economic segregation. With the use of NSI, Yang and Jargowsky (2006) claimed that economic segregation was reduced across all racial and ethnic groups in the 1990s.

Different hypotheses exist for explaining how economic segregation affects academic achievement at the neighborhood level. Numerous studies suggested that affluent neighbors tend to bring positive outcomes for both rich and poor children who live in the same neighborhood due to healthy social networks, positive role models, effective neighborhood monitoring, and other neighborhood resources (Johnson, 2010; Mayer, 2002; Wilson, 1987). However, this idea was questioned by whether such the unequal distribution of resources hurt children outcomes in general and their academic achievement in particular because of the poor's relatively impoverished conditions compared to their rich neighbors (Jencks & Mayer, 1990; Reardon, 2011). Mayer (2002) argued that the increase in economic segregation from the 1970s to the 1990s led to aggravated inequality in school outcomes.

2.3.2. Neighborhood-Level Social Disorganization Theory

Social disorganization theory has been used to explain neighborhood disorders. It is contended that one consequence of disorganized neighborhoods is an impairment of the individual outcomes (Kornhauser, 1978; Kubrin & Weitzer, 2003; Markowitz, Bellair, Liska, & Liu, 2001; Sampson & Groves, 1989). Social disorganization theory indicates an "inability of a community structure to realize the common values of its residents and maintain effective social controls" (Sampson & Groves, 1989, p. 777).

Neighborhood social disorganization theory can be traced back to the 1940s and a study of adolescents' delinquent behaviors and criminal rates regarding Early Chicago School (Shaw & McKay, 1942). After a period of ebbs, social disorganization theory reemerged around the 1970s along with the reemergence of poverty theory (Leventhal & Brooks-Gunn, 2000; Wilson, 1987). Studies in this period advanced social disorganization theory to a more comprehensive level and proposed the "system model" (Kornhauser, 1978; Kubrin & Weitzer, 2003; Sampson & Groves, 1989). The system model argued that neighbors impose controls and supervisions to address problems through social networks or social ties in informal (e.g., kinship or friendship) and formal ways (e.g., institutional interventions or participations) (Bursik, 1988; Sampson et al., 2002).

Although the prevalence of social disorganization theory is closely related to crimes and social delinquencies, it has also been used to direct research in education. Social disorganization theory is one of the major theories to explain heterogeneities in academic achievement (Ainsworth, 2002, p. 118). Knowing the mechanisms of neighborhood-level social disorders is critical for identifying unseen dangers and guiding neighborhood-achievement research (Ainsworth, 2002; Gonzales, Cauce, Friedman, & Mason, 1996). Researchers have identified several mechanisms to support the maintenance of an organized neighborhood, including: 1) social control: the ability of the neighborhoods to regulate or supervise individual and group behaviors, especially showing control for teenage peer groups, 2) social networks, such as friendship and kinship, 3) differential vocational opportunities, 4) collective socialization, and 5) participation in local formal and informal organizations (Ainsworth, 2002; Sampson & Groves, 1989). These five dimensions are consistent with social capital theory, which recognizes values and significances of the social contacts or social networks on productivity of individuals and groups (Putnam, 2001).

With the lens of neighborhood, Shaw and McKay (1942) suggested several neighborhood structural characteristics to study neighborhood disorders, including neighborhood poverty, residential mobility, single-parent households, and racial/ethnic heterogeneity. The imbalance of these structural characteristics might result in disorganized social values and the malfunction of neighborhoods, which can lead individuals to negative outcomes such as delinquency or criminal behaviors, high unemployment rate, drug use, increased death rate, high dropout rate in school, and low academic performance. Lenzi, Vieno, Santinello, and Perkins (2013) also suggested that social connectedness is closely linked to neighborhood structural characteristics such as SES, ethnic compositions, household structures (e.g., single-parent family), and other institutional resources. As discussed in the previous sections, high-poverty neighborhoods lack the resources to maintain healthy function and support local participation in organizations, which may hinder neighbors to build favorable social ties and exert effective social controls (Ainsworth, 2002; Lenzi et al., 2013).

2.3.3. Integrated Five Neighborhood-Level Models

Jencks and Mayer (1990) proposed relatively comprehensive five-dimensional, neighborhood-level models to explain individual behaviors in terms of neighborhood conditions, based upon previous studies and theories in social science. These five models are: 1) neighborhood institutional models, 2) epidemic models, 3) collective socialization models, 4) relative deprivation models, and 5) competition models. Majorly rooted in poverty theory, social disorganization theory, and social capital theory, the synthesis of these five models further emphasizes associations between neighborhood contexts and productivities of individuals from pros and cons.

Neighborhood institutional models highlight the impact of neighborhood-level institutional resources on children's growth and academic attainments (Jencks & Mayer, 1990; Leventhal & Brooks-Gunn, 2000). These institutional resources include libraries, learning centers, schools, parks, police stations, pharmacies, grocery stores, hospitals, and other neighborhood institutions. It is suggested that affluent neighborhoods have a higher probability than inferior neighborhoods of possessing quality neighborhood institutional resources (e.g., quality schools and teachers), which largely contributes to the growth in student academic achievement. Learning centers and community design learning-related activities or programs may aid in organizing healthy neighborhoods and promoting students' learning abilities (Jencks & Mayer, 1990; Lenzi et al., 2013). On the other hand, rich and poor neighborhoods have different levels of crime rates. Children's behaviors and performances are influenced by police attitudes and implementations toward delinquencies or crimes, which may also correlate with schooling outcomes and academic achievement (Jencks & Phillips, 2011). Thus, understanding the roles of institutional resources played in community improvement is critical to investigating the relationships between academic achievement and neighborhood conditions.

Epidemic models are referred to as contagion models, or peer influence models. They are based on the logic that thoughts and ideas are infected among close neighbors to form collective behaviors. Based on the logic of mutual influences among peers, epidemic model implies that academic achievement is related to neighborhood conditions. In other words, children with similar family contexts in affluent neighborhoods perform better than those in poor neighborhoods (Garner & Raudenbush, 1991; Jencks & Mayer, 1990; Reardon, 2011).That is, exposure to positive attitudes and behaviors may inspire a child's desire to learning thus reducing their problem behaviors. Furthermore, neighborhood chaos and delinquent behaviors exhibited by neighbors can evoke negative feelings about school in children, and hurt their learning interests (Christakis & Fowler, 2013). Moreover, children in affluent neighborhoods, where most neighbors complete their education with a high school diploma or college degree may perform well in school and earn good grades. In contrast, children tend to be less obligated to complete school, and become indifferent to academic achievements if there are high percentages of dropout rates, teenage mothers, and school absences in their neighborhoods (Jencks & Mayer, 1990). Similarly, the social collective model emphasizes how children are affected by organized social neighborhood norms, values, or atmosphere, such as adults monitoring, exemplary behaviors, and other community routines (Leventhal & Brooks-Gunn, 2000).

The relative deprivation models indicates that “neighborhood conditions affect individuals by means of their evaluation of their own situation relative to neighbors or peers” (Leventhal & Brooks-Gunn, 2000, p. 310). It refers to a type of psychological state that interprets one’s own performances as success or failure based upon other individual’s status. Comparisons provide a type of standards to interpret self-performances in reference to others, which may produce “side effect”. That is, some children work hard to offset relative depriving status while others refuse to make improvements with the focus on depressive aspects of comparisons (Bowen et al., 2002). Directed by this model, it is argued that students compare themselves to other individual’s successes and failures in school as a reference to assess their own academic achievements (Jencks & Mayer, 1990; Walker & Pettigrew, 1984). This probably can hurt a child’s faith and confidence in achieving academic success.

Competition models explore competition for scarce neighborhood resources among neighbors. Lack of social and economic capital places poor neighbors in a disadvantaged position when the residents compete for neighborhood resources. In such situations, unequally distributed neighborhood resources tend to affect poor students more than students from affluent families (Jencks & Mayer, 1990).

2.4. Neighborhood Conditions and Academic Achievement

After debating the effects of family characteristics on academic achievement, the context of "neighborhood" has increasingly gained researchers' attention since the 1980s (Wilson 1987; Solon, Page, and Duncan 2000). Influences of neighborhood conditions on youth and adolescent outcomes has been identified in health (Wen, Browning, & Cagney, 2003), the presence of alcohol, cigarette, and marijuana use in schools (Ennett et al., 1997), student competencies (Kohen et al., 2002), and participation in physical activities (Estabrooks, Lee, & Gyurcsik, 2003). Furthermore, research has been devoted to investigating school outcomes, in particular at the neighborhood level (Boyle et al., 2007; Johnson, 2010), such as: continuing schooling (Duncan, 1994; Rivkin, 1995; Williams et al., 2002), dropout rate (Harding, 2003; Vartanian & Gleason, 1999), reading (or verbal)/mathematic achievement (Baker, 2015; Sampson, Sharkey, & Raudenbush, 2008), school completion (Ensminger et al., 1996), years of schooling (Duncan, 1994; Ginther, Haveman, & Wolfe, 2000), graduation of high schools or colleges (Crowder & South, 2011; Fischer & Kmec, 2004), and attendance of different schools (Lauen, 2007). However, relationships between neigborhood context and students achievement has not been fully investigated and has not reached consensus. In addition, most neighborhood-achievement studies did not consider neighborhood charactersitics as spatial. They failed in recognizing spatial properties of neighborhood attributes, in which the spatial processes among them, tend to affect individual outcomes in general and academic achievement in particular.

2.4.1. Neighborhood SES/Poverty/Income/Joblessness

In the study conducted by Dornbusch, Ritter, and Steinberg (1991), neighborhood SES was expressed as a composite of the standardized mean of the per capita income, the household income, the percent of families above poverty, the percent of adults employed as professionals or executives, and the mean level of completed education over age 25. The neighborhood SES showed significance in academic achievements of European Americans and African Americans. Yet with family-level variables, neighborhood SES strongly predicted grades solely for African Americans. Crowder and South (2003) created a neighborhood disadvantage index with six measures, including average additive scale of neighborhood poverty rate, percentage of families receiving public assistance, male unemployment, percentage of families without high incomes, percentage of adults with less than a college education, and the percentage of adults not employed in professional or managerial occupations. Results supported the assumption that a higher dropout rate occurred in more socioeconomically disadvantaged neighborhoods. Boyle et al. (2007) identified the average household income, the percentage of population in managerial/professional occupations, and the percentage of population with high school diplomas or university degrees as a composite for representing the affluence of a neighborhood, while the percentage of families headed by lone parents, and the percentage of families living in rental accommodations suggest neighborhood socioeconomic (SES) disadvantages. It was indicated that years of education were positively affected by neighborhood affluence. Instead, low-neighborhood SES did not show significance. Drukker, Feron, Mengelers, and Van Os (2009) used neighborhood-level data along with school-and individual- level to explain the gender-based achievement gap in Maastricht, Netherlands. The study represented poverty as a neighborhood socioeconomic disadvantage with several additional items loaded on this factor: the percentage single parent families, ethnicity, the number of nonvoters, unemployment rates, unemployment for more than 1 year, social security usage, social security usage for more than 3 years, mean income, mean income for persons employed 52 weeks a year, the percentage of high and low incomes, and the percentage of economically inactive residents. According to this study, poverty (represented by neighborhood socioeconomic disadvantage) had influence on narrowing the achievement gap. Although without specifying measures of poverty, Harding (2003) adopted counterfactual models, in which propensity score matching and sensitivity analysis were used to better deal with selection bias in comparisons to instrumental variable methods and sibling fix-effects models. The counterfactual models seemed to demonstrate relatively robust results, and suggested that a higher dropout rate in high schools was more likely to be associated with high-poverty neighborhoods than those in low-poverty (Breen & Jonsson, 2005).

Studies related to neighborhood-level income did not yield consistent results for explaining variations in academic achievement. Neighborhood-level income was not identified as a profound predictor in the review study conducted by Johnson (2010) (it may be due to their targeted research population as African Americans). Yet, when neighborhood-level income is bundled with other factors, it exhibited a significance regarding academic achievement, especially related to disadvantaged American African students (Johnson, 2010). In the study conducted by Duncan (1994), income was categorized into low-, middle-, and high-level categories, which was used to examine influences of economic advantages and disadvantages on school completion by race and gender. Results suggested that the presence of high-income neighbors was more beneficial for motivating students to complete school, but not for African American males. Furthermore, a concentration of low-income residents did not show negative effects on completion of schooling across all groups, as opposed to the common assumption of adversities of impoverished neighborhoods on academic achievement (Harding, 2003; Wilson, 1987). Sastry and Pebley (2010) argued that neighborhood median family income positively contributed to reading and mathematics achievements.

Joblessness, conceptualized as structural unemployment within neighborhood studies, is also a major component that is often included into composite measures of neighborhood conditions in neighborhood-achievement research (Johnson, 2010). Structural unemployment refers to permanent unemployment due to a lack of job availability and quality. This phenomenon is closely associated with spatial mismatch hypothesis, which explores the availability and quality of jobs instead of merely their quantities (Johnson, 2010; Kain, 1992). Neighborhood joblessness is harmful to mainstream values (e.g., the achievement ideology: hard work and good grades in school aids in finding good jobs and living a better life). As opposed to achievement ideology, disadvantaged residents believe that hard work in school is no longer associated with better jobs and quality of life (Ainsworth, 2002; Wilson, 1996). Neighborhoods with a higher rate of joblessness may fail to provide role models, effective supervisors, and adequate resources for children, which tends to degrade their academic achievements overall (G. Becker, 1974; Jargowsky & El Komi, 2011; Johnson, 2010; Vartanian & Gleason, 1999). Past studies have indicated that male joblessness is detrimental to academic achievement (e.g., African American in particular) (Johnson, 2010). Surprisingly, female employment significantly improved European American males' academic achievement (Duncan, 1994). Ainsworth (2002) included that the proportion of employed persons with professional or managerial occupations was one of the two factors to represent neighborhood high-status residents (the other one is the proportion of college graduates among persons over 24 years of age). Results suggested that high-status residents at the neighborhood level significantly predicted mathematics/reading test scores, and the amount of time spent on homework. Neighborhood economic deprivation emerged as a non-significant predictor when concurrently presenting with neighborhood high-status residents, suggesting that the lack of high-status neighbors within neighborhoods is more harmful to a students' academic achievement than the presence of disadvantaged neighbors (Ainsworth, 2002).

2.4.2. Ethnic Composition and Residential Mobility

Ethnic composition has been recognized as an important neighborhood structural characteristic, which helps maintain organized neighborhoods, and thus produces positive outcomes for narrowing the achievement gap (Lenzi et al., 2013; Shaw & McKay, 1942; Wilson, 1987). It has been observed that unbalanced ethnic composition weakens neighborhood collective socializations. Diverse ethnic groups aggregate cultural heterogeneities, which are barriers for building accordant collective norms and maintaining close social ties. Student achievement tends to be degraded by lacking adequate and quality social capital (Emory, Caughy, Harris, & Franzini, 2008; Garner & Raudenbush, 1991; Johnson, 2010). However, whether or not African Americans or European Americans were affected more by ethnic composition within neighborhoods is a disputable concept. Duncan (1994) contended that school completion rates for African Americans, rather than European Americans, were significantly affected by neighborhood ethnic composition (i.e., racial integration improved Africa American schooling outcomes without hurting European Americans). Furthermore, results also indicated that African American males benefited from affluent neighbors only when those neighbors were also African American. This study suggested that African Americans were more sensitive to racial composition. This viewpoint was consistent with the previous argument that academic achievement for African Americans has closer associations with neighborhood conditions than European Americans (Dornbusch et al., 1991), yet opposed the results reported by Halpern-Felsher et al. (1997). The review study of academic achievement of American Africans concluded that: 1) large percentages of African American within neighborhoods were negatively associated with general learning achievement, attending college, and high school graduation rates; 2) ethnic diversity contributed to the improvement of adolescent achievement, yet decreased cognitive development of young children; 3) the presence of other racial and ethnic groups, other than European Americans produced positive learning outcomes for African Americans (Johnson, 2010). However, Ainsworth (2002) and Sastry and Pebley (2010) reported that racial/ethnic diversity did not significantly affect reading and mathematics achievement.

Furthermore, residential mobility is detrimental for building long-standing relationships. Frequently moving has considerable disadvantages to maintain balanced racial composition, establish social-ties, and preserve social control for academic interventions (Bowen et al., 2002; Madyun, 2011). Two recent neighborhood desegregation projects (Moving to Opportunity for Fair Housing Demonstration (MTO) and Younker Family and Community program (YFC)) used experiments, or quasi-experiment methods, to compare the effects of moving low-income families to low-poverty or middle-class neighborhoods. Although the MTO programs significantly improved academic achievement in males (11-18 years old and from moving families), more so than their counterparts (Leventhal & Brooks-Gunn, 2004). Living in more economically advantaged neighborhood did not yield benefits for movers who were in YFC economic desegregation program. Instead, school engagement and mathematics/reading achievement for these movers was found to be lower than their peers who did not move, which raised questions about the effectiveness of such programs (related to residential stability and racial compositions) in addressing the achievement gap (Fauth, Leventhal, & Brooks-Gunn, 2007). In contrast, analysis by the study of Sastry and Pebley (2010) did not support the argument that residential stability was helpful to close the achievement gap. Their results showed that residential stability was negatively related to mathematic achievement. Based upon assumptions proposed by Duncan and Aber (1997) and Korbin and Coulton (1997), one possible explanation they gave was that residents living in problem neighborhoods were incapable for moving due to a lack of economic support and inertness in social and cultural networks. Turley (2003) also echoed this perspective that longer stays in distressed neighborhoods decreased the test scores of children.

2.4.3. Safety

It has been suggested that unsafe neighborhoods were closely associated with high rates of neighborhood property crimes, violent crimes, drug use, delinquent behaviors, teen pregnancies, unemployment, and low academic achievement (Johnson, 2010; McCoy et al., 2013; Milam, Furr-Holden, & Leaf, 2010; Wilson, 1987). Such factors raise the risk of hurting educational desires in students and lowering their academic achievement. Students who live in unsafe neighborhoods were reported with low achievement and high dropout rates. How to create safe and healthy residential environments for better schooling outcomes and narrowing achievement gap concerns researchers. McCoy et al. (2013) examined how neighborhood crime affected elementary school-level academic achievement and how school climate explained bidirectional relationships between neighborhood crime and school-level achievement. In their study, they created an index for violent crimes and property crimes based upon information from the Federal Bureau of Investigation (FBI). Structural Equation Modeling was used to test direct and indirect relationships between neighborhood crimes, elementary school climate, and school-level student achievement across time. Results suggested that school-level academic achievement was significantly predicted by crime index (violent crime in particular), yet the reverse relationship was untenable. Meanwhile, school climate, especially school socio-emotional learning played a mediating role in shaping aforementioned unidirectional relationships.

2.4.4. Neighborhood Context with School Characteristics

Schools embedded in neighborhoods were taken as one of the important neighborhood-level institutional resources. As two of the most important out-of-home environments, neighborhoods and schools play pivotal roles in a student' academic success (McCoy et al., 2013; Wilson, 1987). Although past research focused more on the examination of school characteristics instead of neighborhood attributes in explaining variations of academic achievement, the concept of "neighborhood" has emerged as a pivotal consideration when contextual factors such as school and neighborhood are jointly considered (Ellen & Turner, 1997). Neighborhood features, along with school characteristics, may provide alternative perspectives for the explanation of the achievement gap. Past studies have suggested that drawing neighborhoods from which schools are located, instead of selecting neighborhood in terms of students' residential locations, tends to yield more robust results in predicting student achievement (McCoy et al., 2013; Welsh et al., 2000). Wacquant (1996) stated that low quality school students were mostly from inferior neighborhoods. Schools are affected by neighborhood atmosphere. Schools embedded in poor neighborhood usually lack resources to retain quality teachers, which in turn worsens school quality and decreases academic achievement (Johnson, 2010; McCoy et al., 2013; Welsh et al., 2000; Wilson, 1996). School poverty and absenteeism emerged as significant predictors for eighth-grade mathematics scores by jointly considering neighborhood and school characteristics (Catsambis & Beveridge, 2001). Dobbie and Fryer Jr (2011) advocated that it was imperative to improve the quality of both neighborhoods and schools in order to gain academic achievement.

Meanwhile, it has been observed that neighborhood disorders lead to school violence, crime, and low-school level achievement. In contrast, when exploring how neighborhood effect was mediated by different factors, teacher quality at the school level emerged as a profound mediator in explaining the association between neighborhood quality and mathematics/reading test scores (Ainsworth, 2002). Owens (2010) connected neighborhood characteristics with school traits to examine educational attainments (i.e., high school graduation and earning a college degree). Analysis supported the relative deprivation model: attending a school with more European Americans and high-SES neighbors did not help low-SES students improve academic achievement. In contrast, absolute levels of neighborhood advantages significantly and positively predicted college graduation. These results revealed that sharing similar neighborhood backgrounds within the same school was beneficial for students to boost academic achievement, which implied that considering neighborhood and school settings together was pivotal regarding neighborhood-achievement research. McCoy et al. (2013) explored multi-relationships among neighborhoods, schools, and school-level achievement, suggesting that school climate mediated effects of neighborhoods on achievement while perceived school safety was also influenced by neighborhoods where schools are located.

2.4.5. Student Age and Neighborhood Involvement

Levels of neighborhood involvement, and the influence of neighborhood conditions on academic achievement, are dependent on the various life stages of students (Crowder & South, 2003). Previous studies have examined adolescent school dropout rates (Crowder & South, 2003; Harding, 2003; McBride Murry et al., 2011), eighth-grade mathematics achievement (Catsambis & Beveridge, 2001), adolescent school completion rates (Duncan, 1994), youth educational attainment (Duncan & Raudenbush, 1999; South, Baumer, & Lutz, 2003), and through early-childhood to late-adolescent schooling outcomes (Fauth et al., 2007; Sastry & Pebley, 2010). However, to what specific life stage academic achievement is more influenced by neighborhood conditions is inconclusive. Crowder and South (2003) argued that children and young adolescents living in disadvantaged neighborhoods are more associated with school failure than older adolescents. Moreover, other studies contended that neighborhood involvement is more observed in early-childhood and late-adolescence, and less observed during middle childhood years (Leventhal & Brooks-Gunn, 2000; McBride Murry et al., 2011).

In general, the associations between influences of neighborhood conditions and academic achievement increase from early-childhood stages to late-adolescence (Aber, Gephart, Brooks-Gunn, Connell, & Spencer, 1997; McCulloch & Joshi, 2001; Sastry & Pebley, 2010). Inspired by this finding, many studies focused on the academic outcomes of late adolescents. However, it is also reasonable to expect strong associations between elementary school students' academic achievements and neighborhood conditions than children in early childhood who are highly dependent on their parents' control and interact less freely and directly with their neighborhoods. Nevertheless, associations between neighborhood conditions and academic achievement of elementary school-age children are given less attention. Elementary-school children are at the stage of transition from childhood to adolescence, in which children are less circumscribed by parents and they start to spend more time within neighborhoods and schools. Compared to early childhood, elementary-school children are more often involved in neighborhood activities, becoming socialized through building social networks with peers, and seeking support from neighbors (Attar, Guerra, & Tolan, 1994; Shumow, Vandell, & Posner, 1999). Under such a situation, physical and social environments within neighborhoods (e.g., institutional resources, socioeconomic conditions, or neighbors' monitoring) are pivotal to elementary school-age children's outcomes in general and academic achievement in particular (Greenman, Bodovski, & Reed, 2011; Sastry & Pebley, 2010).

2.5. Rational and Purpose of This Study

A body of researchers has been devoted to detailing neighborhood-achievement associations, and different trends and perspectives have emerged. Among them are the negative association between students' achievement and disadvantaged neighborhoods (Crowder & South, 2003; Harding, 2003), the importance of presence of affluent neighbors (Ainsworth, 2002; Duncan & Raudenbush, 1999), and the detrimental influence of advantaged neighborhoods on poor neighbors (Owens, 2010). Neighborhood-achievement studies thus far have not yielded consistent and conclusive results. Very little is known about how, and in which ways, different dimensions of neighborhood conditions are related to academic achievement (McBride Murry et al., 2011). Moreover, previous studies seldom considered spatial process as exploring neighborhood-achievement associations. In addition, in light of assumptions of the increasing trend of neighborhood influences on student achievement as age increases (Aber et al., 1997; McCulloch & Joshi, 2001; Sastry & Pebley, 2010), elementary students are considered less in neighborhood-achievement studies. Elementary students are in the transitional stage from early childhood to late adolescents. This stage lays the basis for later educational and career developments (Bailey, Siegler, & Geary, 2014; Siegler et al., 2012). Thus, it is of pivotal importance to explore associations between neighborhood conditions and academic achievement (mathematics scores in particular) in elementary schools.

2.6. Chapter Summary

Examinations of associations between neighborhood conditions and students' academic achievement began with discussions in the literature regarding causes for the achievement gap (the African American-European American achievement gap in particular) and efforts to close it. The achievement gap is an inequality-related, socio-economic problem, which is associated with race/ethnicity, gender, SES, family background, school conditions, and neighborhood attributes. This race-based achievement gap has been a central focus of government officials and researchers. In general, African American (and Hispanic) students perform lower in academic achievement than European American counterparts (Braun et al., 2010). Movement to close the achievement gap has been through ebbs and flows. Government-enforced school desegregation had effects on narrowing the achievement gap during the 1970s to the1980s. The study of Equality of Educational Opportunities conducted by Coleman et al. (1966) pioneered desegregation-based achievement gap research. While a body of researchers confirmed the effects of desegregation on narrowing the achievement gap, other researchers questioned the robustness of methodology and reliability of their results during that time (Carver, 1975; Hanushek & Kain, 1972). After the first wave of closing the achievement gap, it widened again from the 1990s to the 2000s (Barton & Coley, 2010) . The ups and downs during this process triggered researchers to investigate related factors that played significant roles across time, such as family background and school characteristics. Recognition of the importance of family background (e.g., family SES) on narrowing the achievement gap has had a long history. In contrast, school characteristics have drawn less attention. A long-standing debate on the effectiveness of school characteristics for narrowing the achievement gap concerned researchers. Although some researchers argued that school environment was less effective to close the achievement gap, improving school quality and teacher quality was also recognized (Dobbie & Fryer Jr, 2011; Rivkin, 2000).

Discussions of the roles of neighborhood conditions to close the achievement gap started with an introduction of recent theoretical roots. Poverty theory refined by Wilson (1987) has led neighborhood-achievement studies since the late 1980s. Inner-city poverty intensified the loss of neighborhood resources and inaccessibility of job and educational opportunities, and led to neighborhood disorders. This substantially contributed to negative educational outcomes in general and degraded academic achievement in particular. Low academic achievement was more often presented in distressed neighborhoods. Dropout rates in distressed neighborhoods were three times higher than those in affluent neighborhoods (Ainsworth, 2002). Extended from poverty theory, social disorganization theory has argued that variations of neighborhood structural characteristics might account for neighborhood-level social disorders. These neighborhood structural characteristics include neighborhood poverty, residential mobility, single-parent households, and racial/ethnic heterogeneity (Sampson et al., 2002; Shaw & McKay, 1942). Neighborhood social disorders mainly refer to low levels of collective socialization, inferior social networks, and an inability to produce social control, and inadequate vocational opportunities and participation in local organizations. Low academic achievement was also a consequence of neighborhood disorders. Furthermore, Jencks and Mayer (1990) integrated different perspectives and proposed five neighborhood-level models, which enhanced studies of neighborhood factors on academic achievement.

Neighborhood-achievement studies in the past 30 years generally focused on neighborhood SES (or poverty, income, and unemployment), ethnic/racial compositions, residential mobility, safety, household characteristics along with parental involvement, and social process. A myriad of researchers confirmed the negative associations between distressed neighborhoods and student achievement, while others argued for the importance of the presence of affluent neighbors. In addition, a bunch of studies also suggested the detrimental influence of advantaged neighbors on academic achievement of disadvantaged neighbors.

However, most studies failed to consider the spatial process, which is a critically important component in studying associations between neighborhoods and academic achievement. Due to the inconsistence of measurement of neighborhood conditions, selection bias of neighborhoods, and various methodology adopted, acquaintance and conclusion regarding neighborhood-achievement studies are still elusive and inconclusive, which deserves further research.

CHAPTER 3: METHODOLOGY

To investigate relationships between neighborhood quality (or conditions) and mathematics achievement of elementary school students in Charlotte-Mecklenburg County schools (CMS), this chapter introduces the methodological procedures that help explain neighborhood-achievement associations. Sources and attributes of the data along with participant demographics are also presented. To explore how neighborhood conditions are associated with elementary students' mathematics achievement, the research questions are listed as follows:

1) What are the relationships between school factors and mathematics achievement of elementary school students?
2) What are the relationships between neighborhood contextual factors and mathematics achievement of elementary school students?

3.1. Participant, Data, and Study Area

Based upon previously reviewed literature and theories, and also enlightened by the frameworks presented by McMaken (2014) and Hogrebe (2012), this study proposed a new conceptual framework (see Figure 1).

3.1.1. Participant

The primary sources of data in this study included two parts—the mathematic achievement data of elementary school students and the neighborhood level data (i.e., neighborhood quality of life data). The students' achievement data came from North

Carolina Department of Public Instruction (NCDPI—in charge of the public-school systems of North Carolina in the United States). All students who had valid data on Grades 5 reading and mathematics End-of-Grade (EOG) test scores were selected for this study. There were 49.9% female students (3735) and 50.1% male students (3748). European American student accounted for 36.8% (2756), African American took the proportion of 40.2%, and the rest of 23% were Hispanic students.

3.1.2. Validity and Reliability of the EOG Tests

The students' academic achievement in the current study adopted North Carolina (NC) EOG tests in mathematics and reading mandated by state through the North Carolina testing program. NC Students through grades 3 to 8 have to take the EOG tests as an evaluation of their academic achievement in multiple subjects (Bazemore & Van Dyk, 2004; Sanford, 1996). The EOG reading test aims at evaluating "a student's ability to read and comprehend written material that was appropriate for the grade level in terms of difficulty and content" while the mathematics test "assesses a student's ability to do routine computations and to apply mathematical principles, solve problems, and explain mathematical process" (Sanford, 1996, pp. 6-7). Through almost 20-year efforts, the EOG mathematics and reading test have evolved through several editions with provided reliability and validity information (Bazemore, Kramer, Gallagher, Englehart, & Brown, 2008; NCDPI, 2006, 2009, 2014a; Sanford, 1996).

The first edition of EOG tests in reading and mathematics was administered in 1993. In the report of North Carolina EOG tests, Sanford (1996) put emphasis on reporting the internal-consistency and reported coefficient alpha values all beyond 0.90 for both EOG mathematics and reading through grades 3 to 5. Regarding the content validity, all items in EOG mathematics and reading tests of this edition were constructed and evaluated by NC teachers (Sanford, 1996). The construct validity was tested through correlating NC open-ended test with the EOG tests. The correlation coefficients ranged from 0.54 to 0.58 between open-ended reading and EOG reading, and from 0.64 to 0.68 between open-ended mathematics and EOG mathematics (Sanford, 1996). It also demonstrated strong positive correlations between Iowa Tests of Basic Skills and the NC EOG mathematics and reading tests on grades 5 and 8. Furthermore, the EOG reading comprehension was compared with the Lexile reading inventory, suggesting an overall correlation of 0.90 from grades 3 to 8 (Sanford, 1996).

After 10-year implementation, the NC EOG test was evolved to the second edition in use from 2003 to 2007. The roles teachers played in item development and evaluation helped build the content validity of the EOG mathematics test. Meanwhile, a high degree of the consistency between the test and course curriculum was reflected through surveying teachers with an 85% agreement (Bazemore, Van Dyk, Kramer, Yelton, & Brown, 2004; NCDPI, 2006). A moderate to strong correlation between EOG tests and teachers' judgments of student achievement, expected grade, and assigned achievement levels suggested an acceptable condition of criterion validity in both mathematics and reading (Bazemore & Van Dyk, 2004; NCDPI, 2006). A Cronbach's alpha of 0.96 was evidenced as the reliability of EOG mathematics in grade 3. With respect to reading, the reliability indices (coefficient alpha) for the NC EOG reading in grades 3 through 8 and 10 ranged from 0.82 to 0.94 (Bazemore & Van Dyk, 2004). The content validity of EOG reading was assessed based upon four basic strands (i.e., cognition, interpretation, critical stance, and connections) that were used to develop all items (Bazemore et al., 2004).

The third edition of the EOG mathematics and reading tests was administered from 2008 to 2012. The procedures used to test the reliability and validity of the EOG mathematics and reading tests in current version were similar to previous ones. High reliabilities (the mean Cronbach's alpha > 0.90) were both evidenced in EOG mathematics and reading (Bazemore et al., 2008; NCDPI, 2009). The North Carolina Testing Program still valued the roles of NC teachers in item development and evaluation to ensure the content validity of EOG mathematics and reading tests (Bazemore et al., 2008). Similar procedures were adopted to test the criterion-related validity through linking teacher judgments and expectations of student achievement to EOG mathematics and reading assessment, in which a moderate to strong correlations were evidenced (Bazemore et al., 2008; NCDPI, 2009).

In response to the *Common Core State Standards* in mathematics and reading, advocated by NC State Board of Education (SBE), corresponding students' academic assessments (i.e., EOG tests) were revised to the fourth edition in the 2012-2013 school year (NCDPI, 2014b). A set of content standards and associated weight distributions for grades 3-5, and grades 6-8 in mathematics and reading were built to support the content validity through item development and assessment process that emphasized the roles of teachers. Furthermore, The inter-reviewer agreement was achieved for the alignment between EOG mathematics and reading tests through a re-designed process by the NCDPI curriculum staff (NCDPI, 2014b). The external validation of the alignment was also based on surveying NC teachers in summer 2015 and the studies conducted by

Wisconsin Center for Education Research. The internal-consistency was evidenced by the Cronbach's alpha values ranging from 0.88 to 0.93 for EOG mathematics and reading tests (NCDPI, 2014a, 2014b).

3.1.3. Neighborhood Data

The neighborhood data were from Charlotte Neighborhood Quality of Life Study, which first included 73 inner-city neighborhoods in the year of 1997, and then developed to 461 neighborhoods in 2014. The first-level unit of analysis of neighborhoods was depicted based on US Census blocks while community feedback was used to better describe neighborhood boundaries. The City of Charlotte, Mecklenburg County, and the UNC Charlotte Urban Institute, with the towns of Cornelius, Davidson, Huntersville, Matthews, Mint Hill, and Pineville all partner together to create the quality of life data. Over 80 variables provided detailed neighborhood information, including neighborhood safety, crime rates, household income, jobs, health, education, and community services, to name a few.

3.1.4. Study Area

Study area in current study was the Charlotte-Mecklenburg area. Charlotte is the largest city in the state of North Carolina and Mecklenburg is the focal county of Charlotte with the largest population, including the City of Charlotte, south and southeast of Charlotte-towns of Pineville, Matthews, and Mint Hill, and north of Charlotte-towns of Huntersville, Cornelius, and Davidson. The Charlotte-Mecklenburg area had a diverse racial and cultural mix with 49.3% European American, 32.1% African American, 12.6% Hispanic, and 5.2% Asian in 2012. In Charlotte-Mecklenburg, 40.7% of residents had bachelor's degree or higher and the homeownership rate was around 59.5%. The median household income was around $55,965 and 15.2% of residents lived below poverty level, which was lower than the state poverty rate (17.9%) in 2013 (Mecklenburg County Office, 2015). The U.S. Census 2013 American Community Survey reported that 28.3% Mecklenburg County residents had bachelor's degree, 28.2% with some college or associates' degree, 18.7% graduated from high school, 13.6% with graduate or professional degree. It also reported that the median income of county residents with graduate or professional degree was 2.5 times higher than those with a high school diploma. In addition, the county unemployment rate was higher than the national average since 2009 (Mecklenburg County Office, 2015). As the focal county of Charlotte, The Charlotte-Mecklenburg area has its uniqueness. It includes not only the "downtown" area, but also the better developed suburbs, which leads to large variations of culture, ethnicity, and economics. This uniqueness may affect the generalization of current study to other focal counties of other cities.

In recent years, Charlotte-Mecklenburg area has gone through rapid economic development, population growth, and the urban expansion, which brings more students into schools for better education (Delmelle, 2012). The public school system at Charlotte-Mecklenburg was known as Charlotte-Mecklenburg Schools (CMS). During 2014-2015 school years, total number of schools in CMS was 164 (91 elementary schools) with 145,363 enrolled students. Over 90% of a four-year cohort graduation rate was observed among 15 of 73 high schools. There was a diverse mix of students in CMS from different cultural and ethnic backgrounds with 42% African American, 32% European American, 18% Hispanic, 5% Asian, and 3% American Indian/multiracial. It has documented that graduation rate between all racial/ethnic groups have narrowed from 2010 to 2014

(Mecklenburg County Office, 2015). Regarding 4th graders' reading scores, according to 2013 and 2015 National Assessment of Educational Progress (NAEP) reported the average score in Charlotte was 226 for both years, higher than the average reading scores (212 in 2013 and 214 in 2015) for other public school students in large cities. In addition, there was no significant differences regarding the average reading score of 4th graders in Charlotte between the year of 2015 and 2013. In 2015, 39% of Charlotte students performed at or above the NAEP proficient level while the percentage was 40% in 2013. Moreover, in 2013 and 2015, 72 percent of 4th graders in Charlotte scored at or above the NAEP basic level. The average mathematics scores of 4th grade students in Charlotte scored higher than their counterparts in other public schools in large cities in 2013 and 2015. In the two years, 50-51% Charlotte 4th graders outperformed NAEP proficient level and 87% higher than NAEP basic level. Regarding gender differences, female performed better than male in reading while no significant differences were observed in mathematics achievement (NAEP, 2013a, 2015a). Both African American and Hispanic students scored lower than European American students in reading and mathematics in 2013 and 2015. Students who received free/reduced-price school lunch (i.e., from low income family) in Charlotte had lower reading scores than their counterparts in both two years (NAEP, 2013, 2015).

CMS has a long history to fight the segregation and inequality in education. After the most important event of the Supreme Court decision regarding Brown v. Board of Education, CMS has been devoting efforts to address racial educational inequality and close the achievement gap, which have played an important role in school desegregation history (Mickelson, 2001). With another landmark event of Swann v. Charlotte

Mecklenburg Board of Education in 1971, CMS implemented mandatory busing and reassigned neighborhood school zones into non-contiguous areas to achieve racial diversity and close school segregation (Billings et al., 2012). However, around 1990s, the Capacchione case and reopend Swann case urged CMS to stop the use of race-based policies for students' assignment. Thus the busing practice was replaced by a Family Choice Plan (a neighborhood-based school attendance measure) after 30-year implementation in 2002 (Mickelson, 2001). This neighborhood-based school attendance measure aimed at maintaining racial balance with redrawing school boundaries in CMS. Under this re-zoning plan, new school attendance boundaries were re-divided as contiguous neighborhood zones around schools (Billings et al., 2012). Although the redrawing of CMS boundaries also had been questioned about its effectiveness to support racial balance, this neighborhood-based attendance plan was still the current measure to ensure the educational equality in CMS (Billings et al., 2012). Overall, CMS and their students represented most of schools and students in Southeastern cities of United States. In current study, 74 elementary schools (only traditional neighborhood schools were included) formed 74 school attendance areas covering 461 neighborhoods. The division of elementary school attendance areas was consistent with neighborhood boundaries. Yet there were exceptions that a neighborhood was covered by several schools without overlap. To address this issue, GIS technologies were used to overlay school boundaries with neighborhoods. To protect individual students' privacy, all identifiable information including their residential addresses was anonymous. Due to the lack of geocoded individual students' residential addresses in current stage of this study, the spatial unit of analysis was formed as neighborhood-based regions based upon elementary school attendance boundaries.

3.2. Procedures

Four major procedures were developed to investigate neighborhood-achievement associations: 1) developing neighborhood-level measures; 2) designing geodatabase; 3) conducting exploratory spatial data analysis; 4) building Hierarchical Linear Models for the final statistical analyses. These four procedures explicitly considered relationships between spatial properties of neighborhood conditions and students' mathematics achievement.

3.2.1. Neighborhood-Level Measures

It has been challenging to develop consistent measures of neighborhood conditions across studies. There was no consensus agreement on which factors or variables could better represent overall conditions of neighborhood and explain the dynamics of neighborhood. Since Shaw and McKay (1942) proposed four neighborhood structural characteristics (neighborhood poverty, residential mobility, single-parent households, and racial/ethnic heterogeneity) for reflecting the malfunction of neighborhoods and disorganized social values, these four constructs generally directed the development of neighborhood conditions measures for later researchers. For example, some studies solely divided neighborhood median income into low-, medium-, and high-level to represent overall neighborhood socio-economic conditions (Duncan, 1994), while others chose different measures to composite neighborhood-SES (Dornbusch et al., 1991). Among these studies, Sampson, Raudenbush, and Earls (1997) proposed three-construct measures of neighborhood conditions: 1) concentrated poverty, composed by the percent of the population below poverty, the percent receiving public assistance, the percent unemployed, the percent of female-headed households, the percent of the population under 18 years of age and the percent of African American residents; 2) immigrant concentration (i.e., the percent of Hispanic residents and the percent of the population that was foreign-born; 3) residential stability (the percent of population living in the same residence for at least five years and the percent of all housing units that are owner-occupied). This three-way neighborhood measure has been widely used in the investigation of neighborhood collective efficacy, which helped to explain varied levels of disorganized neighborhoods. Yet, McMaken (2014) argued that the neighborhood data from a midsized New England city did not fit this three-dimensional neighborhood measure. McMaken (2014) extended Sampson et al. ’s (1997) three-dimensional to four-dimensional structure to measure neighborhood conditions in investigating 6th grade students’ mathematical achievements. However, as previously argued, neighborhood measures highly depend on contexts (e.g., area- and data-specific). It was pivotal to develop a set of neighborhood condition measures that fit current study. Therefore, based on the two studies and previously reviewed studies in Chapter 2, Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) was used to empirically develop neighborhood condition measures specific to this current study.

3.2.2. The Integration of Neighborhood Geodatabase

In order to capture spatial properties of neighborhood data for further spatial and non-spatial analyses of neighborhood-achievement association, it was necessary to integrate the neighborhood geodatabase for storing and manipulating neighborhood quality of life data along with school- and individual-level data using Geography

Information System (GIS) (Burrough, 1986). Based on the idea of geographical differences leading to variations of many factors and their relationships, GIS was used to deal with geospatial data with multi-functions (e.g., storing, manipulating, interpreting, and presenting spatial and geographical data) (Burrough, 1986). Geodatabase, as a core component in GIS, referred to a collection of various types of geographic datasets, for supporting analytical and geographical analysis. Objects or entities defined in a geographic space were represented as feature classes with coordination in geodatabase using points (locations, such as retail stores and schools), lines (e.g., hydrography and road centerlines), and polygons (e.g., urban areas, administrative boundaries, and land parcels). A geodatabase was composed of several these feature classes (used as layers in GIS), which served to explore spatial relationships and patterns. Following sections presented technology and process used to integrate the geodatabase of neighborhood quality of life (using Esri's ArcMap) with elementary school attendance boundaries, school locations, and other neighborhood attributes related to the current study (Bernhardsen, 2002).

The first step was to integrate neighborhood boundaries with school attendance boundaries. Because each individual student's home address was confidential (classified by NCDPI), it was impossible to identify each student with each neighborhood. However, the school in which each student studies could be linked to neighborhoods. To proceed with further analysis, it was necessary to integrate neighborhood boundaries with school attendance boundaries. In Charlotte-Mecklenburg schools (CMS) area, each student was assigned a home school on their residential address. Then, there was a school attendance boundary for each elementary school. As Figure 2 showed, each elementary school attendance area covered several neighborhoods. Generally, school attendance boundaries overlapped with neighborhood boundaries. However, special cases also existed. Certain neighborhoods were associated with multiple school attendance area without overlap. In such a situation, neighborhood boundaries were not consistent with elementary school boundaries. Therefore, GIS technology is needed to overlay neighborhood boundaries with elementary school attendance boundaries. The shapefile data (a type of data format in GIS geodatabase) of elementary school attendance boundary was downloaded from Open Mapping website (http://maps.co.mecklenburg.nc.us/openmapping/data.html), a portal to access to Mecklenburg county GIS data in different areas, such as education, county cadastral, political, and environmental management, job, health, and transportation. In ArcMap, the neighborhood boundary layer was joined and overlaid with elementary school attendance layer. Neighborhoods which sat across multiple school attendance areas were divided into corresponding attendance areas, so that their attributes were also attached to corresponding attendance areas.

Second, the point location of all elementary schools in CMS was added as another map layer, joining together with school attendance and neighborhood boundaries. Attributes of neighborhood areas were aggregated into corresponding elementary schools within each neighborhood-based regions of school attendance. Meanwhile, student-level characteristics were also merged with neighborhood attributes due to their associations with schools. In this current study, school was one type of institutional resources closely associated with neighborhood contexts. Neighborhood attributes, along with school characteristics, became the same level and was named as contextual-level compared to student-level.

3.2.3. Exploratory Spatial Data Analysis (ESDA)

As discussed in the literature review, neighborhood theories had assumed that neighborhood resources were not equally distributed across space. They might cluster in some spatial patterns. Clusters of neighborhood resources might associate with varied levels of students' academic achievement. It was pivotal to measure the degree to which a group of spatial features and their relationships were clustered. This section aimed at depicting procedures to examine the presence and degree of spatial autocorrelation of neighborhood attributes with ESDA, which was usually ignored by neighborhood-achievement studies. Most neighborhood-achievement studies took neighborhood attribute as non-spatial with exploratory data analysis and ignored the importance of location, area, spatial arrangement, and their relationships. In such a case, the validity of statistical techniques and accuracy of analysis tended to be affected by spatial interdependencies (Banerjee, Carlin, & Gelfand, 2014). Thus, a set of techniques and processes, which served to quantify and visualize spatial autocorrelation, was needed. These techniques and processes were called ESDA based upon exploratory data analysis (Haining, 2003). ESDA combined spatial analysis with GIS technologies, which served as depiction of spatial patterns, discovery of spatial relationships, and detection of outliers (Fotheringham & Rogerson, 2013; Goodchild, Haining, & Wise, 1992). Global presence (across the entire study area) of these spatial phenomenon or characteristic (e.g., clustering) could be tested by global techniques, such as global Moran's *I* (Moran, 1950). Although global techniques provided holistic picture of spatial autocorrelation across the entire study area, it offset local instabilities due to averaging local variations of spatial autocorrelations (Anselin, 1995, 1997). Local homogeneities that varied from global patterns also deserve focus of attention. This inspired the development of locally-based statistical procedures using such techniques as local Moran's *I* statistics (Anselin, 1995, 1997)

The neighborhood constructs derived through EFA and CFA would be examined by ESDA, which provided supports for further analysis. If spatial autocorrelation existed, general non-spatial statistical methods would not fit the spatial-related neighborhood data. Spatial-related statistical techniques were required in subsequent Hierarchical Linear Models. To conduct ESDA, two steps were applied: 1) global Moran's *I*; 2) local Moran's *I*.

Resemblance of the Pearson correlation coefficient, Moran's *I* statistics were also based on the product moment term, varying between -1 (negative indicating spatial dispersion) and 1 (positive indicating spatial cluster) (Anselin, 1995, 1997). However, Moran's *I* was different from the Pearson correlation coefficient in describing the relationship between a variable and its spatial lags instead of correlations of two variables. The interpretation and visualization of Moran's *I* statistics sourced from ArcMap (see Figure 3).

The global Moran's *I* was used for the detection of global trend of spatial phenomenon across the entire study area, whereas local Moran's *I* described individual-level (regional) heterogeneity or similarity (Anselin, 1995). High values around high values (or low values around low values) were represented as positive (similarity) while high values around low (or low values around high) were indicated as negative (heterogeneity) (Dale & Fortin, 2014). The formula of global Moran's *I* was listed as follows (Moran, 1950):

$$I = \frac{n}{(\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij})\sum_{i=1}^{n}(x_i - \overline{X})^2}\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}(x_i - \overline{X})(x_j - \overline{X})$$

Where n was the number of study objects, x_i was the variable value at location *i*, x_j was the variable value at location *j*, $\overline{X}$ was the mean of the variable across the entire region, and ω_{ij} was the spatial weight matrix between location *i* and location *j* (*i*≠ *j*).

To better understand regional-level variations of spatial features. Local Moran's *I* was calculated as (Anselin, 1995, 1997):

$$I_i = \frac{(x_i - \overline{X})}{S_i^2}\sum\nolimits_{j=1}^{n}\omega_{ij}\,(x_i - \overline{X})$$

Where x_i was the variable value at location i, $\overline{X}$ was the mean of the variable across the entire region, ω_{ij} was the spatial weight matrix between location *i* and location *j* (*i*≠ *j*), n was the number of study objects, and:

$$S_i^2 = \frac{\sum_{j=1}^{n}\omega_{ij}}{n-1} - \overline{X}^2$$

3.2.4. Hierarchical Linear Modeling (HLM)

After the detection of spatial autocorrelation, the final statistical procedure was to conduct transformed Hierarchical Linear Models (HLM, or called multilevel spatial modeling (MLM) in some other social science area, such as geography) to particularly handle spatial autocorrelation of neighborhood attributes. With Maximum Likelihood Estimation method, HLM was adept at dealing with hierarchically-structured data (Raudenbush & Bryk, 2002). Such form of data was normally associated with groups of units which were nested in different levels. In education, students were often nested within teacher-, then school-, and then even city-level, which formed a hierarchy. Under such a situation, individual student outcomes might be explained by predictors at varying hierarchical levels (Raudenbush, 1988). As previously discussed, most of neighborhood studies failed to consider the spatial dynamics of neighborhoods using HLM. Dong, Ma, Harris, and Pryce (2016) concluded three pivotal considerations that support the integration of modeling spatial dependence in different models, especially the HLM: 1) the proximity may go beyond the geographic boundaries of spatial units, such that individual outcomes are affected by neighboring conditions; 2) the continuously varied geographical data are not limited by geographical area; 3) arbitrarily delineated geographic boundaries may lead to the inappropriately chosen spatial scales at which the spatial processes occur. Failing to consider the spatial interactions across different spatial units results in the inappropriate estimations of variance components, regression coefficient, and measure of fits (Arcaya et al., 2012; Dong et al., 2016). Under these considerations, how to catch the spatial process in HLMs has been a concern to researchers in different fields. In order to investigate the effect of geographical settings and spatial process on health outcomes, Arcaya et al. (2012) integrated a conditional autoregressive (CAR) model (based on Markov property that assume the values of variables of interests affected only by its neighbors instead of neighbors of neighbors) to explore varied levels of covariate effects with three-level a cross-classified MLMs: the first level is county-related independent variable; the second level is the spatial patches to describe the adjacency between counties; and the third level is administrative-based independent effect related to states. Dong et al. (2016) proposed a two-level transformed MLM with modeling a spatial random slope, which was realized through incorporating a LCAR (a new CAR formulation) model into MLM (called MLM-MLCAR) (a transformed CAR model that better "retrieve predefined spatial parameters and covariate effects across a wide range of spatial dependence scenarios") (Dong et al., 2016, p. 23). This MLM-MLCAR model was applied to explore individual's subject travel satisfactions. The first level was the combination of individual-level variables as socio-demographic attributes, travel-related variables, and locational variables and the district-level as population density, while the second level was to describe the spatial dependence through the spatial patches defined by the LCAR. With accounting for the spatial random effect, the within-group covariate effect and area-level spatial dependence effect were explained. With the aim of exploring the effect of neighborhood on students' academic achievement, a two-level cross-classified HLM was designed considering the spatial dependence effect across neighborhoods (McMaken, 2014). The neighborhood-based spatial random effect was modeled through adding an auto-correlated error term to the neighborhood-based error structure. Other techniques are also employed, such as the Gaussian process incorporated in MLM (Chaix, Merlo, Subramanian, Lynch, & Chauvin, 2005)

In the current study, a two-stage HLM with two levels would be applied at individual student- and contextual-level (neighborhood-based regions). The contextual level referred to the integration of school characteristics and neighborhood attributes. The first stage model was the unconditional model with no predictors included. Individual student's mathematics achievement in fifth grade was the outcome variable. Elementary mathematics achievement has drawn extensive attention due to its close association with other subjects and future academic success (e.g., middle school fraction knowledge) (Bailey et al., 2014; Guay & McDaniel, 1977; Siegler et al., 2012). Past research has suggested that mathematics preparation (e.g., knowledge of fraction at age 10) in elementary schools predicted overall mathematic achievement at age 16 (Siegler, Thompson, & Schneider, 2011). Furthermore, numerous studies have long confirmed the positive relationships between elementary mathematics achievement and spatial abilities (Bishop, 1980; Guay & McDaniel, 1977; Gunderson, Ramirez, Beilock, & Levine, 2012). Adult SES could also be positively predicted by elementary mathematics at age 7 (Ritchie & Bates, 2013). In addition, mathematics achievement has significant association with years of schooling, academic motivation intelligence scores, and other schooling outcomes (Ritchie & Bates, 2013; Siegler et al., 2012). On the other hand, fifth-grade students in particular were in a critical transition phase from elementary to middle school and also at the age that had more involvement in neighborhood activities and built a closer relationship with peers in neighborhoods or other neighbors (Lerner et al., 2005; Sastry & Pebley, 2010). Fifth grade students were less circumscribed by parents and seek power outside of home. High academic achievers at fifth grade helped students build confidence in future study and formed healthy academic and social networks (Aber et al., 1997; English, 1997; Ladapo et al., 2014; Raphael & McKinney, 1983). The study conducted by Lerner et al. (2005) suggested positive effects of participation in community youth development programs on fifth-grade students. Good performance of academic achievement in general and mathematics achievement in particular in fifth grade helped build health transition of education and laid solid basis for future school success (Lerner et al., 2005; Ottmar, Decker, Cameron, Curby, & Rimm-Kaufman, 2014).

The student-level model included control variables such as ethnicity, gender, and reading achievement. The contextual-level model chose school characteristics as school-level poverty, percentage of licensed teacher, percentage of teachers with advance degree, percentage of national board certified teachers, percentage of students who required free lunch, percentage of European American students, and average class size. Further, neighborhood attributes were represented as six dimensions, including residential instability, concentrated poverty, affluence, educational conditions, educational resources, and life convenience. In the first level, the dependent variable was fifth grade students' EOG mathematics scores, the control variables were fifth grade students' EOG reading scores, gender (dummy variables were used and male was treated as the reference group), ethnicity (dummy variables was used and White was treated as the reference group). The second level, the dependent variable was the intercepts which were produced in the first level model, and the independent variables were school quality variables (i.e., economic conditions, school safety, and school-building structure) and region (school attendance area)-based neighborhood variables (residential instability, affluence, and educational resources).

Unconditional model:

The stage one HLM was an unconditional model without including any predictors as a baseline model for comparing with other more complicated models. The unconditional model was presented as student-level model and region-level model:

Student-level Model (level1): Academic mathematics achievement for each student as a function of a region mean plus a random error:

$$Y_{ij} = \beta_{oj} + r_{ij}$$

where

Y_{ij} was the expected mathematics achievement of child i in region j;

β_{oj} was the expected mean mathematics achievement of region j; and

r_{ij} was a random "student effect," that is the deviation of child ij's score from the region mean. These effects are assumed normally distributed with a mean of 0 and variance σ^2

The indices i and j denoted student and region where they are

$i = 1,2, \ldots, n_j$ student within region j;

$j = 1,2, \ldots, J$ regions.

Region-level (Region was based on the school attendance area) Model (level2): Region mean, β_{oj}, as an outcome varies randomly around grand mean:

$$\beta_{oj} = \gamma_{00} + u_{0j}$$

where

γ_{00} was the expected mean mathematics achievement in region j;

u_{0j} was a random "region effect," that was, the deviation of region j's mean from the grand mean. These effects were assumed normally distributed with a mean of 0 and variance τ_{β}.

Conditional model

The second stage HLM was also a two-level conditional model with student-level covariates and region-level characteristics.

Student-level Model (level-1): Student mathematics scores were explained by a set of student-level characteristics and an error term:

$$Y_{ij} = \beta_{0j} + \sum_{n=1}^{N} \beta_{nj} X_{nij} + r_{ij}$$

Where

Y_{ij} was the expected mathematics achievement of child i in region j;

β_{oj} was the expected mean students' mathematics achievement of region j;

$\sum_{n=1}^{N} \beta_{nj}$ were the regression coefficients associated with student-level variables;

X_{nij} were the student-level variables, including, gender, ethnicity, and reading achievement;

r_{ij} was a random "student effect," that was the deviation of child ij's score from the region mean. These effects were assumed normally distributed with a mean of 0 and variance σ^2.

Regional (School Attendance Area)-based Neighborhood Model (level2):

$$\beta_{0j} = \gamma_{00} + \sum_{q=1}^{Q} r_{0qj} S_{qj} + \sum_{r=1}^{R} \gamma_{0rj} N_{rj} + b_{0j} + c_{0j}$$

Where,

β_{oj} was the expected mean students' mathematics achievement of region j while γ_{00} was the expected grand mean;

$\sum_{q=1}^{Q} r_{0qj} S_{qj}$ were school characteristics associated with their regression coefficients;

$\sum_{r=1}^{R} \gamma_{0rj} N_{rj}$ were neighborhood measures associated with their regression coefficients;

b_{0j} was random effects related to schools while c_{0j} was the neighborhood-based random effects of a region.

Then, spatial autocorrelation was modeled by adding an auto-correlated error term to the region (school attendance area)-based neighborhood error structure (c_{0j}):

$$\hat{c}_{0j} = \rho \sum_{j=1}^{J} \omega_{ij}\, c_{0j} + \mu_{0j}$$

Where

c_{0j} was spatially dependent neighborhood-based region residuals, while ω_{ij} was the contiguity spatial weights matrix, describing the adjacency of regions.

ρ was the estimated coefficient of spatial effect of neighborhood-based regions.

μ_{0j} was the random regional error, which follows iid (independent and identical distribution).

The Queen's case was used to define neighbors (contiguity-based), that is areas that share any boundary point can be defined as neighbors. Moreover, the row-standardized weights matrix was used to generate proportional weights with unequal number of neighbors.

The global and local Moran's *I* statistics helped identify the global trend of six dimensions of measuring neighborhood conditions (i.e., residential instability, concentrated poverty, affluence, educational conditions, educational resource, and neighborhood convenience) across entire study area while how these six dimensions were spatially presented at a regional level was described by the local Moran's *I* (regional heterogeneity or similarity of spatial patterns). With the two approaches (i.e., the global and local Moran's *I*), the spatial variations of the neighborhood-based regional attributes could be examined globally and regionally. After identifying the presences of spatial autocorrelations in the study area, transformed two-level HLM with consideration of the spatial dependency were used to investigate the relationships between contextual factors and mathematics achievement of elementary school students with spatial autocorrelation.

In the first level, students' characteristics, including reading achievement, gender and ethnicity, were added to HLM as individual variables of mathematics achievement. Then school factors and six dimensions of neighborhood-based regional attributes were added to the second level of HLM. The spatial autocorrelation was modeled by adding an auto-correlated error term to the neighborhood-based error structure. Through aforementioned techniques, the two research questions in current study were answered.

3.3. Chapter Summary

In this chapter, methodological procedures along with data, study area were presented. First, CFA and EFA were used to develop six-dimensional measures of neighborhood conditions, which included residential instability, concentrated poverty, affluence, educational conditions, educational resource, and neighborhood convenience. Second, the neighborhood boundaries were overlaid with elementary school attendance boundaries to form the neighborhood-based regional area. Third, principles and logics of Exploratory Spatial Data Analysis (ESDA) were introduced along with specific approaches, including the global and local Moran's *I*. After that, subsequent section described how a two-level HLM was transformed as a new two-level HLM with considering the spatial autocorrelation by adding an auto-correlated error term to the neighborhood-based error structure. The final section described how the two research questions in current study were answered through aforementioned spatial and non-spatial statistics.

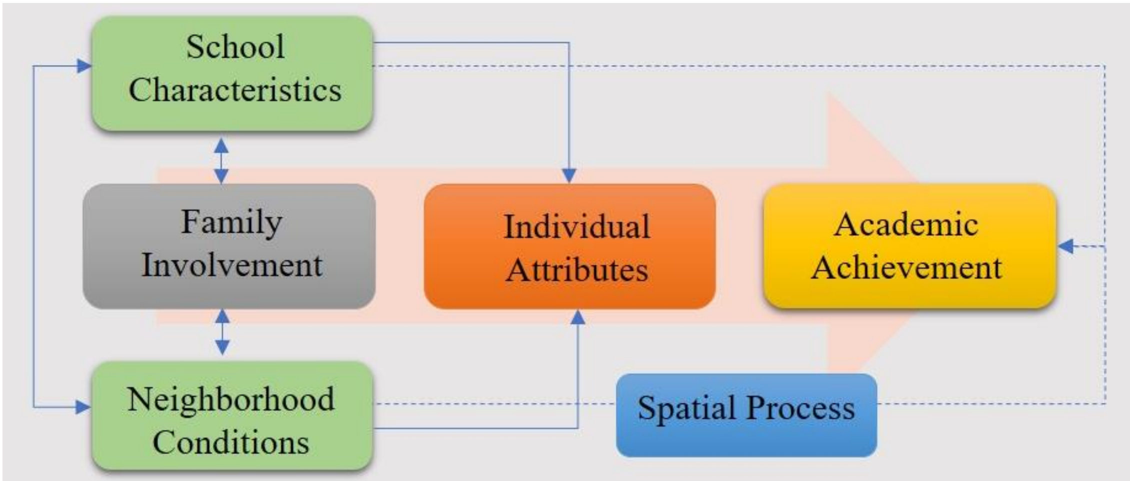

Figure 1: Conceptual Framework

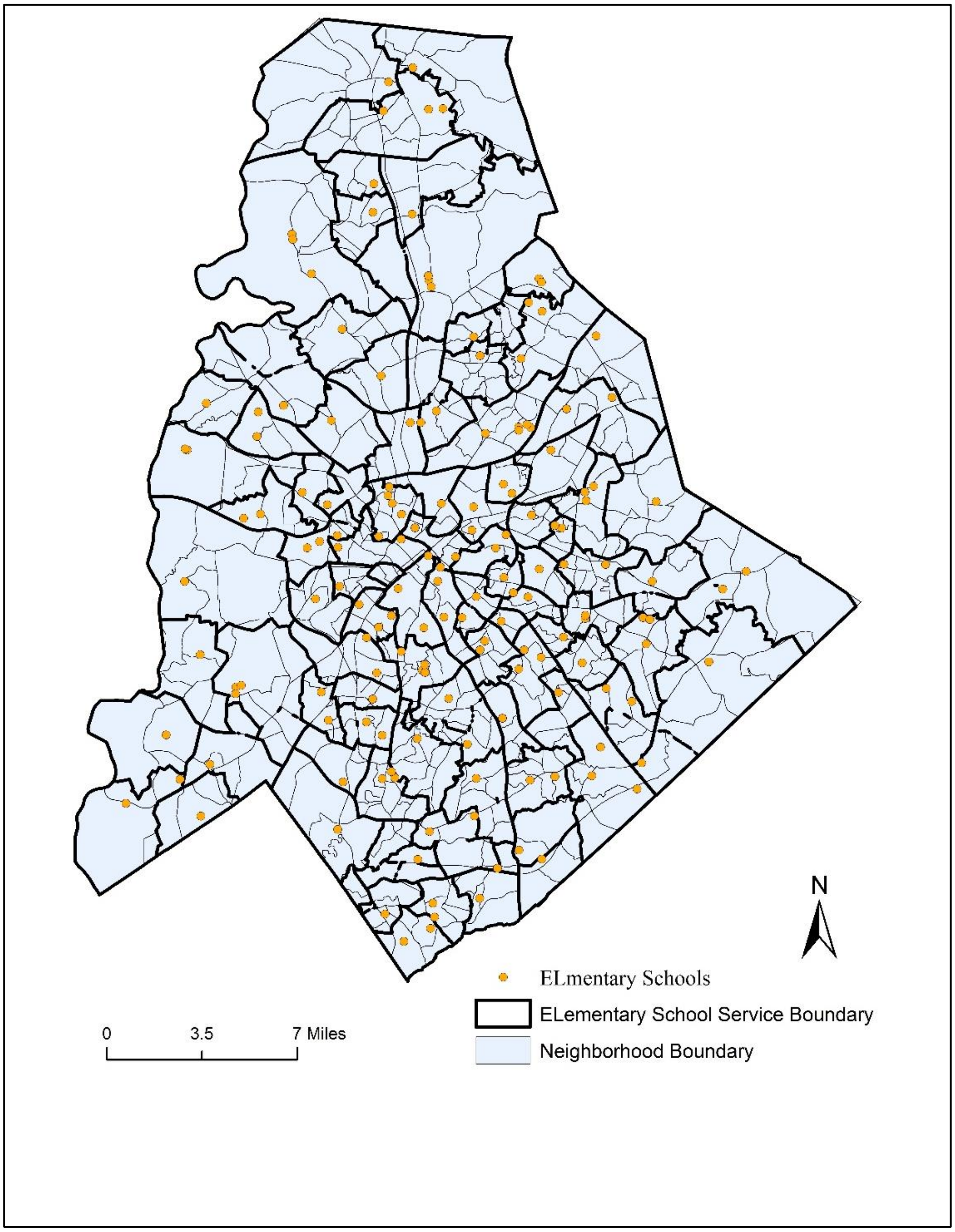

Figure 2: Neighborhood and School Attendance Boundaries

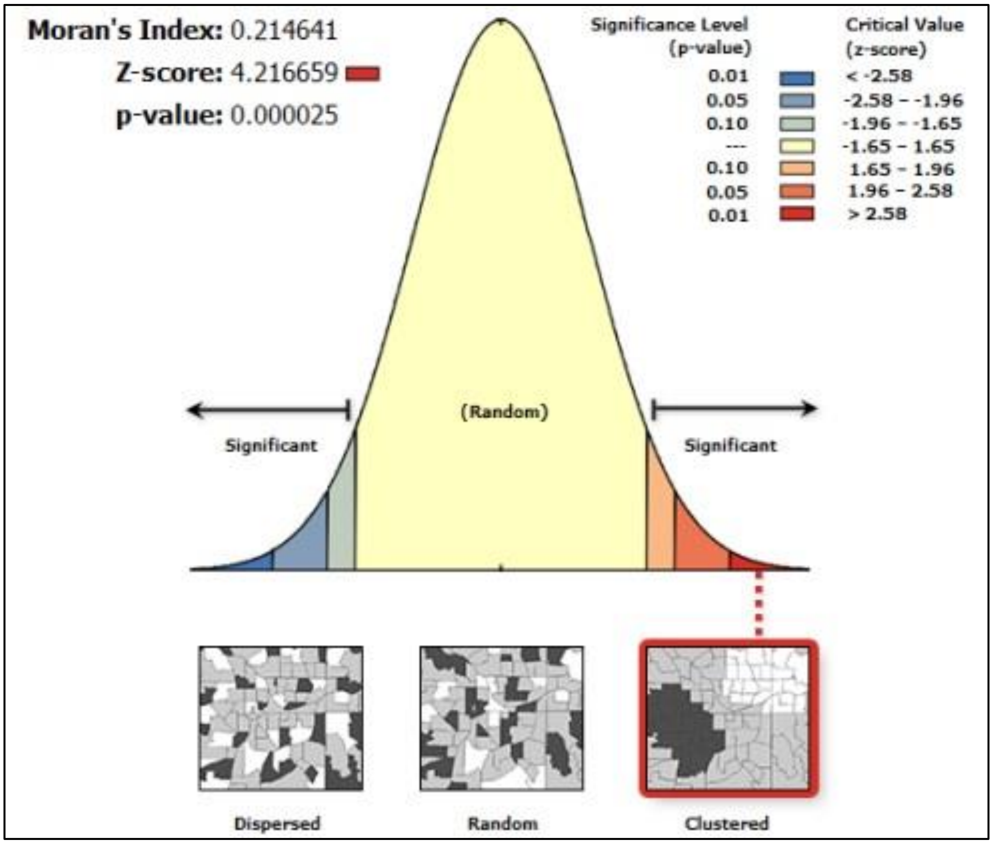

Figure 3: Spatial Autocorrelation Tool Graphical Output

Note: Sample graphical output from the Spatial Autocorrelation (Global Moran's *I*) tool (http://desktop.arcgis.com/en/arcmap/latest/tools/spatial-statistics-toolbox/h-sa-tool-popup.htm)

CHAPTER 4: RESULTS

The purpose of this study was to examine the neighborhood conditions in relation to students' academic achievement in elementary schools. Directed by this purpose, this chapter was organized as follows: first, the results of developing neighborhood measures through EFA and CFA with modified model fits were presented. Then, global and local Moran's *I* statistics for neighborhood-level measures and aggregated neighborhood measures at school level were discussed. Finally, this chapter described the results of two-level HLM to explain the relationships between neighborhood conditions and students' academic achievement in mathematics.

4.1. Neighborhood Measures

This section aimed to empirically develop neighborhood condition measures specific to this current study with the use of Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA).

4.1.1. Exploratory Factor Analysis (EFA)

In order to uncover the underlying factor structure of the neighborhood quality of life data (total 461 cases), the data were randomly divided into two halves. EFA was used with one set of data and CFA was used with the other set to confirm the factor structure developed through EFA. In light of the study conducted by McMaken (2014) and previously reviewed studies in Chapter 2, this study developed specific neighborhood measures based on "quality of life" data. This study included variables related to residential instability, concentrated poverty, and affluence as McMaken (2014) and Sampson et al. (1997) suggested. However, variables related to immigrant concentration were not included due to the lack of such variables in the quality of life dataset. Instead, this study included neighborhood institutional resources variables associated with educational development (at neighborhood level), such as licensed school-age care programs, neighborhood school attendance, early care programs, library card prevalence, and academic proficiency levels of elementary, middle, and high schools. Meanwhile, other types of neighborhood institutional resources variables that represented neighborhood life convenience were also selected, including low cost healthcare proximity, grocery proximity, and pharmacy proximity. In sum, 33 variables were included in the exploratory model. The sources and descriptions of 33 variables are listed in Table 1 and their descriptive statistics in Table 2. Initially, the factorability of the 33 items was examined. In addition, the median and Inter Quartile Range (IQR) of Household Income was reported as 55965.00 and 41734.00. Results revealed that in general skewness of items was positive (ranging from 6.49 to -1.94, see Table 2), which were aligned with the argument in previous studies that neighborhood indicators were skewed (McMaken, 2014). Kurtosis ranging from -1.20 to 47.83 indicates leptokurtic, which was also in line with the properties of neighborhood data in the study of McMaken (2014). McMaken (2014) argued that positive skewness and kurtosis did not exert heavy influence on the constriction of variance. In addition, correlations among items were moderate in general.

After a close examination of the distribution of selected variables, 33 variables were included in the exploratory model with Principal Axis Factoring extraction and

Direct Oblimin rotation (Kaiser, 1958). The Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) (used for comparing correlations and partial correlations between variables) was .90, above the recommended value of .6, and Bartlett's test of sphericity was significant (χ^2 (528) = 5982.53, $p < 0.05$), which indicated that the observed correlation matrix significantly diverged from the identity matrix and there were some relationships between the variables. The significance of Bartlett's test of sphericity provided support for further analyses. The communalities were all above .3. Absolute value below .40 was used to suppress small coefficients. Overall, 21 items were retained on 6 factors, explaining 71.93% of the variance. Based on factor loading structures and previously reviewed neighborhood measures, 6 factors named in the neighborhood measures are residential instability (3 items), concentrated poverty (7 items), affluence (4 items), educational conditions (3 items), educationally-related resources (4 items), and convenience (3 items). Other 11 items (property crime rate, Hispanic-Latino population, youth population, public nutrition assistance, public health insurance, housing assistance, home ownership, high school graduation rate, high school diploma, attendance of neighborhood school, library card holders, and art participation) were excluded from CFA due to salient loadings (less than 0.40) or multicollinearity. presents exploratory structure of neighborhood measures of the 21 items (factors, loadings, and items).

4.1.2. Confirmatory Factor Analysis (CFA)

CFA was conducted (using LISREL 9.1) to verify the structure of measures of neighborhood constructs with hypothesized model. The conceptual model is presented in Figure 4. The fit of the 6-factor (21 items) exploratory model was evaluated based upon statistical standards (such as goodness-of-fit indices and modification indices), theoretical hypothesis, and others' empirical studies in previous literature review sections. Brown (2015) and Hu and Bentler (1999) indicated standards of good model fit as Comparative Fit Index (CFI) ≥ 0.95, and a Root Mean Squared Error of Approximation (RMSEA) and Root Mean Square Residual (RMR) < 0.06. It was also suggested that CFA ≥ 0.90, and RMSEA and RMR < 0.08 were indicative of an acceptable model (Hu & Bentler, 1999; Kline, 2010). Before conducting CFA, missing values in the dataset were replaced by the mean of responses of items within the same construct for each participant. In CFA, the error variance of the six latent variables was set to be 1.0 for setting the scale of latent variables while the errors for each item were uncorrelated in the first model. The original theoretical model was tested with six latent variables containing 21 items. However, this model was not a good fit to the data (χ^2 = 594.80, df = 174, $p < 0.001$; RMSEA = 0.10 ([90%CI] = 0.09, 0.11); CFI = 0.95; GFI = 0.80; RMR = 0.09) (see Figure 5).

4.1.3. Modified Model Fit

This model was modified based on the modification indices. After checking the path diagram, the error terms of two items (single family housing (ITE9) and library card prevalence (ITE29)) were big (0.99) and the loadings were small (-0.11 and -0.08, respectively). Therefore, these two items were removed from the original model. The second model were performed, demonstrating a good fit of model to the data (χ2 = 365.03, df = 137, $p < 0.0001$; RMSEA = 0.08 ([90%CI] = 0.07, 0.09); CFI = 0.97; GFI = 0.90; RMR = 0.06) (see Figure 6). Table 4 presents the final model with 6 constructs, containing 19 items. Measures of neighborhood conditions in the current study were directed by theoretical framework and consistent with empirical analyses of previous studies. After finalizing the measures of neighborhood condition, each factor score was created through: 1) corresponded item loading (produced in CFA) multiplying by original values of each item, 2) sum of the products in step one divided by the number of items within each factor.

4.2. Exploratory Spatial Data Analysis (ESDA)

This section presented results of ESDA, including global and local Moran's *I*. After obtaining the neighborhood measures, the global and local Moran's *I* statistics were run (Queen's case was adopted). The Global Moran's *I* statistics showed there were spatial autocorrelations for the six neighborhood measures: residential instability (Moran's *I* index = 0.63, $p < 0.001$), concentrated poverty (Moran's *I* index = 0.71, $p < 0.001$), affluence (Moran's *I* index = 0.62, $p < 0.001$), educational condition (Moran's *I* index = 0.72, $p < 0.001$), educational resource (Moran's *I* index = 0.48, $p < 0.001$), and life convenience (Moran's *I* index = 0.32, $p < 0.001$). Map for local Moran's *I* of neighborhood measures at the neighborhood level was presented in Figure 7.

In order to overlay school attendance boundaries with the neighborhood measures, the neighborhood data (majorly the neighborhood measures) was intersected with school boundaries using the "Intersect" tool in ArcMap 10.4. The silver polygons that were the result of "Intersect" were removed using the "Eliminate" tool. Then the neighborhood measures were aggregated based upon the school boundaries. The reason that the neighborhood measures were aggregated at the school level was due to a lack of geo-coded neighborhood data to link to each individual student. Before aggregation, there were 461 neighborhoods. Based on school attendance area, 461 neighborhoods were aggregated into 91 school attendance regions.

The global and local Moran's *I* statistics (both using Queen's case) were also run for the aggregated neighborhood measures at school attendance region level. The Global Moran's *I* statistics showed there were spatial autocorrelations for the six neighborhood measures aggregated correspondingly at the school level: residential instability (Moran's *I* index = 0.72, $p < 0.001$), concentrated poverty (Moran's *I* index = 0.65, $p < 0.001$), affluence (Moran's *I* index = 0.48, $p < 0.001$), educational condition (Moran's *I* index = 0.59, $p < 0 .001$), educational resource (Moran's *I* index = 0.56, $p < 0.001$), and life convenience (Moran's *I* index = 0.24, $p < 0.001$). Map for local Moran's *I* of aggregated neighborhood measures at the school attendance area-based regional level is presented in Figure 8. Comparing to Figure 7 and Figure 8, it could be seen that there were differences of local spatial patterns of neighborhood measures between neighborhood-level and school-district level.

4.3. School Measures

In order to develop the school measures, 11 items (see Table 5) were selected from NC school report cards during 2012-2013 school year. In the exploratory model, Principal Axis Factoring extraction and Varimax (orthogonal) rotation method was used. The Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) was 0.82, above the recommended value of 0.6, and Bartlett's test of sphericity was significant (χ^2 (55) = 724.71, $p < .05$). Absolute value below 0.40 was used to suppress small coefficients. Overall, 10 items were retained on 3 factors, explaining 60.28% of the variance. Based on factor loading structures, 3 factors named in the school measures are student performance (4 items), school safety (3 items), and school-building structure (3 items). The number of all students who took the North Carolina End-of-Grade Tests was not loaded in any factor. Table 6 presents the exploratory structure of the school measures (factors, loadings, and items). Then the school measures were linked to the shapefile of school attendance boundaries which had included the neighborhood measures. Factor scores were created using Bartlett's approach for further analyses. Bartlett's approach is the one that produces unbiased estimates of true factor scores with emphasis on the impacts of shared factors on factor scores and reducing effect of error factors with maximum likelihood estimates (DiStefano, Zhu, & Mindrila, 2009). There were two reasons that the Bartlett's approach was used to create school factor scores (instead of the approach used for creating neighborhood measures): 1) school variables were normally distributed in general, 2) due to small sample, CFA was not used to confirm the structure of the school measures. Thus, the method used in developing neighborhood measures was not suitable here. Descriptive Statistics of School-level items are presented in Table 7.

Prior to major HLM analysis, Pearson Correlations were run for all school and neighborhood variables to see if multicollinearity could be an issue. Neighborhood poverty had a super strong correlation with residential instability (r = 0.83), neighborhood affluence (r = -0.88), educational conditions (r = -0.92), educational resources (r = 0.82), and school economic conditions (r = -0.74). Educational conditions also had a super strong correlation with some of these variables while life convenience showed a very low correlation with some of these variables (see Table 14). As a result, residential instability, neighborhood affluence, and life convenience were excluded from HLM.

4.4. Hierarchical Linear modeling (HLM)

Before conducting HLM, missing data were examined in the student dataset. In the student mathematics data, there were 8361 valid cases and 271 cases with missing math scores (the missing percentage was 3.2%), and there are 8232 valid cases and 400 cases with missing reading scores in the student reading data (the missing percentage was 4.9%). Table 8 reports the descriptive statistics for the original data. Although the percentage of missing values were less than 5%, the Little's MCAR test showed that missing data were not missing completely at random (χ^2= 217.02, df = 2, p < 0.001). Thus, the multiple imputations for the missing values were not performed. Then all missing values in the student mathematics data were deleted because the number of cases with missing values in the student mathematics data was less than that in the student reading data (see Table 8). After the removal of missing values related to mathematics data, there were still missing values in reading data. Then, the Little's MCAR test was performed again. The missing data were still not missing completely at random (χ^2= 206.80, df = 1, p < 0.001). This procedure was repeated with deleting missing values in the student reading data, and results of the Little's MCAR indicated that it failed to reject the null hypothesis that the data was missing completely randomly (χ^2 = 3.72, df = 1, p = 0.054). Table 9 reports the descriptive statistics for the data after deleting missing values in mathematics and reading data. The descriptive statistics of fifth grade mathematics and reading data after deleting missing values (Only White, Africa American, and Hispanic included) are reported in Table 10. For the mathematics and reading data, descriptive statistics for female students and male students are listed in Table 11. Table 12 reports descriptive statistics by ethnicity: European American students' mathematics (M =

456.85, *SD* = 8.40) and reading (*M* = 455.73, *SD* = 8.20), African Americans (mathematics: *M* = 446.74, *SD* = 8.74; reading: *M* = 446.28, *SD* = 9.02), and Hispanic (mathematics: *M* = 449.12, *SD* = 9.02; reading: *M* = 446.25, *SD* = 8.89).

4.4.1. Unconditional HLM

All HLM were performed through software R 3.3.0. In the first model, a two-level unconditional HLM was used as the baseline model. The level 1 and level 2 variances of the model were used to calculate the intra-class-correlation (ICC) coefficient. The between-group variance was 0.234, the within-group variance was 0.762, and the value of ICC was 23.4% (Table 13). That was, 23.4% of the total variation in mathematics achievement could be accounted for by between-school differences. Regarding the random effects, the *R* packages do not provide significance tests, however, the confidence interval could be obtained.

4.4.2. General Conditional HLM

All continuous variables entered into two-level model were standardized with a mean of zero and standard deviation of 1. Since standardizing all continuous variables without grouping, it was the same as grand-mean centering. In addition, the dummy variables for ethnicity were uncentered. The first two-level conditional models included only the school variables in the level 2 model and excluded the neighborhood variables. The intercept of the level 1 model would be the estimated group mean of mathematics achievement of European American male students when other continuous variables were equal to the grand mean. All student variables in level 1 showed statistically significantly differences regarding mathematics achievement. The statistically significant mathematics achievement differences between African American and European American students (β

= -0.32, $p < 0.01$), as well as between Hispanic and European American students (β = -0.10, $p < 0.01$) were observed. Reading achievement was a statistically significant predictor for mathematics ($\beta = 0.65$, $p < 0.01$). Female statistically significantly reported lower mathematics scores than male students did ($\beta = -0.06$, $p < 0.01$). Regarding the school variables, students in schools with higher level of safety statistically significantly reported higher mathematics achievement ($\beta = 0.05$, $p < 0.01$). School economic conditions and school-building structure were not significant predictors in this model. The Pseudo r^2 for the first model was 45.93% (within-group variance), and 89.23% (between-group variance). In the second conditional model, the student variables in the level 1 model kept the same while only neighborhood variables were added into level-2 model. All student variables were statistically significant as the first conditional models. Nevertheless, none of the neighborhood variables showed statistical significance in relation to mathematics achievement. The Pseudo r^2 for the second model was 45.93% (within-group variance), and 88.20% (between-group variance). The third conditional model was a two-level general model to investigate neighborhood conditions (along with school quality variables) in relation to students' mathematics achievement. In level-1 model, all variables had statistically significant relationships with students' mathematics achievement. Regarding ethnicity, the statistically significant academic achievement gap of mathematics was observed between African American and European American students, as well as between Hispanic and European American students. Mathematics achievement gap was also statistically related to gender in a significant way: Male students statistically significantly outperformed female students in mathematics (β = -0.06, $p < 0.01$). Students who performed better on reading tended to have higher mathematics scores (β = 0.65, p < 0.01). One unit change in reading achievement would lead to 0.65 standard deviation increases in mathematics achievement. (see Table 15).

In the second level, with respect to the school condition variables, school safety still had a statistically significant positive relationship with mathematics achievement. That was, one standard deviation change in school safety (β = 0.10, p < 0.01) would be associated with 0.10 standard deviation increase in mathematics achievement. However, school economic and school-building structure did not show significance. With respect to neighborhood conditions, only residential instability statistically significantly predicted mathematic achievement in a negative way (β = -0.10, p < 0.05) (see Table 15). That was, students who lived in a neighborhood with more rental house, higher violent crime, and nuisance violations had lower performance in mathematics. There was no significant difference in relation to affluence and educational resources. The Pseudo r^2 for the third model was 45.93% (within-group variance), and 90.60% (between-group variance).

4.4.3. Transformed Conditional HLM

In the transformed two-level HLM, the first level stayed unchanged while an auto-correlated error term was added to the region (school attendance area)-based neighborhood error structure (c_{0j}) to model the spatial autocorrelation. In order to add the spatial error term in the second level, the entire HLM model was separated into two steps. In the first level, a separate multiple regression was run for each school. Then intercept estimates were saved and used as the dependent variable for level-2 models. Before using the spatial error model in the second level, a general multiple regression was performed and the residuals was check for spatial autocorrelation. Although the Moran's *I* statistic was -0.10 (p = 0.17), which was statistically nonsignificant, the spatial error term model was used to check if there were changes in different models. The reason that the spatial error model was chosen for two considerations: 1) the Lagrange multiplier diagnostics for spatial dependence suggested the spatial error term model, which showed a smaller *p*-value than the choice for the spatial lag model (although both were statistically nonsignificant), 2) the global Moran's *I* was run for the dependent variable (the Moran's *I* statistic = -0.06, and $p = 0.42$), which was also statistically nonsignificant and the *p*-value was larger than the one for the residuals diagnosis. After performing the spatial error model, the residuals were checked again to see the changes. The Moran's *I* statistic was -0.01 ($p = 0.98$), and the *p*-value was much higher than 0.17, which suggested that the spatial error model reduced the spatial autocorrelation in residuals. In addition, AIC (262.06) was slightly reduced in the level-2 spatial error model compared to AIC (262.94) in the general multiple regression. In the level-2 spatial error model, the default method of the *R* packages assumes asymptotic normality, thus it used the *z*-test and provided *z* values (Table 16). In the level 1 model, all variables had significant relationships with students' mathematics achievement. Students who performed better on EOG reading tended to have higher EOG mathematics scores ($\beta = 0.66$, $p < 0.01$). Regarding ethnicity, African American ($\beta = -0.39$, $p < 0.01$) and Hispanic ($\beta = -0.15$, $p < 0.01$) statistically significantly scored lower than their European American counterparts in mathematics. Mathematics achievement gap was also observed in relation to gender: Male students outperformed female students in mathematics ($\beta = -0.06$, $p < 0.01$) (see Table 16).

In the second level, all the three school variables statistically significantly predicted mathematics achievement as expected. Better school economic conditions were positively associated with higher achievements in mathematics (β = 0.49, $p < 0.01$) while students who studied in a safer school environment (β = 0.29, $p < 0.01$) and were taught by quality teachers (β = 0.22, $p < 0.05$) had higher performance on mathematics EOG tests. Regarding neighborhood conditions, residential instability has a statistically significantly negative relationship with mathematics EOG scores (β = -0.32, $p < 0.05$). In addition, affluence of neighborhood emerged as a significant predictor: neighborhood affluence had a negative relationship with academic achievement in mathematics (β = -0.49, $p < 0.01$) (see Table 16). That is, one standard deviation increase in neighborhood affluence was associated with 0.49 standard deviation decrease in mathematics achievement. Moreover, the variance was reduced to 0.85 with all variables compared to the variance ($\sigma^2 = 0.92$, AIC = 266.83) of spatial error term second-level model which excluded school safety (school safety was the only statistically significant variables in the general HLMs).

4.5. Chapter Summary

This chapter presented the detailed statistical produces and results to investigate the relationships between neighborhood conditions and students' mathematics achievement considering spatial autocorrelations among neighborhoods.

The first section of this chapter explained in detail about how to develop neighborhood measures. Through EFA and CFA, six neighborhood measures were developed, including residential instability, concentrated poverty, affluence, educational condition, educational resource, and life convenience. Then the Global Moran's *I* statistics showed there were spatial autocorrelations for the six measures at the neighborhood level and at the school attendance area level. Before the HLM, the three-factor school measures were also developed (i.e., economic condition, school safety, and school-building structure).

Unconditional HLM was first conducted in the major analysis of HLM. There was 23.4% of the total variation in mathematics achievement accounted for by between-school differences. This baseline model provided the information about the degree to which mathematics achievement depends on the schools and neighborhoods the students were clustered with, and also provided the basic statistics from which subsequent models were compared. In the second stage, the HLM did not consider the spatial autocorrelations among neighborhoods: three models were compared to see the differences when incorporating school and neighborhood predictors in the same model and different models. Without considering the spatial autocorrelations, only residential instability was negatively related to students' mathematics achievement. However, in the last model of HLM, the spatial autocorrelation was modeled by adding an auto-correlated error term to the region (school attendance area)-based neighborhood error structure in the second level, and the results showed that the neighborhood affluence had a negative relationship with students' academic achievement. In the meanwhile, all school factors show statistical significance in the model considering spatial autocorrelation.

Table 1: Descriptions and Sources of Related Items

Item	Description	Source
Rental House (ITE1)	Number of single-family (detached) that is rented divided by the total number of single-family (detached) units.	Mecklenburg County Tax Parcels, 2013
Violent Crime Rate (ITE2)	Number of violent offenses, divided by the total population estimate, multiplied by 1,000.	Charlotte-Mecklenburg, Cornelius, Huntersville, Matthews, and Mint Hill Police Departments, 2013; Population Estimate, 2013
Property Crime Rate (ITE3)	Number of property offenses, divided by the total population estimate, multiplied by 1,000.	"Charlotte-Mecklenburg, Cornelius, Huntersville, Matthews, and Mint Hill Police Departments, 2013; Population Estimate, 2013"
Nuisance Violations (ITE4)	Number of cited nuisance violations, divided by total housing units, times 100.	City of Charlotte Code Enforcement; Town of Cornelius; Town of Matthews; Town of Mint Hill; Mecklenburg County Code Enforcement, July 1, 2012-June 30, 2013; Mecklenburg County Tax Parcels, 2013
Hispanic-Latino (ITE5)	Population self-identified as Hispanic or Latino divided by total population.	U.S. Census Bureau 2010 Census
Black (ITE6)	Population self-identified as non-Hispanic Black or African American alone divided by total population.	U.S. Census Bureau 2010 Census
Public Health Insurance (ITE7)	Number of residents with public health insurance, divided by the total population estimate.	Mecklenburg County Department of Social Services, September 2014; Population Estimate, 2013
Public Nutrition Assistance (ITE8)	Number of residents receiving public nutrition assistance, divided by the total population estimate.	Mecklenburg County Department of Social Services, September 2012; Population Estimate, 2013
Single Family Housing (ITE9)	Number of single-family units, divided by total housing units.	Mecklenburg County Tax Parcels, 2013
Youth Population (ITE10)	Population under age 18 divided by total population	U.S. Census Bureau American Community Survey, 2009-2013 5-Year Estimates
Housing Assistance (ITE11)	Number of housing units with development based rental assistance.	Charlotte Housing Authority; Charlotte-Mecklenburg Housing Partnership; City of Charlotte Neighborhood & Business Services; National Housing Preservation Database; North Carolina Housing Finance Agency; U.S. Department of Housing and Urban Development Multifamily Properties Database, 2013; Mecklenburg County Tax Parcels 2013
Foreclosure (ITE12)	Number of single-family, condominium and townhome foreclosures, divided by the number of single-family dwellings, condominiums and townhomes.	Mecklenburg County Register of Deeds, July 1, 2012-June 30, 2013

Table 1 (continued)

Births to Adolescents (ITE13)	Number of births to females under age 19, divided by all births. These data are cumulative for the previous 24 months.	Mecklenburg County Health Department, 2011 and 2012
Student Absenteeism (ITE14)	Number of students absent 10 percent or more of days in membership (number of days enrolled), divided by the total number of students. These data include both excused and unexcused absences.	Charlotte-Mecklenburg Schools, 2012-13
Home Ownership (ITE15)	Number of owner-occupied housing units, divided by the total number of occupied housing units	U.S. Census Bureau American Community Survey, 2009-2013 5-Year Estimates
Prenatal Care (ITE16)	Number of births where prenatal care was deemed "Adequate" using the Kessner Index, divided by all live births. “Adequate care” means prenatal care began in the first trimester and the minimum number of visits for each gestational age period of the baby's growth at different points during the pregnancy was met or exceeded. These data are cumulative for the previous 24 months.	Mecklenburg County Health Department, 2011 and 2012
Bachelor Degree (ITE17)	Population age 25 or older with a Bachelor's degree or higher divided by total population age 25 or older.	U.S. Census Bureau American Community Survey, 2009-2013 5-Year Estimates
Household Income (ITE18)	Median household income as estimated in the American Community Survey. Median household income is inflation-adjusted to the most recent year of the five-year estimate. When a Neighborhood Profile Area is comprised of more than one block group, the median household income is calculated by linear interpolation from a range of ages published in the American Community Survey.	U.S. Census Bureau American Community Survey, 2009-2013 5-Year Estimates
Employment Rate (ITE19)	Number of individuals ages 16 to 64 that are employed divided by the number of individual’s ages 16 to 64 in the labor force.	U.S. Census Bureau American Community Survey, 2009-2013 5-Year Estimates
Proficiency Elementary School (ITE20)	Number of students in grades 3-5 achieving a proficient score on both reading and math end of grade tests divided by the total number of students in grades 3-5 taking both reading and math end of grade tests.	Charlotte-Mecklenburg Schools, 2012-13

Table 1 (continued)

Proficiency Middle School (ITE21)	Number of students in grades 6-8 achieving a proficient score on both reading and math end of grade tests divided by the total number of students in grades 6-8 taking both reading and math end of grade tests.	Charlotte-Mecklenburg Schools, 2012-13
Proficiency High School (ITE22)	Number of students in grades 9-12 achieving a proficient score on two or more end of course tests divided by the total number of students in grades 9-12 with valid scores on two or more end of course tests.	Charlotte-Mecklenburg Schools, 2012-13
High School Graduate Rate (ITE23)	Number of students that graduated from high school in 4 years, using 4-year cohort data. A cohort refers to a high school class and is calculated by: students who entered ninth grade in a particular year, plus students who transferred into the district in the grade appropriate to the cohort, minus students who transferred out of the district or are deceased. Drop-out students count as non-graduates unless they later enroll in another school and graduate on time. Students who receive a GED are not counted as high school graduates for these calculations.	Charlotte-Mecklenburg Schools, 2012-13
High School Diploma (ITE24)	The number of people age 25 or older with a high school diploma or equivalent divided by the total population age 25 or older.	U.S. Census Bureau American Community Survey, 2009-2013 5-Year Estimates
Neighborhood School Attendance (ITE25)	Number of students attending their assigned school divided by the total number of students.	Charlotte-Mecklenburg Schools, 2012-13
Early Care Proximity (ITE26)	The number of housing units within ½-mile of a licensed early care and education program for children birth to age 5, divided by the total number of housing units.	Child Care Resources, Inc., 2013; Mecklenburg County Tax Parcels, 2013
School Age Proximity (ITE27)	The number of housing units within ½-mile of a licensed school-age care program for children ages 5-12, divided by the total number of housing units.	Child Care Resources, Inc., 2013; Mecklenburg County Tax Parcels, 2013
Library Card Holder (ITE28)	Number of active library card holders. Active cards have been used at least one in the last year.	Charlotte-Mecklenburg Public Library, Oct. 2012- Oct. 2013
Library Card Prevalence (ITE29)	Active library card holders divided by total population estimate.	Charlotte-Mecklenburg Public Library, 2012-2013; Population Estimate, 2013

Table 1 (continued)

Arts Participation (ITE30)	Number of households that participated in at least one art and culture activity and/or organization sponsored by the Arts & Science Council (ASC), divided by total number of households. Total households are calculated by multiplying the occupancy rate from the US Postal Service by the number of housing units from the Mecklenburg County tax parcel database.	Arts and Science Council 2012-2013; Household Estimate, 2013
Low Cost Healthcare Proximity (ITE31)	Number of housing units within ½-mile of a Medicaid provider or free clinic, divided by the total number of housing units.	Mecklenburg County Department of Social Services, Community Care of North Carolina, Mecklenburg County Tax Parcels, 2013
Grocery Proximity (ITE32)	Number of housing units within ½-mile of a chain grocery store, divided by the total number of housing units.	Chain grocery store addresses, 2014; Mecklenburg County Tax Parcels, 2013
Pharmacy Proximity (ITE33)	Number of housing units within ½-mile of a pharmacy divided by the total number of housing units. Only includes pharmacies located inside Mecklenburg County.	NC Board of Pharmacy, 2013; Mecklenburg County Tax Parcels, 2013

Table 2: Descriptive Statistics for the 33 Neighborhood Items Subjected to EFA

Item	Min	Max	Mean	Median	SD	Skewness	Kurtosis
Rental House (ITE1)	0	100	23.38	19.00	16.76	1.59	2.95
Violent Crime Rate (ITE2)	0	94	5.09	2.20	8.24	5.13	42.79
Property Crime Rate (ITE3)	0	854	39.00	23.70	62.08	7.79	82.30
Nuisance Violations (ITE4)	0	66	7.22	3.40	9.47	2.24	6.23
Hispanic-Latino (ITE5)	0	74	11.69	7.60	11.46	2.17	5.91
Black (ITE6)	0	100	31.18	25.60	25.70	0.76	-0.36
Public Health Insurance (ITE7)	0	94	15.73	12.00	13.97	1.60	3.99
Public Nutrition Assistance (ITE8)	0	91	16.25	11.00	15.85	1.41	2.09
Single Family Housing (ITE9)	0	100	64.12	71.00	32.28	-0.57	-0.88
Youth Population (ITE10)	0	49	24.42	25.00	8.66	-0.19	0.22
Housing Assistance (ITE11)	0	97	2.86	0.00	10.45	5.90	40.04
Foreclosure (ITE12)	0	7	1.09	0.90	0.87	1.48	4.98
Births to Adolescents (ITE13)	0	22	3.07	1.70	3.84	1.40	1.86
Student Absenteeism (ITE14)	0	23	8.33	8.00	3.97	0.61	0.32
Home Ownership (ITE15)	0	100	59.49	64.00	28.13	-0.49	-0.83
Prenatal Care (ITE16)	35	100	73.91	74.00	12.98	-0.08	-0.56
Bachelor Degree (ITE17)	0	90	38.96	38.00	22.74	0.16	-1.03
Household Income (ITE18)	9492	214408	62354	55965	33764	1.31	2.38
Employment Rate (ITE19)	23	100	88.63	91.00	9.20	-2.20	8.89
PES (ITE20)	4	100	37.76	31.60	22.19	0.50	-0.90
Proficiency Middle School (ITE21)	2	92	35.48	26.85	23.27	0.71	-0.76
Proficiency High School (ITE22)	3	100	41.19	37.05	23.21	0.54	-0.68
High School Graduate Rate (ITE23)	20	100	80.85	84.00	15.85	-0.86	0.30
High School Diploma (ITE24)	34	100	88.20	93.00	12.27	-1.39	1.64
School Attendance (ITE25)	21	100	81.14	82.00	12.27	-1.19	2.76
Early Care Proximity (ITE26)	0	100	64.08	79.00	37.29	-0.59	-1.21
School Age Proximity (ITE27)	0	100	65.41	78.00	35.85	-0.62	-1.12
Library Card Holder (ITE28)	20	1431	298.19	271.50	174.99	2.39	11.15
Library Card Prevalence (ITE29)	1	30	14.05	14.00	3.31	0.29	1.95
Arts Participation (ITE30)	0	72	14.15	10.00	12.01	1.54	2.97
LCHP (ITE31)	0	100	23.70	1.00	31.53	1.11	-0.06
Grocery Proximity (ITE32)	0	100	29.79	19.00	31.88	0.77	-0.67
Pharmacy Proximity (ITE33)	0	100	32.99	25.00	33.95	0.65	-0.92

Note: PES = Proficiency Elementary School; LCHP = Low Cost Healthcare Proximity.

Table 3: Exploratory Structure of the Neighborhood Condition Measures (21 items)

Item		I.	II.	III.	IV.	V.	VI.
I.	Residential Instability						
	Rental House (ITE1)	-0.76					
	Violent Crime Rate (ITE 2)	-0.85					
	Nuisance Violations (ITE 4)	-0.82					
II.	Concentrated Poverty						
	Black (ITE 6)		-0.52				
	Single Family Housing (ITE 9)		-0.72				
	Foreclosure (ITE12)		-0.75				
	Births to Adolescents (ITE13)		-0.67				
	Student Absenteeism (ITE14)		-0.48				
III.	Affluence						
	Prenatal Care (ITE16)			0.64			
	Bachelor Degree (ITE17)			0.57			
	Household Income (ITE18)			0.71			
	Employment Rate (ITE19)			0.59			
IV.	Educational Condition						
	Proficiency Elementary School (ITE20)				0.77		
	Proficiency Middle School (ITE21)				0.81		
	Proficiency High School (ITE22)				0.67		
V.	Educational Resource						
	Early Care Proximity (ITE26)					0.68	
	School Age Proximity (ITE27)					0.67	
	Library Card Prevalence (ITE29)					0.52	
VI.	Convenience						
	Low Cost Healthcare Proximity (ITE31)						0.75
	Grocery Proximity (ITE32)						0.85
	Pharmacy Proximity (ITE33)						0.87

Table 4: Final Structure of the Neighborhood Condition Measure (19 items)

	Constructs with Items
I.	Residential Instability
	Rental House (ITE1)
	Violent Crime Rate (ITE 2)
	Nuisance Violations (ITE 4)
II.	Concentrated Poverty
	Black (ITE 6)
	Foreclosure (ITE12)
	Births to Adolescents (ITE13)
	Student Absenteeism (ITE14)
III.	Affluence
	Prenatal Care (ITE16)
	Bachelor Degree (ITE17)
	Household Income (ITE18)
	Employment Rate (ITE19)
IV.	Educational Condition
	Proficiency Elementary School (ITE20)
	Proficiency Middle School (ITE21)
	Proficiency High School (ITE22)
V.	Educational Resource
	Early Care Proximity (ITE26)
	School Age Proximity (ITE27)
VI.	Convenience
	Low Cost Healthcare Proximity (ITE31)
	Grocery Proximity (ITE32)
	Pharmacy Proximity (ITE33)

Table 5: Descriptions and Sources of School Condition Items

Item	Description	Source
EOG Reading (ITE1)	Fifth grade overall EOG reading percentage at or above grade level.	2012-2013 NC school Report Cards
EOG Math (ITE2)	Fifth grade overall EOG math percentage at or above grade level.	2012-2013 NC school Report Cards
Test Taken (ITE3)	Number of students who took fifth grade EOG tests.	2012-2013 NC school Report Cards
Fully Licensed Teachers (ITE4)	The percentage of classroom teachers with clear initial or clear continuing licenses in all license areas in your school and the percentage of teachers with licenses in schools with similar grade range at the district and state levels.	2012-2013 NC school Report Cards
Teacher Retain Rate (ITE5)	100 minus the percentage of classroom teachers who left the classroom from March of the prior year to March of the current year.	2012-2013 NC school Report Cards
Experienced Teachers (ITE6)	100 minus the percentage of teachers who have taught for 0 - 3 years.	2012-2013 NC school Report Cards
White (ITE7)	The percentage of White students who passed BOTH the reading and math tests.	2012-2013 NC school Report Cards
National Board Certified Teachers (ITE8)	The percentage of school staff, including teachers, administrators and counselors, who have received National Board Certification.	2012-2013 NC school Report Cards
Non-Suspensions (ITE9)	100 minus the percentage of short-term (10 days or less) out-of-school suspensions, long-term (more than 10 days) out-of-school suspensions, and expulsions.	2012-2013 NC school Report Cards
Non-Crime (ITE10)	100 minus the percentage of acts of crime or violence.	2012-2013 NC school Report Cards
Not Economically Disadvantaged Students (ITE11)	100 minus the percentage of Economically Disadvantaged Students.	2012-2013 NC school Report Cards

Table 6: Exploratory Structure of the School Condition Measures (10 items)

Factor/Item		I.	II.	III.
I.	Economic Condition			
	EOG Reading (ITE1)	0.88		
	EOG Math (ITE 2)	0.80		
	White (ITE 7)	0.89		
	Not Economically Disadvantaged Students (ITE11)	0.90		
II.	School Safety			
	Fully Licensed Teachers (ITE4)		0.61	
	Non-Suspensions (ITE9)		0.67	
	Non-Crime (ITE10)		0.52	
III.	School-Building Structure			
	Teacher Retain Rate (ITE5)			0.44
	Experienced Teachers (ITE6)			0.71
	National Board Certified Teachers (ITE8)			0.58

Table 7: Descriptive Statistics of School-level Items

Percentage	*N*	Min	Max	Mean	*SD*	Skewness	Kurtosis
EOG Reading (ITE1)	76	12.00	86.20	40.66	21.22	0.51	-1.09
EOG Math (ITE 2)	76	10.50	91.30	47.32	20.73	0.25	-0.92
White (ITE 7)	76	0.87	82.77	30.20	29.42	0.60	-1.33
Not ED (ITE11)	76	0.90	95.32	38.10	32.12	0.45	-1.40
Fully Licensed Teachers (ITE4)	76	84.00	100.00	97.07	3.62	-1.55	2.23
Non-Suspensions (ITE9)	76	75.38	100.00	96.03	4.86	-2.19	5.22
Non-Crime (ITE10)	76	95.22	100.00	99.52	0.79	-3.62	15.53
Teacher Retain Rate (ITE5)	76	70.00	98.00	85.22	6.83	-0.29	-0.39
Experienced Teachers (ITE6)	76	48.00	94.00	71.46	12.62	-0.11	-1.11
NBCT (ITE8)	75	0.30	5.40	2.47	1.12	0.40	-0.21

Note: ED = Economically Disadvantaged; NBCT = National Board Certified Teachers

Table 8: Descriptive Statistics of Original Fifth Grade Mathematics and Reading Score

	Valid	Missing	*SD*	Mean	Skewness	Kurtosis	Max	Min
Math	8361	271	9.99	451.24	-0.13	-0.65	475	426
Reading	8232	400	9.83	450.03	-0.20	-0.47	472	421

Table 9: Descriptive Statistics of Mathematics and Reading Score

	Valid	Missing	*SD*	Mean	Skewness	Kurtosis	Max	Min
Math	8220	0	9.89	451.43	-0.13	-0.62	475	426
Reading	8175	0	9.83	450.05	-0.21	-0.46	472	421

Note: Fifth Grade Mathematics and Reading Data after Deleting Missing Values

Table 10: Descriptive Statistics of Mathematics and Reading Score by ethnicity groups

	Valid	Missing	*SD*	Mean	Skewness	Kurtosis	Max	Min
Math	7483	0	9.80	475	-0.12	-0.63	475	426
Reading	7483	0	9.82	472	-0.19	-0.49	472	421

Note: Fifth grade mathematics and reading data by ethnicity (Only European American, Africa American, and Hispanic included) after deleting missing values.

Table 11: Descriptive Statistics of Mathematics and Reading by Gender

		Mean	*SD*	Skewness	Kurtosis
Math	Male	450.96	10.09	-0.11	-0.69
	Female	451.07	9.51	-0.14	-0.57
Reading	Male	449.19	9.98	-0.18	-0.55
	Female	450.31	9.62	-0.18	-0.44

Note: Fifth grade mathematics and reading data by gender after deleting missing values.

Table 12: Descriptive Statistics of Mathematics and Reading by Ethnicity

		Mean	*SD*	Skewness	Kurtosis
Math	European American	456.85	8.4	-0.51	0.19
	African American	446.74	8.74	0.10	-0.61
	Hispanic	449.12	9.02	-0.15	-0.62
Reading	European American	455.73	8.20	-0.58	0.49
	African American	446.28	9.02	-0.06	-0.43
	Hispanic	446.25	8.89	-0.03	-0.46

Note: Fifth grade mathematics and reading data by ethnicity after deleting missing values.

Table 13: Statistics of HLM Baseline Model

Fixed Effects	Estimate	*SE*	*t*	*p*
Intercept (γ_{00})	-0.06	0.06	-0.1	0.36

Variance Components	Estimate	SD	95% CI
Residual	0.76	0.87	(0.86, 0.89)
Intercept	0.23	0.48	(0.41, 0.57)

Table 14: Correlation Coefficients for School and Regional Neighborhood Variables

	Residential Instability	Concentrated Poverty	Affluence	Educational Condition	Educational Resource	Convenience	School Economic Condition	School Safety	Teacher Quality
Residential Instability	--	0.83	-0.68	-0.72	0.67	0.08	-0.57	-0.62	-0.23
Concentrated Poverty		--	-0.88	-0.92	0.82	0.02	-0.74	-0.49	-0.30
Affluence			--	0.94	-0.82	0.01	0.73	0.29	0.24
Educational Condition				--	-0.83	-0.07	0.82	0.34	0.25
Educational Resource					--	0.26	-0.63	-0.29	-0.34
Convenience						--	-0.02	0.03	0.00
School Economic Condition							--	0.15	0.07
School Safety								--	0.17
Teacher Quality									--

Note: Pearson Correlation Coefficients. Region: School Attendance Area-based Neighborhood

Table 15: HLM Results of the Models for Outcome Measure-Mathematics

		Model 1				Model 2				Model 3			
Fixed Effects		Estimates	*SE*	*t*	*p*	Estimates	*SE*	*t*	*p*	Estimates	*SE*	*t*	*p*
Level 1 predictors													
Student	Reading	0.65	0.01	68.77	<0.01*	0.65	0.01	68.92	<0.01*	0.65	0.01	68.84	<0.01*
	Black	-0.32	0.03	-12.9	<0.01*	-0.33	0.03	-13.2	<0.01*	-0.32	0.03	-12.9	<0.01*
	Hispanic	-0.10	0.03	-3.75	<0.01*	-0.10	0.03	-3.94	<0.01*	-0.10	0.03	-3.73	<0.01*
	Female	-0.06	0.02	-3.56	<0.01*	-0.06	0.02	-3.58	<0.01*	-0.06	0.02	-3.56	<0.01*
Level 2 predictors													
school	School Economic	0.03	0.02	1.56	0.12					0.06	0.03	1.92	0.06
	School Safety	0.05	0.02	3.01	<0.01*					0.10	0.02	4.62	<0.01*
	School-Building Structure	0.01	0.02	0.44	0.66					0.01	0.02	0.72	0.47
Neighborhood	Residential Instability					0.01	0.03	0.43	0.67	-0.10	0.03	-3.29	<0.01*
	Affluence					0.02	0.04	0.59	0.56	0.02	0.04	0.54	0.59
	Educational Resource					-0.02	0.04	-0.46	0.65	-0.01	0.04	-0.26	0.80
Pseudo r^2	Within-group		45.93%				45.93%				45.93%		
	Between-group		89.23%				88.20%				90.60%		

Table 16: HLM Results of the Transformed Models for Outcome Measure-Mathematics

		Transformed two-level HLM			
Fixed Effects		*β*	*SE*	*t*	*p*
Level 1 predictors					
Student	Reading	0.66	0.01	76.63	<0.01*
	Black	-0.39	0.02	-20.22	<0.01*
	Hispanic	-0.15	0.02	-6.63	<0.01*
	Female	-0.06	0.02	-4.20	<0.01*
Level 2 predictors (spatial error model)				*z*	
school	School Economic	0.49	0.09	4.96	<0.01*
	School Safety	0.29	0.10	2.67	<0.01*
	School-Building Structure	0.22	0.10	2.21	<0.05*
Neighborhood	Residential Instability	-0.32	0.14	-2.33	<0.05*
	Affluence	-0.49	0.19	-2.58	<0.01*
	Educational Resource	-0.26	0.17	-1.49	0.14

Note: AIC = 262.06 and $\sigma^2 = 0.85$ in the spatial error model with all level-2 variables. AIC = 262.94 and $\sigma^2 = 0.87$ in the multiple regression with all level-2 variables, and AIC = 266.83 and $\sigma^2 = 0.92$ in the spatial error model with level-2 variables but excluding school safety.

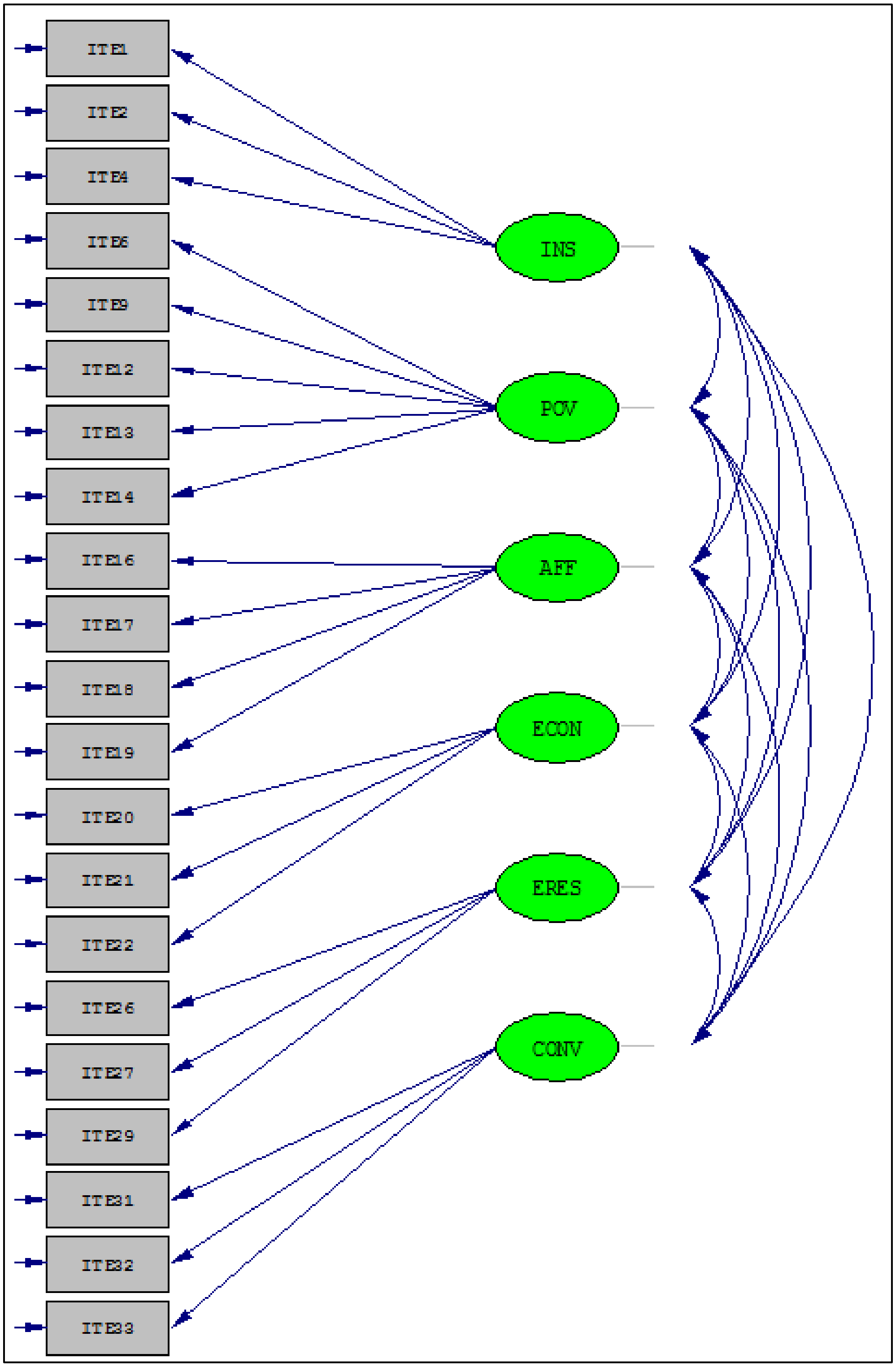

Figure 4: Conceptual Model for the Neighborhood Measures

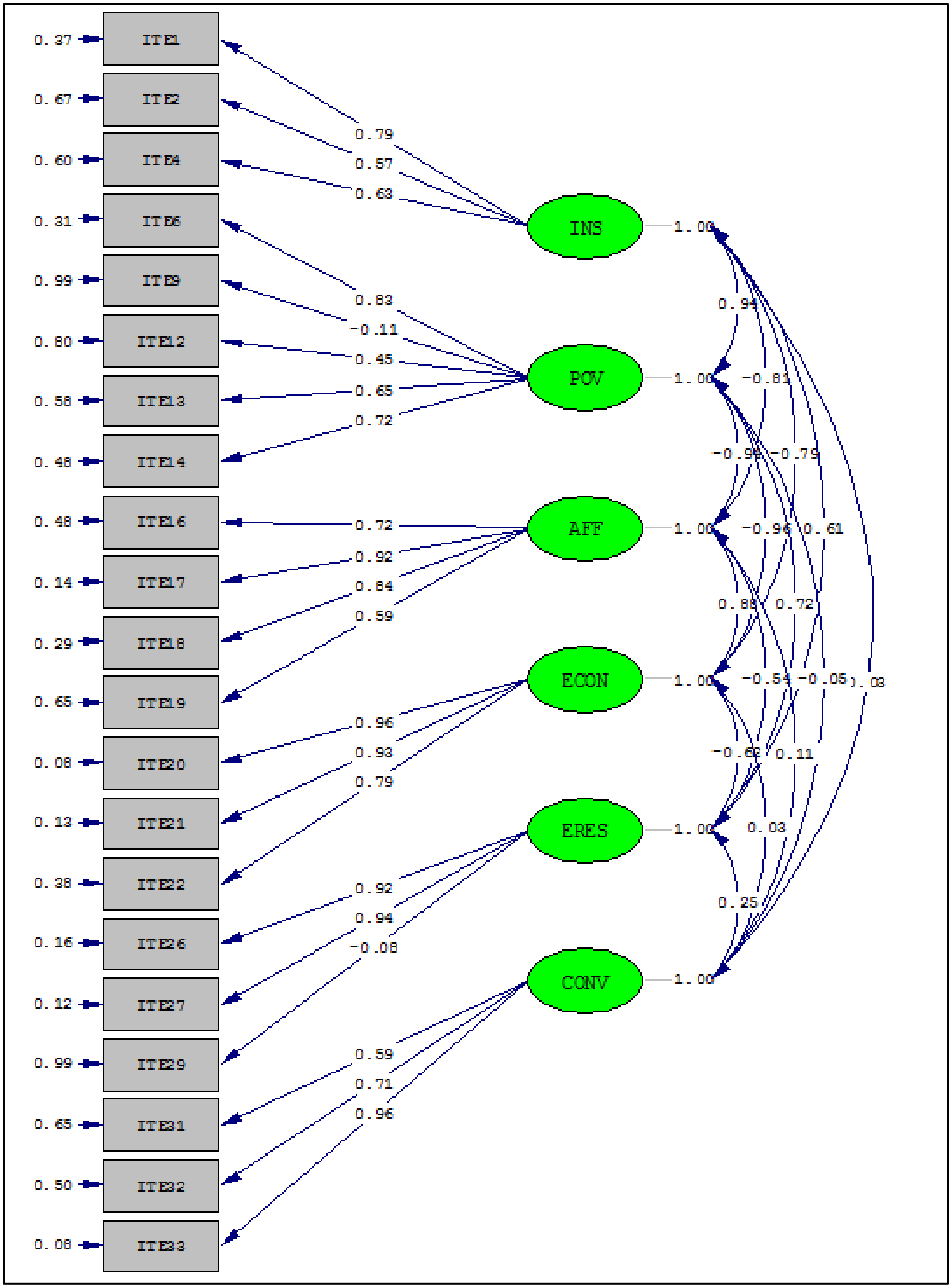

Figure 5: First Model for the Neighborhood Measure

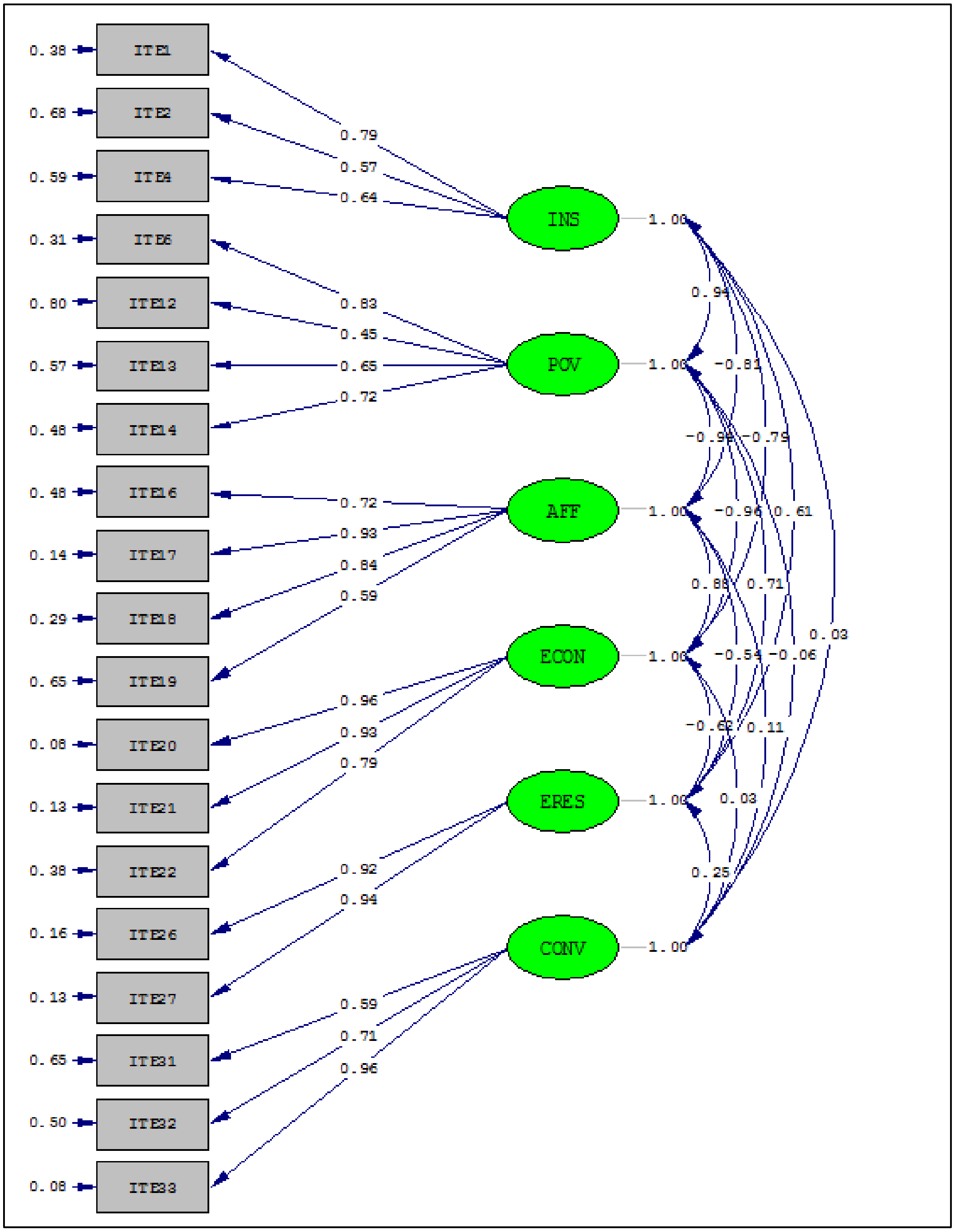

Figure 6: Final Model for the Neighborhood Measures

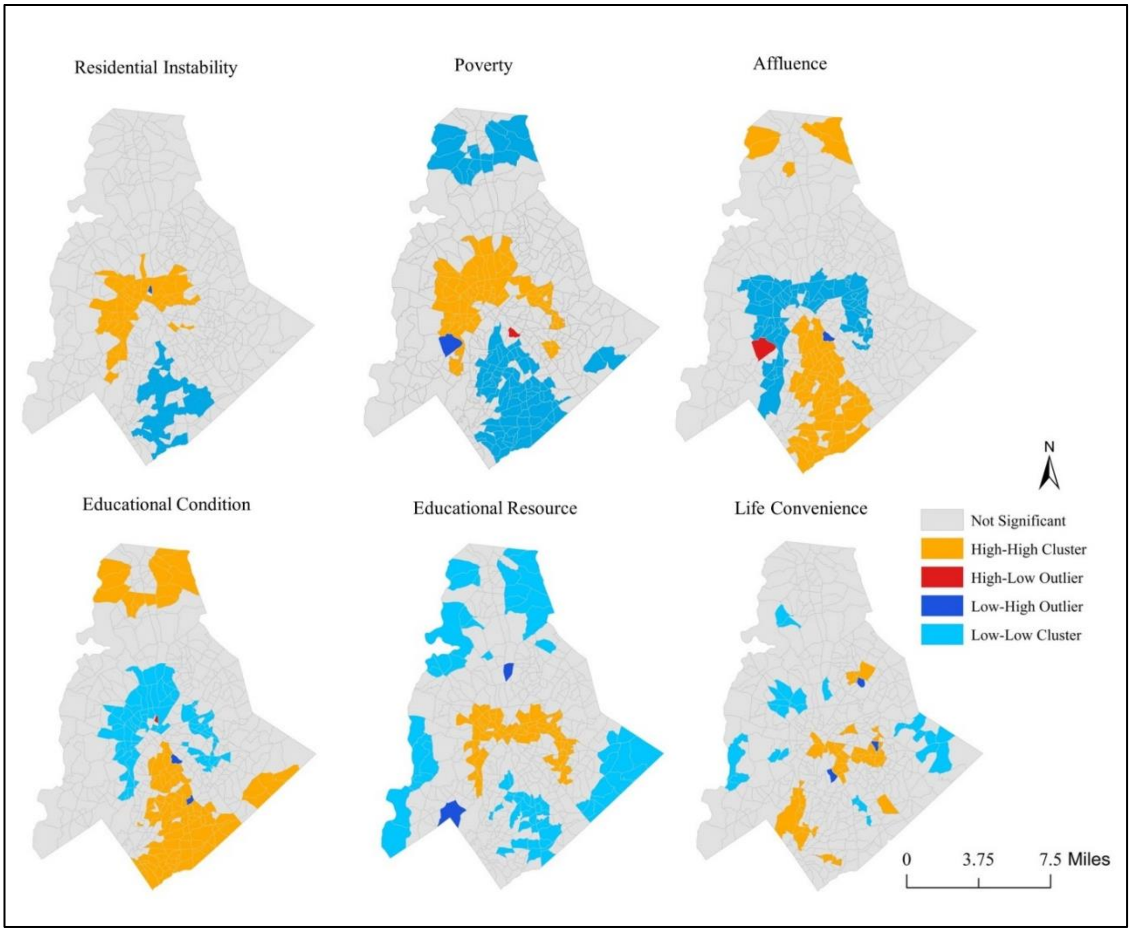

Figure 7: Local Moran's *I* for Neighborhood Measures at the Neighborhood Level

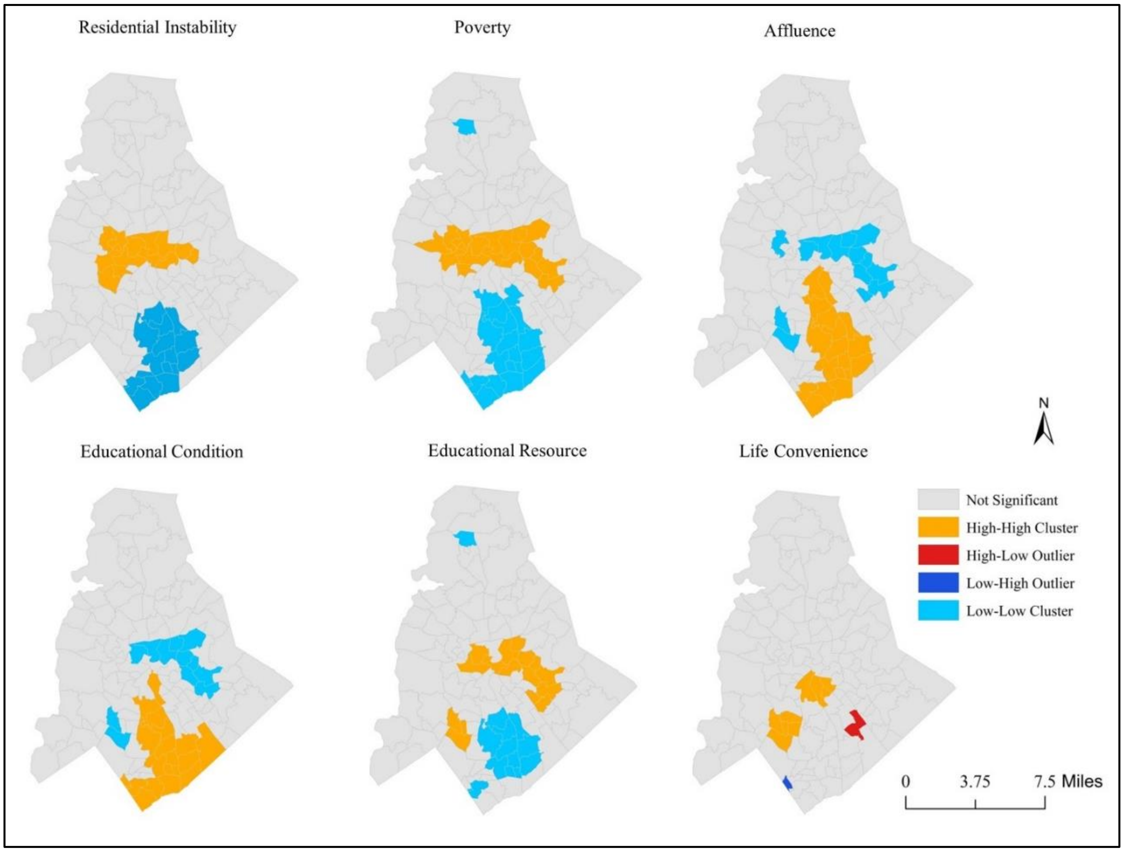

Figure 8: Local Moran's *I* for Aggregated Neighborhood Measures
Note: Aggregated at the School Attendance Area-based Level.

CHAPTER 5: DISCUSSION

The academic achievement gap has drawn attentions for several decades. However, broader perspectives (such as neighborhood effects) and more solid theoretical bases (such as neighborhood-level social disorganization theory) have been ignored in this course (Bradley & Bradley, 1977; Braun et al., 2010; Coleman et al., 1966; Crain & Mahard, 1978). The renaissance of neighborhood studies in social science fields in recent years has provided us in-depth insights in understanding the neighborhood-academic achievement link (Attar et al., 1994; Garner & Raudenbush, 1991; Sampson et al., 1997). However, most of these studies solely take neighborhood attributes as non-spatial and failed to explain how spatial processes among neighborhoods (i.e., how one neighborhood is linked to its ambient neighborhoods) are related to students' academic achievement (McMaken, 2014). For example, neighborhood attributes in education were taken as solely place-based characteristics. That is, the spatial interrelationships among neighborhoods (e.g., spatial dependencies) were not considered (Berg et al., 2013; Greenman et al., 2011). The current study considers neighborhood attributes as not only place-based, but also space-based (e.g., considering the spatial autocorrelation). These spatial interrelationships may lead to variations of educational outcomes (e.g., academic achievement), because "individuals are not uniformly dispersed over space" (McMaken, 2014, p. 104). Understanding these underlying spatial processes among neighborhoods can help better explain the academic achievement gap and look for possible solutions to narrow down the gap.

Directed by solid theoretical bases (e.g., poverty theory, neighborhood-level social disorganization theory, integrated five neighborhood-level models), the purpose of this study was to investigate the relationships between neighborhood conditions and students' academic achievement (mathematics in particular) in elementary schools considering spatial autocorrelation among regional (school attendance area)-based neighborhoods. That was, the spatial autocorrelation was considered by adding an auto-correlated error term to the region (school attendance area)-based neighborhood error structure in the second level of HLM, which was transformed to spatial error model. This method was used to capture the spatial dynamics among neighborhoods and how it was related to mathematics achievement in elementary schools, which has been ignored by most studies about neighborhood-academic achievement (Jargowsky & El Komi, 2011; Owens, 2010). Various methods tend to yield different estimates. It is necessary to consider spatial autocorrelation among neighborhoods in the neighborhood-academic achievement studies, because it accounts for the between-neighborhood variances due to spatial autocorrelations. This approach also provides more robust estimates, accurate results, and reliable inferences. Based upon this purpose, a methodological framework was proposed in response to the need of considering the geographical context (e.g., spatial dependencies) in neighborhood-academic achievement studies. This framework attempted to better capture the relationships between neighborhood attributes and academic achievement with accounting for the spatial dependencies.

This chapter aimed at reviewing and linking findings from this empirical study of neighborhood conditions in relation to student academic achievement in elementary schools to the previously reviewed literature. This chapter was organized into three sections. The first section presented findings and discussed implications in relation to the similar studies reviewed in the first two chapters. Then limitations and future research were outlined. Finally, a summary of the chapter was concluded.

5.1. Findings and Discussions

The major contribution of current study was to consider the spatial dependency within neighborhoods, which improved the stability and consistency of the regression coefficients with more robust estimates, and raised the level of accuracy of measure of fit as well as the interpretation of significance. In the current study, the spatial variations of neighborhood attributes were firstly investigated. This step was often missed in previous neighborhood-academic achievement studies. Most of the previous studies did not consider spatial autocorrelations among neighborhoods, and unclear about how academic achievement would be varied due to the presence of spatial autocorrelations. This study addressed these issues through developing geo-database and performing spatial analyses, such as global and local Moran's *I* statistics. Through these robust procedures, spatial autocorrelation among neighborhoods was identified. The interplay of spatial dependency among neighborhoods tended to influence how individual behaved and might lead to the variations of educational outcomes (e.g., academic achievement), because individuals were not uniformly distributed and had social activities as well as other interactions within or across geographical neighborhood boundaries. The presence of spatial dependence may lead to low robustness of estimators (Anselin & Rey, 1991). Further, it biases the interpretation of significance and measure of fit to some degree, such as inflating the estimated R2 (Florax & Folmer, 1992). In addition, the validity of a set of standard misspecification tests will be affected by the presence of spatial dependence, including the heteroskedasticity test, stability and consistency of the regression coefficients, and other model selections (Anselin & Griffith, 1988; Florax & Folmer, 1992). The results suggested that it was necessary to account for spatial dependency in order to obtain consistent and robust estimates (Crowder & South, 2011; McMaken, 2014). In addition, the presence of spatial autocorrelations provided the evidence that it was reasonable and necessary to account for spatial dependency in multi-level data analysis.

In the major HLM analyses without modeling the spatial autocorrelation (model 3) and with modeling it (model 4), both school and neighborhood factors were controlled at the second level. Surprisingly, affluence only showed negative relationship with mathematics achievement in the model with modeling spatial autocorrelations, which contradicted findings in other studies. The positive relationships between neighborhood affluence and academic achievement were supported by most of the neighborhood-academic achievement studies. That is, neighborhood affluences were associated with better educational outcomes (Bowen et al., 2002; Fischer & Kmec, 2004; Sampson et al., 2002). As in other studies, it was also suggested that neighborhood affluence, especially the unequally distributed neighborhood resources, would have adverse influence on poor residents (Reardon, 2011). Boyle et al. (2007) concluded that neighborhood affluence had a positive influence on years of education for students from advantaged families, not for those from poor families. However, all these studies failed to consider another situation:

the presence of spatial autocorrelation might affect the relationship between neighborhood affluence and academic achievement. That was, an affluent neighborhood might be affected by the adverse impact of its surrounding poor neighborhoods due to spatial autocorrelations among neighborhoods. The transformed HLM (model 4) accounted for not only characteristics related to students, schools, and neighborhood, but also the spatial autocorrelations among neighborhoods through adding an auto-correlated error term to the region (school attendance area)-based neighborhood error structure in the second level. Through modeling the spatial autocorrelations, it was identified that neighborhood affluence was negatively associated with mathematics achievement. This argument was aligned with the ideas of diverse types of spatial processes, for example, sharing similar characteristics or attributes among neighborhoods (spatial dependence) (Crowder & South, 2011; Delmelle, 2012; Páez & Scott, 2005). That was, if an affluent neighborhood was surrounded by disadvantaged neighborhoods, the negative attitudes towards education and bad life habits associated with disadvantaged neighborhoods might affect affluent neighborhoods through spatial autocorrelations. This phenomenon might also explain reasons that the negative influence of residential instability when modeling spatial autocorrelation was stronger than the model without considering spatial interrelationships. These two findings regarding neighborhood factors suggested the importance of considering spatial interrelationships (e.g., spatial autocorrelations) for better explaining the relationships between neighborhood and academic achievement.

It has been a long argument that whether school characteristics had a profound impact on student academic achievement (Dobbie & Fryer Jr, 2011). The school characteristics had been underestimated during various times. For example, during the implementation of school desegregation around the 1960s, most of the research supported that the decreased academic achievement gap were due to race-based school desegregation (Coleman et al., 1966). On the contrary, findings from the current study supported another group of researchers who have been arguing the importance of school quality in achieving high results of academic achievement (Boozer et al., 1992; Dobbie & Fryer Jr, 2011; Hogrebe, 2012). At the school level, only school safety and school-building structure was a profound predictor with positive associations with academic achievement no matter modeling the spatial autocorrelation or not. The first difference was that when considering spatial autocorrelations, the associations between school safety and mathematics achievement were much larger. The second difference was that the school economic factor became a significant predictor in the model considering spatial autocorrelation. Thus, all three school factors showed significance when modeling spatial autocorrelation. In other words, the importance of school quality must be valued more with the presence of neighborhood factors and their spatial interrelationships. The interplay of spatial autocorrelations makes students more easily affected by neighborhood risk factors if they live in an area with more disadvantaged neighborhoods. Moreover, school environments has a close association with mathematics achievement especially for students living in disadvantaged neighborhoods with more risk factors. In such a situation, better school environment serves as a buffering area that prevents students from getting hurt by those risk factors. The implication of this finding is that if students live in disadvantaged neighborhoods with more risk factors, such as high rate of crimes, drug use, unemployment, and delinquent behaviors, ameliorating school environments and improving school quality may be a choice in order to achieve better results of academic achievement.

At the student level, the academic achievement gap between African Americans and European Americans as well as between Hispanic and European American students was widened in the model with modeling spatial autocorrelation. These findings suggest that minority students were more vulnerable to those neighborhood risk factors with the presence of spatial interrelationships. Special attentions should be given to the minority students (e.g., African American and Hispanic students) who live in distressed neighborhoods (Dornbusch et al., 1991; Duncan, 1994; Johnson, 2010). In addition, reading had a positive relationship with mathematics scores, and the academic achievement gap between males and females stayed unchanged no matter modeling spatial autocorrelation or not.

Another contribution of this study was the development of neighborhood measures. The major premise of this study was to hypothesize the roles of the spatial interrelationships played among neighborhoods in leading to variations of the educational outcomes in general and the mathematics achievement in particular. In order to capture these spatial interrelationships, reliable neighborhood measures had to be developed first. Among neighborhood-academic achievement studies, how to capture neighborhood mechanisms with reliable neighborhood measures had been a challenge (Duncan & Aber, 1997; Duncan & Raudenbush, 2001; McCoy et al., 2013; McMaken, 2014). There may be several reasons that result in the lack of reliable neighborhood measures: 1) Sources of neighborhood data are different, 2) Qualities of neighborhood data vary, 3) Standards used to develop neighborhood boundaries are inconsistent, 4) Unified theoretical basis is lacking. In response to the need for developing reliable neighborhood measures tailored to the data and requirement of current study, the neighborhood measures, including 6 factors were firstly developed through reliable procedures of EFA and CFA. After running Pearson correlation, three-factor neighborhood measures (i.e., residential instability, affluence, and educational resources) were entered into the HLM in order to reduce multicollinearity. The three-construct neighborhood measures were based upon theories discussed in chapter 2, previously reviewed studies (McMaken, 2014; Sampson et al., 2002; Sampson et al., 1997), and the neighborhood data in current study. These neighborhood measures contributed the literature of neighborhood measures related to neighborhood-academic achievement studies and could be used as a reference in order to develop more reliable neighborhood measures for further research.

5.2. Implications for Practitioners

Findings from the current study provide several implications for practitioners regarding how to improve student academic achievement and narrow the academic achievement gap. First, the presence of affluent neighbors or neighborhoods is critical important for policymakers to divide the neighborhood-based school attendance areas. The presence of affluent neighborhoods may better reduce risk factors of disadvantaged neighborhoods due to spatial dependencies, which in turn boost student educational engagement and help improve academic achievement. Numerous studies have supported this argument (Ainsworth, 2002; Brooks-Gunn, Duncan, Klebanov, & Sealand, 1993; Dupere, Leventhal, Crosnoe, & Dion, 2010; Jencks & Mayer, 1990). However, in the meantime, it is profoundly pivotal to give special attention to how to balance the numbers of disadvantaged and affluent neighborhoods in a neighborhood-based school attendance areas (Carpiano, Lloyd, & Hertzman, 2009). Because one of the findings suggested that risk factors associated with disadvantaged neighborhoods could affect affluent neighborhoods that was sounded by poor neighborhoods through the interplay of spatial autocorrelations among neighborhoods. Carpiano, Lloyd, and Hertzman (2009) argued that not the neighborhoods with highest proportion of affluent neighbors, but the areas with the balanced presence (“relatively equal proportions”) of affluent and disadvantaged neighbors were associated with highest average score of children’s readiness for school.

Second, schools embedded in neighborhoods are considered as one of the important neighborhood-level institutional resources. The positive interactions between school and neighborhood environment ensure better results of academic achievement, which was supported by other studies (Catsambis & Beveridge, 2001; McCoy et al., 2013). Ameliorating school qualities and providing school environments, which are favorable to improving students’ academic achievement, are especially necessary for students who live in distressed neighborhoods. This finding was consistent with the argument from the study of Dobbie and Fryer Jr (2011): good school conditions can serve as buffering areas, which may make disadvantaged neighborhood conditions less harmful to students who live in such neighborhoods.

Third, neighborhood is a place with unequal opportunities for African Americans (or Hispanic) and European Americans. Other studies have argued that European American students reap more benefits-from affluent neighborhoods than African American students (Brooks-Gunn et al., 1993). Meanwhile, current study implies that minority students are more vulnerable to the risk factors of disadvantaged neighborhoods with the presence of spatial interrelationships among neighborhoods. This finding was consistent with studies conducted by Johnson (2010) and Crowder and South (2003). Johnson (2010) reviewed a number of studies and most of the studies suggested that African Americans tended to be affected more by disadvantaged neighborhoods. Crowder and South (2003) concluded that African American adolescents had a higher dropout rate than European American counterparts with the exposure to the disadvantaged neighborhoods. Thus, it is pivotal to give special attentions to these groups of minority students who live in poor neighborhoods to narrow the academic achievement gap.

5.3. Implications for Researchers

In order to better understand the relationships between neighborhood conditions and academic achievement considering spatial interrelationship, the first step is to develop reliable neighborhood measures (McMaken, 2014). Although researchers in neighborhood-academic achievement studies showed effort to the development of neighborhood measures, work on creating consistent and reliable neighborhood measures to quantify neighborhood conditions is inadequate. In current situation, consolidated theoretical support, rigorous factor analytic techniques and procedures, and high quality of neighborhood data are needed in this process. Moreover, there lies a need to understand the dynamics of neighborhood conditions, especially the roles of the spatial processes played, in relation to academic achievement to measure neighborhood conditions (Hogrebe, 2012).

Second, most of the neighborhood-academic achievement studies failed to recognize the importance of spatial interrelationships among neighborhood in shaping the development of academic achievement and the roles they played to narrow the academic achievement gap. Thus, beyond the need to find ways to develop neighborhood measures, it also raises calls to understand neighborhood dynamics and underlying spatial processes more deeply (Crowder & South, 2011). In the meanwhile, how to develop reliable and robust statistical models to model spatial interrelationship in neighborhood-academic achievement studies should be highly considered (McMaken, 2014).

Finally, this study shed light on the potential relationships between neighborhood conditions and academic achievement considering spatial interrelationships. Although a certain amount of crossover occurs between education and geography and a group of researchers have called on to integrate GIS into educational filed (Mulvenon & Wang, 2006), more geographical perspectives and GIS-related technologies should be brought into neighborhood-academic achievement research (Hogrebe, 2012). This may inspire a group of interdisciplinary researchers to explore a new and exciting area of inquiry on neighborhood-academic achievement studies or other geography-related educational studies.

5.4. Limitations of Current Study

There are several limitations of current study. First, there was a two-year gap between neighborhood conditions data (from the year of 2014) and student academic achievement data (5^{th} grade EOG mathematics and reading data from the year of 2012). The mismatch between the two sets of data may not accurately reflect true situations of the academic achievement conditions.

The second limitation of current study is related to the protection of individual's confidential information. No individual residential address was identified and linked to neighborhoods. Thus, neighborhood-level variables could only have connected to schools. In such situation, current study had to aggregate neighborhoods into larger regions, which was based upon school attendance area. The accuracy and robustness might be reduced due to this limitation.

The third limitation of current study is that poverty is not available at the individual level. It suggests that poverty has been an important predictor at the individual level. The absence of individual-level poverty may omit important information and reduce the power of the model to explain the variations.

5.5. Need for Future Study

A number of needs were highlighted for future research. First, the current study aggregated neighborhoods into larger school attendance area-based regions due to the lack of geocoded individual address data. In the future, if possible, the geocoded individual address data can be obtained, then new statistical models can be developed to improve the less-biased estimates and explore the relationships between neighborhood conditions and academic achievement. More work on geocoding individual data to link students' data to neighborhoods deserves attentions. In addition, it is of critical importance that more studies need to focus on how to create technologies or methods that can be used to protects students' identity but produce more accurate data in neighborhoods.

Second, how neighborhood conditions are related to academic achievement longitudinally leaves for an exciting inquiry. This will lead to a new research field of spatiotemporal inquiry to combine time and space into neighborhood-academic achievement research. For example, it is quite common that students across different time and grade levels move between neighborhood and schools, thus how to model students' instability related to educational attainments across space and time would be one recommendation for the further studies.

Third, family as an indispensable connection between neighborhood and school provides valuable information in neighborhood-academic achievement studies. In future studies, it is pivotal to collect family data and include family variables to better understand the relationships between neighborhood conditions and student academic achievement with the consideration of spatial dependencies.

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