Examining the Effects of School-Level Variables on Elementary School Students' Academic Achievement: the Use of Structural Equation Modeling

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EXAMINING THE EFFECTS OF SCHOOL-LEVEL VARIABLES ON ELEMENTARY SCHOOL STUDENTS’ ACADEMIC ACHIEVEMENT: THE USE OF STRUCTURAL EQUATION MODELING

A Dissertation
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy
Educational Leadership

by
Matthew Robert Della Sala
May 2014

Accepted by:
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Dr. Russ Marion
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ABSTRACT

School finance scholars have called for the alignment of accountability policies with state finance formulae to allocate resources toward student learning goals (Adams, 2008; Ryan, 2008; Superfine, 2009; Verstegen, 2002). With the presence of accountability policies that focus on improving students’ academic achievement, state finance systems must be repurposed to allocate educational resources to schools based on research-based practices that are linked to student achievement. The purpose of this study is to test the sufficiency of a new conceptual model of the effects of educational resources on student achievement using structural equation modeling. The goal of this study is to provide further clarity to the discourse on whether researchers can model how variations in educational resources allocated specifically to schools, rather than school districts, affect variations in student achievement.

Descriptive statistics were conducted on the variables in order to calculate the appropriate transformations for the Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). CFA was conducted on the new conceptual model of the effects of educational resources on student achievement and yielded a poor model fit. A post hoc model of the effects of educational resources on student achievement was created and found to be a good model fit. Student characteristics and personnel were found to be significant predictors of student achievement, explaining 34.3% of the variation in the latent variable. The instructional condition latent variable was found to be a poor latent variable and a non-significant predictor of student achievement.
Findings were used to inform implications for methodological improvement. Implications included enhanced measures of the observed variables, the use of students’ previous achievement scores, and the use of multi-level analyses to analyze the effects of variations simultaneously between schools and within schools. In addition, two policy implications emerged from the findings to inform state allocation practices to meet the demands of educational adequacy. First, policymakers and researchers may need to develop better measures of the resources within the instructional conditions of schools in order to capture the educational process and then redistribute those resources to schools based on students’ differential needs. Second, modifications may be made to the current state finance formula to include an additional weighting for poverty. The funds generated from the additional weighting in this state could then be allocated to schools for them to devise programs or structures that have been proven to help students from low socioeconomic backgrounds achieve proficiency on accountability exams.
ACKNOWLEDGMENTS

“We keep moving forward, opening up new doors, and doing new things, because we’re curious…and curiosity keeps leading us down new paths.” - Walt Disney

Curiosity has always driven me. Yet, it would be an understatement to say that this dissertation would not have been possible without the invaluable guidance, support, love, and encouragement of many individuals.

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CHAPTER ONE
INTRODUCTION

Background of the Study

In order to ensure that students have attained the necessary knowledge to participate in economic and political life in the United States, current federal and state accountability policies mandate that all students achieve proficiency of academic standards as measured by statewide testing systems. Wong and Nicotera (2007) explained the purpose of education accountability policy as embodying the logic of focusing reform efforts and resources toward improving instructional practices to increase student achievement based on increasing expectations. With the emphasis on schools’ requirements to continuously raise student achievement, state-level educational leaders and policymakers must make strategic resource allocation decisions to help schools meet the desired student learning goals. To make these decisions, leaders and policymakers need reliable evidence of the effects of specific educational resources on student achievement.

School finance scholars have called for the alignment of accountability policies with state finance formulae to allocate resources toward student learning goals (Adams, 2008; Ryan, 2008; Superfine, 2009; Verstegen, 2002). Presently, state finance systems are premised on notions of equity, which seek to distribute comparable funding amounts to school districts. Adams (2008) noted that the dollars allocated to school districts rarely are traceable to individual students’ learning needs. With the evolution of accountability policies that focus on improving students’ achievement, state finance systems must
allocate resources toward meeting specific learning goals. This repurposing of resources with research-based practices that are linked to student achievement may result in significant improvements in student learning (Governors Education Symposium, 2011).

Since the 1960s, researchers have made attempts to investigate the relationship between educational resources and student achievement (Archibald, 2006; Coleman et al., 1966; Cooper et al., 1994; Fortune & O’Neil, 1994; Greene, Huerta, & Richards, 2007; Greenwald, Hedges, & Laine, 1994; Hanushek, 1981, 1989, 1991; Knoeppel, Verstegen, & Rinehart, 2007; Okpala, 2002). To discern the effects of resources on achievement, many of these researchers developed conceptual models and tested them using multiple regression and production function methods; findings have been mixed. Whereas some researchers have found significant relationships between variations in resources and variations in student achievement (Archibald, 2006; Cooper et al., 1994; Fortune & O’Neil, 1994; Greenwald et al., 1994; Knoeppel, Verstegen, & Rinehart, 2007), other researchers have found non-significant effects (Coleman et al., 1966; Hanushek, 1981, 1989, 1991; Okpala, 2002).

Differences among findings may be due, in part, to limitations in research designs and the types of data that were accessible to test the conceptual models. According to Verstegen and King (1998) and Okpala (2002), the majority of studies that investigated the relationship between resources and achievement examined variables that did not represent the actual effects of resources within schools; rather, the studies made use of variables that were either situated at district levels or school levels. Cohen, Raudenbush, and Loewenberg Ball (2003) argued for the use of conceptual models that examine
resources within schools. They claimed that the effects of specific resources on
achievement should not be examined in isolation. Instead, those resources should be
"situated in instruction…resources can enable or constrain the causal agents in
instruction, thus moderating their impact on student achievement." (p. 119). Okpala’s
(2002) conceptual model best represents Cohen’s et al. (2003) reasoning by situating the
resources, such as teacher quality, class size, and per-pupil expenditures for instructional
support, as proxies for each school’s quality of instruction. The variables in Okpala’s
model were examined using multiple regression techniques.

In addition to limitations of using district level variables to extrapolate the effects
of resources on achievement, previous studies are also limited by the use of production
functions and multiple regressions. These methods only account for variations on a single
dependent variable and only portray the direct links between independent and dependent
variables (Monk, 1990). Given these limitations, scholars have yet to model a holistic
representation of the relationship between resources and achievement. The present study
applies aspects of Cohen’s et al. (2003) call to situate the resources in instruction and
Okpala’s (2002) conceptual model to test a new conceptual model of the effects of
educational resources on student achievement. Furthermore, this study will use Structural
Equation Modeling (SEM) to examine the direct and indirect effects of educational
resources on student achievement by making use of variables that are situated at the
school-level.
Purpose Statement

The purpose of this study is to test the sufficiency of a new conceptual model of the effects of educational resources on student achievement using SEM (see Figure 1.1). A second purpose of the study is to examine the effects of the combination of school-level educational resources on students’ academic achievement to see if the findings are relevant to resource allocation policy. By conducting SEM using latent variables situated at the school level, the goal of this study is to provide further clarity to the discourse on whether researchers can model how variations in educational resources that are allocated specifically to schools, rather than school districts, affect variations in student achievement.
Significance of the Study

The present study significantly contributes to the scholarship on the effects of educational resources on student achievement. This study extends the knowledge base by proposing SEM as a viable method to extrapolate the estimated effects of resources on achievement. To date, scholars have examined these effects using production functions and meta-analyses of multiple regression studies (Cooper et al., 1994; Fortune & O’Neil, 1994; Greenwald, Hedges, & Laine, 1994; Hanushek, 1981, 1989, 1991; Okpala, 2002). However, these findings have been mixed and limited due to the fact that the variables
under investigation have been collected at the school levels and district levels and independently regressed on dependent variables (Verstegen & King, 1998). Though school-level and district-level variables provide insight into the effects of resources on achievement, the variables under examination often remain distant from the educational interaction between teachers and students because they are regressed separately. SEM allows for the analysis of variables that are situated within similar theoretical constructs of an organization (Heck & Thomas, 2009). The present study uses a combination of school-level latent variables to better extrapolate the estimated effects.

In addition, this study has practical implications for policymakers and educational leaders. Researchers have called for the alignment between accountability policies and school finance policies to better connect to student learning goals within schools (Adams, 2008; Ryan, 2008; Superfine, 2009; Verstegen, 2002). Given this demand, a deeper understanding of how educational resources that are implemented by policymakers and leaders can affect student achievement is needed in the literature. In order for educational policymakers and leaders to align allocation decisions toward student learning goals, they need reliable evidence to inform their practices (O’Day, 2002; Wong & Nicotera, 2007). This study aims to provide sufficient evidence on the effects of resources on student achievement so that policymakers and leaders can effectively tailor the allocation of resources to improve teaching and learning for all students.

**Conceptual Framework**

Researchers’ philosophical perspectives influence their reviews of literature, framing of research studies, and interpretations of their findings (Kilbourn, 2006). The
philosophical lens for the present study is guided by Rawls’s (1971) theory of justice, varying interpretations of equality of opportunity, and school finance scholars’ conceptions of educational adequacy. Rawls’s theory of justice is predicated on the notion that all people are equally valuable and entitled to the same basic rights and standards of self-worth. Therefore, inequalities between individuals, families, or groups that are the result of economic and social institutions merit redress. Though Rawls acknowledged that natural differences occur between individuals, such as motivation and specific talents, just institutions must ensure that all individuals have the same access and opportunities to achieve their desired goals.

In education, Rawls’s (1971) conception of justice aligns with state education finance systems’ goals to achieve equality of opportunity for all students as evidenced by clearly defined learning objectives. Education finance scholars have studied the adequacy of state finance systems in providing sufficient resources to all students so that they have fair opportunities to be successful in school (Alexander, 2004; Baker, 2005; King, Swanson, & Sweetland, 2005; Ladd, 2008; Toutkoushian & Michael, 2007; Verstegen, 2002). In order to examine whether states are providing adequate and equal opportunities for students, evidence is needed on how the educational resources affect student achievement. Once reliable evidence is gathered, then scholars, policymakers, and educational leaders can begin justifying strategic allocations of school-level resources to improve teaching and learning.
Research Questions and Hypotheses

Given the need for evidence on the effects of educational resources on student achievement, the present study seeks to answer the following research questions:

1. Is the new conceptual model of the effects of educational resources on student achievement a good model fit using elementary school data from South Carolina?
2. In the selected model, what are the estimated effects of the educational resources on students’ academic achievement and how can the findings be used to inform resource allocation practices to meet educational adequacy?

A priori testing of the conceptual model will be conducted to investigate the first question. Due to the confirmatory approach inherent in the research design, the answer to the first question requires a series of hypotheses testing (Byrne, 2012). These hypotheses are stated and justified in chapter three. If a good model fit can be determined, the second question will then be analyzed using appropriate statistical methods.

Design and Analysis Procedures

SEM will be conducted to test the appropriateness of the new conceptual model of the effects of educational resources on student achievement. Below, the data collection process, variables, and the data analysis procedures that will be used to answer the research questions are outlined. Subsequently, the exploratory analysis procedures that will occur if the new conceptual model does not fit the data is explained.

Data Collection

School-level data for the 2012-2013 academic year were collected for elementary schools from South Carolina’s Department of Education website. The state is relatively
diverse, comprising over 765,000 students with the highest proportion of students being Black or African American and White (South Carolina Department of Education, 2013a). The elementary schools’ poverty indices ranged from 10.40 to 100, with 68% of the elementary schools having a poverty index over 70. In addition, about 3.6% of the students were designated with Limited English Proficiency (LEP) and over 12% of the students received services for disabilities. Furthermore, the state had over 650 elementary schools; the sample size was adequate for SEM (Hox & Maas, 2001). A more detailed description of the data collection process is described in chapter three.

Variables

The variables in this study were selected based on two criteria. First, the variables that were used in Okpala’s (2002) conceptual model were included to test the sufficiency of the new model. Second, additional variables relevant to the research question were included in the new conceptual model based on availability. The inclusion of these additional variables is justified in chapter three. Specifically, these variables were described using empirical research on the effects of each additional variable on student achievement. Each variable can be seen in Figure 1.1.

The 2013 school-level variables selected for the student characteristics latent variable included the poverty index, the percentage of students with disabilities other than speech, the percentage of students eligible for gifted and talented, the percentage of students retained, and the percentage of students older than usual for grade. The school-level instructional condition latent variable was comprised of schools' total school enrollment, student-teacher ratio, the principal's years in the school, the percentage
expenditures for instruction, the percentage prime instructional time, number of professional development days per teacher, average teacher salary, percentage of teachers with advanced degrees, percentage of teachers with continuing contracts, and the percentage of returning teachers. Finally, the school-level student achievement dependent variable was represented using schools’ 2013 Elementary and Secondary Education Act (ESEA) waiver index score. The explanations of these variables are clarified in the definitions of terms section in this chapter and the structure of the latent variables is delineated in the hypotheses in chapter three.

Analysis Overview

SEM was conducted on the data. SEM is a causal modeling technique used to test the predictive and correlational relationships between independent and dependent latent variables (Vogt, 2005). Before the SEM was calculated, a Confirmatory Factor Analysis (CFA) was employed to test whether the latent variables identified in the model account for the variation in the associated independent variables. The analysis was employed in a three-stage process: a) tests of statistical assumptions and subsequent transformations, b) CFA, and c) SEM.

First, descriptive statistics were calculated on each variable to test the sufficiency of the dataset against relevant statistical assumptions. If the variables did not meet the assumptions, then the appropriate transformations were made. Next, CFA was used to test the appropriateness of the latent variables that are depicted in the new conceptual model. Finally, SEM was employed to assess the fit of the entire causal model. The conceptual model did not fit the data; therefore, exploratory procedures were employed to
improve the model, including the examination of modification indices, the direction of
the regression estimates, and the suitability of the latent variables illustrated in the model.
These attempts to improve the adapted conceptual model were made so the researcher
could reliably interpret the regression estimates.

Definitions of Terms

The following definitions are provided to clarify the terms that are used
throughout the study:

Adequacy – Adequacy is defined in the literature as the differential treatment of
students with different needs (Brimley, Verstegen, Garfield, 2012; Ladd, 2008).
Specifically, adequacy entails the sufficient deployment of resources to help all
students achieve at desired learning levels.

Conceptual Framework – A conceptual framework is the philosophical basis for
the research study. It “provides not a causal/analytical setting but, rather, an
interpretative approach to social reality” (Jabareen, 2009, p. 51). Whereas a
conceptual framework comprises of inter-related theories and perspectives, it
differs from a conceptual model, which includes variables and factors within a
causal setting (Jabareen, 2009).

Conceptual Model – A conceptual model is a visual “representation of how each
variable influences and/or is influenced by other variables” (Lunenburg & Irby,
2008, p. 123). The model includes a set of hypotheses and latent variables that are
to be tested by the researcher.
**Confirmatory Factor Analysis** – Confirmatory Factor Analysis (CFA) is an apriori statistical approach used to test a specified factor model (Brown, 2006). In particular, the statistic tests “the number and nature of latent variables that account for the variation and covariation among a set of observed measures” (p. 12). Furthermore, the statistic aims “to reproduce the observed relationships among a group of indicators with a smaller set of latent variables” (Brown, 2006, p. 14).

**Class Size** – In this study, the term class size reflects each school’s student-teacher ratio, which is calculated by dividing the total number of students by the total number of teachers in each school. Class size is also defined as the number of students per classroom (Tienken & Achilles, 2009).

**Educational Resources** – Educational resources refer to the personnel and material that is allocated by the state, school districts, or school personnel to affect the instructional program (Greene, Huerta, & Richards, 2007). These resources include, but are not limited to teachers, administrators, class size, technology, professional development, and per-pupil expenditures.

**ESEA Waiver Index Score** – A composite index used by the State Department of Education that comprises of weighted measures of achievement in English Language Arts (ELA), Mathematics, Science, and Social Studies.

**Equality of Opportunity** – Equality of opportunity is defined as the condition where all people have an equal chance to attain positions in society and that
people’s capacity to achieve their desired positions is not affected by their circumstances within the social system (Rawls, 1971).

**Justice** – Justice is sometimes defined as fairness (Rawls, 1971). The term is related to Rawls’ conception of equality of opportunity (i.e., justice is provided when equality of opportunity is achieved).

**Latent Variable** – A latent variable is an unobservable factor that influences multiple observed variables and accounts for the correlations among those variables (Brown, 2006). Moreover, “it is a construct…a theoretical entity inferred from a pattern of relations among observed variables” (Vogt, 2005, p. 313).

**Modification Indices** – Statistics used to identify areas of misfit within CFAs and SEMs. These evaluative statistics focus on diagnosing misspecifications in the model to be corrected by the researcher (Brown, 2006).

**Observed Variable** – As opposed to a latent variable, an observed variable is an indicator that is quantified or measured by the researcher. For example, scores on an achievement test, responses to a survey, and observation scores constitute an observed variable (Byrne, 2012).

**Percentage of Prime Instructional Time** – Amount of time spent on instruction for academic content that is tested on the state accountability assessment.

**Percentage of Teachers with Continuing Contracts** – The percentage of teachers in each school that have successfully completed their pre-probationary contract.
**Poverty Index** – A school-level measure that is based on Free/Reduced Lunch (FRL) data Medicaid eligibility data.

**Principal Characteristics** – Quantifiable measures that comprise of principals’ characteristics. In this study, principal characteristics is defined as the number of administrative years of experience.

**Student Achievement** – For this study, student achievement is defined using students’ performance as measured by state standardized examinations in reading and mathematics. This is consistent with the majority of research studies that examine the effects of educational resources on student achievement (Greene, Huerta, & Richards, 2007).

**Structural Equation Modeling (SEM)** – A statistical approach to analyze complex causal models using latent variables and observed variables. The approach uses illustrations to better conceptualize the theory under investigation (Byrne, 2012).

**Teacher Characteristics** – Quantifiable measures that comprise of teachers’ characteristics. In this study, a teacher characteristic is measured by teacher salary and, which is determined by teachers’ years of experience. In addition, teacher characteristics is measured using each schools’ percentage of teachers with advanced degrees.

**Teacher Quality** – Teacher quality refers to the quality of the teaching staff in each school. Researchers often measure teacher quality using education attainment, years of teaching experience, and teacher certification as variables.
Limitations and Delimitations

Though the present study seeks to advance the scholarship on the effects of educational resources on student achievement, the selected research design and method had several limitations. First, the validity of the findings was contingent on accessibility to data. For instance, the available data for this study was limited because it was from a single school year and could not account for growth in learning over time. Another limitation to the proposed research design was maturation. Maturation posits that people develop and grow at separate times (Shadish & Luellen, 2006). Although the proposed variables for this study have been used in previous research, scholars recognized that those variables were limited in their ability to accurately measure the phenomena under investigation. The limitations of these variables are clarified in chapters two and three.

The present study is also limited due to the quantitative nature of the research design and method. Because this study served as an attempt to extrapolate the effects of educational resources on student achievement, insufficient variables that measured the educational interaction between teachers and students were included in the analysis (i.e., teachers’ salaries as a proxy for teacher quality). According to Okpala (2002), these variables measure schools’ instructional conditions which then affect students’ academic achievement. However, these variables are distant from the interaction between teachers and students because they are not based on observations of variations in actual teaching and learning. In addition, other factors, such as school climate, have been shown to
facilitate increases in student learning; this study did not include every variable that significantly affects student achievement due to data accessibility. Therefore, this study was limited in its ability to truly uncover definite effects of resources on student achievement.

Delimitations also affected the scope and generalizability of the study. Data was collected from elementary schools that tested grades three through five within one state. Therefore, the findings from this study are only generalizable to those elementary schools within the state. This delimitation was chosen for two reasons. First, elementary schools that tested only grades three through five were selected in order to maintain a uniform sample with comparable scores for the dependent variable. Some elementary schools in the state include sixth grade, which could affect the schools’ ESEA waiver score. Therefore, by including schools that tested grades three through five, the effects of the independent variables on the dependent variable could be reliably estimated and compared to each other. Second, the study was limited to a single state to maintain consistency in the sample; every school in the state is influenced by the same policies that are created by the same policymakers in the state. Notwithstanding these delimitations, this study will provide reliable evidence on the effects of educational resources on students’ academic achievement for policymakers within the state to base strategic allocation decisions toward student learning goals.

Summary

Educational leaders and policymakers need evidence of the effects of educational resources on student achievement to strategically align resources with students’ learning
needs. This chapter introduced the significance of the study, guiding conceptual framework, methodology that will be used to discern the effects of school-level variables on elementary students’ academic achievement, and the limitations and delimitations associated with the selected methodology. Further details on the literature and methods relevant to the study are provided in chapters two and three.
CHAPTER TWO
REVIEW OF LITERATURE

School finance researchers study a range of topics, including taxation, state finance systems, litigation, district and school budgeting, and theoretical concepts like equity and adequacy. Though these topics are interrelated and deserving of scholarly attention, the present study is primarily concerned with advancing research on the relationship between educational resources and students’ academic achievement. In particular, this study attempts to discern the effects of school-level resources on elementary school students’ academic achievement. Research investigating the relationship between educational resources and student achievement garnered substantial attention from the 1960s into the early 2000s, fueling scholarly and political debates. Yet, findings of these research studies remain mixed due to variations in research designs, limitations of statistical approaches, and data accessibility. With the increase of education policies centered on improving students’ academic achievement toward proficiency goals, the ability of researchers to confidently define the relationship between educational resources and student achievement becomes even more important. Recent developments in applied statistics have given researchers the tools to extrapolate more precise estimates in their statistical models. Thus, findings from this study may provide policymakers and educational leaders with considerable evidence to align resource allocation decisions with student learning goals.
Overview of the Chapter

This chapter is divided into three sections: a) conceptual framework, b) the convergence of standards and accountability policies with school finance litigation, and c) the relationship between educational resources and student achievement. The conceptual framework provides the philosophical lens for this study. Kilbourn (2006) stated that “A fundamental assumption for any academic research is that the phenomena that we wish to understand are filtered through a point of view…there is no such thing as a value-free or unbiased or correct interpretation of an event” (p. 545). Researchers’ perspectives not only influence how they analyze and interpret the data, but also how they frame the study, make sense of relevant literature, and connect the literature to the findings of this study to convey meaning.

Literature related to the convergence of education accountability policies and school finance litigation as well as the relationship between educational resources and student achievement were synthesized and critiqued for the study. Scholars argued that state education finance systems should be aligned to accountability standards and student learning goals (Adams, 2008; Ryan, 2008; Superfine, 2009; Verstegen, 2002). Therefore, conclusive evidence of the effects of educational resources on student achievement is needed to strategically allocate educational resources to ensure equality of educational opportunities for all students. Given the mixed results in the literature on the relationship between educational resources and student achievement, further inquiry is needed on the methods, variable selection, and conclusions of these studies to advance future research on the topic. The review of the literature yielded gaps in research that support the need
for further investigation of the effects of educational resources on students’ academic achievement. Attention to these gaps may yield more conclusive evidence to influence the practices of educational policymakers and leaders to improve educational opportunities for all students.

**Method for Literature Review**

According to Boote and Beile (2005), quality dissertation literature reviews include purposeful justifications for inclusion of research in the analysis. Justification of criteria for the inclusion of literature ensures that the researcher “thoroughly mined the existing literature and purposefully decided what to review” (p. 7). For the present study, peer-reviewed journal articles, published books and book chapters, and research reports that have been influential in research and policy were included in the review. Literature was extracted from databases including Google Scholar, Education Research Complete, Education Resources Information Center (ERIC), JSTOR Arts & Sciences X Archive Collection, and EconLit. Specific peer-reviewed journals such as *Journal of Education Finance, Educational Policy, Education Policy Analysis Archives, Peabody Journal of Education, and Education Finance and Policy* were searched for literature related to the study. Articles from the *Journal of Education Finance*’s 1994 special edition titled, “Further Evidence on Why and How Money Matters in Education” was particularly useful. Finally, relevant published books and book chapters were included in the review.

**Conceptual Framework**

In *A Theory of Justice* (1971), Rawls articulated a philosophical theory of how a democratic society should arrange its social and economic institutions to ensure justice
and opportunity for all individuals while preserving those citizens’ basic rights and liberties. In order to convey the principles of his theory of justice, Rawls conducted a hypothetical thought experiment. Through this experiment, Rawls sought answers to the question: If people were to be placed behind a veil of ignorance with no knowledge of their standing in society, what principles of justice would be agreed upon by those people? The purpose of the experiment was to derive a working framework of justice from an original position of equality.

Rawls (1971) argued that people would agree on two basic principles of justice independent of their own personal interests or comprehensive worldviews: a) “each person is to have an equal right to the most extensive total system of equal basic liberties compatible with a similar system of liberty for all” and b) “social and economic inequalities are to be arranged so that they are both (a) to the greatest benefit of the least advantaged…and (b) attached to offices and positions open to all under conditions of fair equality of opportunity” (p. 302). In essence, Rawls’ principles of justice were founded under the assumption that all human beings are equally valuable and entitled to the same basic rights and standards of self-worth. Furthermore, Rawls recognized that inequalities exist and perpetuate naturally in society; however, inequalities that are caused by social and economic institutions are deemed unjust. In addition, behind the veil of ignorance, society would agree to arrange social and economic structures to correct for inequalities by favoring the least advantaged.

Though Rawls’ conception of justice permits natural inequalities, his principles rely on the realization of equality of opportunity in society. Rawls hypothesized that fair
equality of opportunity would provide all people an equal chance to attain positions in society and guarantee that people’s circumstances within the social system would not affect their capacity to achieve their desired positions. Rawls postulated that if equality of opportunity in society was achieved, then the reason people would not attain their desired positions would be due to their differences in individual willingness, motivation, and physical and mental natural talents.

In order to clarify his conception of fair equality of opportunity, Rawls (1971) applied the standard of pure procedural justice, stating, “there is a correct or fair procedure such that the outcome is likewise correct or fair, whatever it is, provided that the procedure has been properly followed” (p. 86). That is, society must establish procedures for the treatment of individuals and for the distribution of opportunities so that if followed correctly, the outcomes produced will be fair. In addition, Rawls identified the concept of redress as necessary to ensure fair equality of opportunity for all individuals to help the least advantaged (Freeman, 2007). Rawls (1971) used education as an example of redress, stating that “greater resources might be spent on the education of the less rather than the more intelligent, at least over a certain time of life” and that “the difference principle would allocate resources in education…to improve the long-term expectation of the least favored” (p. 101).

Rawls’ conception of a just society is conditioned on the notion that economic and social structures are arranged so that all citizens are provided with similar opportunities to achieve specified goals and that those who are least favored are provided with enhanced opportunities to enable them to compete fairly within those structures.
When applied to education, Rawls’ notion of equality of opportunity posits that despite various cognitive, social, or cultural backgrounds children come from, they all must have an equal opportunity to pursue a quality education. The concept of pure procedural justice would imply that inequalities in student outcomes are permissible as long as the procedures for educating the students were fair. Furthermore, a just education system would be one that ensures an adequate level of resources for all students to be successful. This would require the education system to level all aspects of the schooling process for which students encounter, including but not limited to the quality of classroom teachers and administrators, the access that students have to curriculum materials, and the nutritional quality of food that is served to students during school hours. The achievement of pure procedural justice would ensure equal educational opportunities for all students.

**Interpretations of Equality of Opportunity**

Equality of opportunity is a dynamic concept consisting of varying interpretations and practical implications. Scholars other than Rawls have spent considerable time formulating definitions and frameworks to conceptualize equality of opportunity. Isbister (2001) made the distinction between two competing interpretations of equality that conflict in principle. On one hand, equality of opportunity posits that all people begin at a level playing field in pursuit of their goals; unequal outcomes are permissible as long as similar opportunities were provided to all people. Equality of outcomes, on the other hand, requires that the results for all people be equal. Isbister articulated the unfeasibility for notions of equality of opportunity and equality of outcomes to coexist:
“if our opportunities are equal, then because some are more skilled or energetic than others, we will necessarily garner different results. If results are to be equal, people will have to be given different opportunities, to compensate for their differences in characteristics (p. 8).

Policy decisions and efforts to improve equality of opportunity and advance social justice must be made in light of conceptions of equality of opportunity and equality of outcomes. If policymakers are to communicate equality as an achievable goal of education, then one of Isbister’s (2001) interpretations of equality must take precedent.

Similar to Rawls’ (1971) conceptualization of pure procedural justice, Betts and Roemer (2005) provided a framework for analyzing the degree to which equality of educational opportunity is met. The author’s framework is comprised of five components: a) circumstances, b) type, c) effort, d) objective, and e) instrument. Typically, in education policy, students are often grouped into types based on their particular circumstances. The instrument is the specific policy intervention that is implemented to achieve the objective of equality of opportunity. The motivation and willingness on behalf of the students constitutes effort as long as those students’ circumstances are accounted for in the instrument. A particular benefit of a calculable interpretation of equality of opportunity, like Betts’ and Roemer’s (2005) framework and Rawls’ (1971) pure procedural justice, is that they provide a structured model to interpret whether opportunity was provided to meet the specific objective. These frameworks may be applied to model how the structures of the education system may be arranged to achieve equality of opportunity.
Adequacy: Achieving Equality of Opportunity in Education Finance

Rawls’ (1971) conception of justice and scholars’ interpretations of equality of opportunity are applicable to education finance and policy. The concept of adequacy is inherent in an ideal education system that achieves equality of educational opportunity toward specific student learning goals. An adequate education system is one that provides the appropriate amount and type of resources and services so that all students have equal opportunities to achieve their learning goals. Many scholars have provided in-depth definitions of adequacy that vary in degree of complexity (Alexander, 2004; Baker, 2005; King, Swanson, & Sweetland, 2005; Ladd, 2008; Verstegen, 2002). Ladd (2008) noted that adequacy requires the differential treatment of students with different needs. In addition, she argued that adequacy also entails sufficiency of resources to meet the learning needs of all students. Adequacy has also been characterized as vertical equity in the ideal (King, Swanson, & Sweetland, 2005); schools with larger percentages of students who require differential services should receive sufficient funding in order to teach those students at high levels (Toutkoushian & Michael, 2007).

Alexander (2004) created a conceptual map for understanding the definition of adequacy that is slightly different than previous conceptions suggested by Ladd (2008), King, Swanson, and Sweetland (2005), and Toutkoushian and Michael (2007). The author discussed how the current education finance landscape has moved away from traditional notions of equity and is now identifying the relationships between resources and the different phases of the schooling process. Adequacy, then, represents a change in thinking with regard to the appropriate financing of schools and includes three
components: adequacy of inputs, process, and outputs. Not only must an adequate overall funding for education be inputted into the school system, but adequacy also requires the appropriate type and amount of resources in order to create sufficient classroom conditions to enable all students to learn.

Similar to Alexander’s (2004) conception of adequacy, Baker’s (2005) conception of the term is multidimensional, deriving from principles of economic theory. Baker noted that educational adequacy consists of two components: absolute standards of adequacy and relative standards of adequacy. Whereas absolute standards of adequacy are concerned with the overall level of funding for education, relative standards of adequacy focus on “the differences in costs of achieving outcomes for children with different educational needs or children learning in different educational contexts” (Baker, 2005, p. 259). In particular, the author was concerned with measuring additional costs associated with providing an adequate education to students situated in varying social and economic contexts. Six theoretical assumptions were presented to conceptualize the varying shape of educational adequacy.

First, Baker (2005) noted that the basic cost of an adequate education varies depending on the difficulty of achieving the desired outcomes. Second, the cost varies by district scale. That is, the cost of providing students with an adequate education is contingent on the enrollment size of the school districts. Third, the costs of achieving the desired outcomes vary by the intensity of student needs. Fourth, the cost of providing an adequate education to students varies depending on the prices districts pay for comparable resources. For instance, the cost of an adequate education may increase for
rural school districts that must exert significantly more resources to recruit and retain high quality teachers. Fifth, district scale, student needs, and varying resource costs interact multiplicatively. In other words, higher concentrations of need will increase the cost of an adequate education. Finally, the costs of achieving desired outcomes increase as performance standards increase, and vice versa. That is, the cost of achieving outcomes with increasing standards exponentially increases when situated in higher needs contexts.

The concept of educational adequacy is contingent on the type, amount, and intensity of resources that are needed to provide the necessary instructional conditions and opportunities for all students to achieve at high levels. Furthermore, Alexander (2004) and Baker (2005) both recognized that adequacy is also influenced by the type and difficulty of outcomes that are determined for the students. The shape of educational adequacy, then, may be directly influenced by the goals of education accountability policies established at the federal, state, and district levels.

The Convergence of Standards and Accountability Policies with School Finance Litigation

The current educational system remains dominated by state and federal accountability policies reliant on standards, testing, and strategic decisions to improve instructional practices and student learning (Goertz, 2005). The primary focus of these policies are to raise the academic achievement of all students, regardless of their particular backgrounds or circumstances, by requiring states to create academic standards and implement statewide testing systems to ensure that those students have attained the
necessary knowledge to participate in economic and political life in the United States (Kress, Zechmann, & Schmitten, 2011). Furthermore, states have passed policies mandating the employment of highly qualified teachers in core content areas to guarantee that all students have access to quality instructors (Wong & Nicotera, 2007). To some degree, education accountability policies are an approach to ensuring equality of educational opportunity for all students (Goertz, 2001; Weiss, Knapp, Hollweg & Burrill, 2001). By law, states must ensure that they are monitoring whether all students have access to well-defined content standards and high quality teachers to maintain similar conditions that are conducive to student learning.

The emergence of standards and accountability in education calls for a systematic rethinking about strategic choices to achieve desired student learning goals. According to Wong and Nicotera (2007), the logic behind states’ accountability systems is to “set high academic expectations and to focus our reform efforts and resources on improving instructional practices to raise student performance” (p. 13). This requires educational leaders and policymakers to utilize tools, such as focused teacher professional development, to facilitate the alignment of standards, instructional practices, and student outcomes:

The tools should be used through an iterative process where standards and results from assessments inform professional development activities and data-driven decisions at the same time that professional development and data-driven decisions work to improve alignment of the standards and the use of assessment results (Wong & Nicotera, 2007, p. 32)
The use of tools to merge educational accountability policies with the improvement of instructional practices and ultimately student learning includes designing assessments that accurately measure school quality to inform school improvement decisions. Indeed, the state and district levels of education maintain central roles in “providing technical assistance and resources to schools to support changes in instructional practices” (Wong & Nicotera, 2007, p. 30). O’Day (2002) noted that district and state accountability mechanisms are successful in changing school operations when relevant, accurate, and reliable information is given to leaders and policymakers on which they base strategic allocation decisions to foster student learning. Evidence detailing the effects of educational resources on student achievement may provide state and district policymakers with the tools to allocate resources that improve schools’ instructional conditions to foster enhanced student learning.

**The Linkage between Educational Accountability and School Finance**

Scholars have recognized that the ideas behind education accountability policies and school finance litigation are interwoven (Ryan, 2008; Superfine, 2009). These scholars have called for the alignment of accountability standards and education finance policy to meet state constitutional clauses that mandate an adequate education for all students. If the goal of current educational accountability policy is for all students to reach proficiency, then states must be in a position to provide adequate educational resources to ensure equal educational opportunities that meet the learning needs of all students. In particular, academic standards have been recognized as a reference point for
researchers and policymakers to determine the specific resources and costs of an adequate education.

Verstegen (2002) recognized that determining an adequate education requires the alignment of resources with academic achievement results, “With the national emphasis on teaching all students to high standards, new models of state finance systems are needed that align school funding more closely to standards based reform aimed at high outcomes for all children and youth” (p. 749). The linkage between accountability standards and education finance policy also has implications for school finance litigation. Ryan (2008) noted that the connection between standards and testing within school finance litigation has dominated the discourse in education law and policy, particularly in adequacy-based cases. Superfine (2009) echoed this sentiment by arguing that the evolution of school finance litigation from equity to adequacy has led to judicial interpretations of laws and evidence concerning standards, testing, and accountability.

Adams (2008) noted that a growing body of research has described a misalignment between resources and student learning. The author indicated that the connection between education finance and student learning tends to be lost at the district level because those dollars are translated into programs, services, and complex staff arrangements that are difficult to trace to individual student learning. Significant improvements in student achievement may be made by examining how education dollars are being used and then repurposing them toward research-based practices linked to improved student outcomes (Governors Education Symposium, 2011). Adams (2008) suggested that conventional finance systems should be repurposed to support student
performance by moving the decision making authority to the local level so that principals may apply principles of strategic management to align resources with intended learner outcomes.

States have begun implementing policies that merge accountability standards and school finance models. Kentucky’s landmark school finance case, *Rose v. Council for Better Education* (1989), marked the convergence of school finance, academic content standards, and accountability policy. The adequacy-based case resulted in the Kentucky Supreme Court determining that the state education system was unconstitutional and in need of a complete overhaul. The Kentucky Supreme Court required the legislature to fully fund education so that students could attain competencies in the state’s defined content areas, which would be measured by the state’s standardized exams.

In other adequacy-based school finance cases, plaintiffs have attempted to link state finance models with standards and accountability to discern whether an adequate education was provided to all students. For instance, plaintiffs in Colorado’s *Lobato v. State* (2009) argued that the constitutional mandate for a thorough and uniform education system was not met, stating that “the state violated the education clause by failing to provide sufficient funds to enable the school districts to satisfy both the content standards and performance objectives in the education reform legislation” (p. 8). The Colorado Supreme Court also noted that “education reform statutes with proficiency targets and content standards…may also be used to help evaluate the constitutionality of the legislature’s actions” (p. 15).
Also, North Carolina’s Supreme Court decision in *Leandro v. State* (1997) supported the linkage between state accountability and school finance policies. The court held that “standards adopted by the legislature are factors that may be considered on remand to the trial court for its determination as to whether any of the state's children are being denied their right to a sound basic education” (p. 4). Moreover, the court suggested that student performance results could be used to discern whether students are receiving an adequate education:

Another factor that may properly be considered in this determination is the level of performance of the children of the state and its various districts on standard achievement tests. In fact, such output measurements may be more reliable than measurements of input such as per-pupil funding or general educational funding provided by the state (p. 4).

Ohio has made efforts to link their school finance formula with state accountability policy. Under the 2009 Ohio Education Opportunity Act, the state finance formula was redesigned from a foundation program into an evidence-based model. The evidence-based formula costs out an adequate education for public schools by identifying successful programs that are linked to student achievement. Whereas the foundation program is premised on the traditional notion of equity, the evidence-based approach attempts to provide the specific and adequate resources to meet the needs of particular schools. Although the courts in Colorado, North Carolina, and Ohio have adopted the notion that student performance outcomes may be traced to resource allocation patterns within states, state education finance systems, except for Ohio’s adequacy model, remain
detached from specific student learning goals. Perhaps more research is required to discern the types, intensity, and combination of resources necessary to be allocated to meet state accountability goals.

**The Relationship between Educational Resources and Student Achievement**

The current educational accountability context necessitates accurate and reliable information for leaders and policymakers to guide strategic allocation decisions toward improved student learning. Within this context, school finance scholars have called for the realignment of state finance systems with standards-based education policy (Adams, 2008; Ryan, 2008; Superfine, 2009; Verstegen, 2002). In particular, scholars have argued that states ought to provide adequate educational resources to ensure equal educational opportunities that meet the learning needs of all students. Understanding the degree to which opportunity has been provided to all students requires a knowledge base of how educational resources affect student achievement.

Scholars have conducted a considerable amount of research investigating the effects of educational resources on student achievement. Most notably, researchers made significant efforts in publishing their studies within the “Does Money Matter?” debate, ranging from the 1980s into the late 1990s. Researchers who took part in the scholarly dialogue sought to provide evidence to answer the question: Do variations in educational resources significantly affect variations in student achievement? Researchers typically relied on production function or multiple regression methods to discern the estimated effects of resources on achievement. The conceptual models that guide these studies are based on the relationship between educational resources (inputs) and student performance.
outcomes (outputs). Figure 2.1 details the common conceptual model used by researchers within the does money matter debate.

Figure 2.1: Common Conceptual Model of the Relationship between Educational Resources and Student Performance Outcomes.

Inputs are comprised of student and community characteristics that typically are measured using independent variables such as household income, percentage of students qualifying for free/reduced lunch, and the educational attainment of the surrounding community. Process is comprised of the resource allocation decisions that directly affect the educational interactions between teachers and students. The independent variables often used to capture the educational process include measures of teacher quality, per-pupil expenditures, class size, and indicators of the use of technology. Furthermore, the
educational process is the particular interaction that researchers attempt to uncover in their statistical models. In the economics discipline, Coase (1991) referred to the process or interaction within an organization as the *black box*. In his Nobel Prize lecture, Coase stated that it is difficult to expose how “resources in a modern economic system are employed within firms, with how these resources are used dependent on administrative decisions” (para. 3). Outputs may be defined as “the result of the initial and continuing influences on individual student background as modified by the schooling process” (Greene, Huerta, & Richards, 2007, p. 53). The dependent variables typically used to measure educational productivity include student performance on standardized exams, graduation rates, and measures that indicate students’ practice of democratic citizenship. The research methods, findings, and critiques of studies that made use of this conceptual model along with similar models are summarized below. To situate these studies within the overall context of the present study, articles have been divided into two sections based on whether they found significant effects of educational resources on student achievement.

**Educational Resources Do Not Significantly Affect Student Achievement**

Much of the research on the effects of educational resources on student achievement was sparked by the findings from the 1966 seminal report headed by James S. Coleman, *Equality of Educational Opportunity*. Coleman et al.’s (1966) study was conducted to assess the progress of the Civil Rights Act of 1964 for the U. S. Department of Health, Education, and Welfare. Using production functions and subsequent descriptive statistics, Coleman and his colleagues reported that student, family, and peer
characteristics were more deterministic of students’ achievement than schools. As Alexander (1998) stated, Coleman’s findings promoted the notion that “the public schools themselves have little discernible value in enhancing student achievement, the most effective forces being those external to the public schools” (p. 239). Because of the political and social consequences and controversies associated with the findings of the report, research on the effects of resources/spending on student achievement increasingly became prevalent among scholars across the United States.

Hanushek conducted the most widely disseminated research on the topic (1981, 1989, 1991, 1996, 1997). Hanushek (1981, 1989, 1991) used vote counting methods to synthesize production function studies to estimate the effects of resources on student achievement. These studies primarily comprised of variables including expenditures per-pupil, teacher quality indicators, and student-teacher ratio measures and found that those resources had little effects in significantly predicting student achievement. Hanushek (1989) detailed the findings of 152 studies that examined the effects of educational resources on student achievement, finding “no strong evidence that teacher-student ratios, teacher education, or teacher experience have the expected positive effects on student achievement” (p. 47). Hanushek concluded that no conclusive evidence exists to support funding increases to education as a means to improve student performance.

Moreover, Hanushek (1997) updated his research using 377 studies, for which 96 or those studies use value-added modeling to control for student demographic characteristics. After analyzing teacher-pupil ratio, teacher education, salary, and experience, and per-pupil expenditures, he found that there was little evidence to support
increasing the amount and intensity of educational resources to promote student achievement. Okpala (2002) also conducted multiple production functions on a single district in North Carolina. The researcher examined the effects of school and student/family characteristics on fourth grade students’ reading and mathematics scores for three consecutive school years. The analysis yielded findings that students’ socioeconomic backgrounds were significant predictors of student achievement. In particular, the percentage of students on free or reduced lunch program ($\beta = -0.377$) and percentage of parents with post-high school education ($\beta = 0.35$) were consistently the strongest predictors of student achievement. Measurements of teacher quality, class size, and expenditures per-pupil were found to be insignificant predictors of student achievement.

**Educational Resources Do Significantly Affect Student Achievement**

In response to the research proclaiming that educational resources do not significantly affect student achievement, the *Journal of Education Finance* released a 1994 special edition titled, “Further Evidence on Why and How Money Matters in Education.” The edition featured methodological critiques on the research designs that had been used in studies that found non-significant relationships between resources and achievement (Fortune & O’Neil, 1994; Greenwald, Hedges, & Laine, 1994) and offered improved methods, showing significant relationships between educational resources and student achievement (Cooper et al., 1994; Fortune & O’Neil, 1994; Greenwald et al., 1994). Furthermore, other scholars have conducted complex studies and have found that
specific resources do have positive effects on variations in student achievement (Archibald, 2006; Ferguson, 1991; Krueger, 2002).

As a research team, Greenwald, Hedges, and Laine (Greenwald et al., 1994; Hedges, Laine, & Greenwald, 1994; Laine, Greenwald, & Hedges, 1996) conducted a series of studies examining the effects of educational resources on student achievement using Hanushek’s (1981, 1989, 1991) data. The researchers began their studies with critiques of Hanushek’s vote counting method. Vote counting is a meta-analysis procedure used to resolve contradictions among research studies (Light & Smith, 1971). In order to conduct the analysis, the researcher combines a set of research studies based on the particular topic and research questions, tabulates the number of significant findings and the number of non-significant findings, and then compares those categories to determine the overall significance. The category with the most results or votes is then deemed as a representation of the aggregate finding of all of the studies on a particular topic.

Greenwald et al. (1994) explained that Hanushek’s (1981, 1989, 1991) inclusion of certain studies in his meta-analysis was not justified or valid and that vote counting yields more conservative findings than other meta-analytic methods. After applying more stringent standards to the inclusion of studies from Hanushek’s data, the authors used a combined significance test meta-analysis method and found that resource inputs of teacher education and salary, administrative inputs, and teacher-pupil ratio have statistically reliable and positive relationships with student achievement. Using an effect
magnitude analysis, the authors concluded that a $500 increase in per-pupil expenditures would yield a .7 standard deviation increase in student achievement.

Fortune and O’Neil (1994) also critiqued Hanushek’s vote counting methods and used an alternative method to discern whether resources significantly affect student achievement. The researchers conducted t-tests on school districts in Missouri and Ohio using student achievement indicators as the dependent variable and per-pupil expenditures to group the districts into low and high spending districts. They found that school districts with higher per-pupil expenditures had significantly higher student achievement scores than school districts with low per-pupil expenditures. However, the researchers also concluded that using expenditures as inputs does not fully capture the instructional conditions of schools.

Cooper et al. (1994) noted that the majority of studies that attempt to estimate the effects of educational resources on student achievement relate inputs to outputs without an understanding of the variations in expenditures within schools and classrooms. Given these limitations, the researchers developed a micro-finance model to trace funds in New York City from the district to 84 high schools and ultimately their classrooms. Using the micro-finance model, the researchers were able to cluster groups based on their socioeconomic status and then include expenditures on instruction (their measure of classroom expenditures) and teachers’ years of experience in their multiple regression analysis. The researchers found that per-pupil dollars spent on direct instruction ($\beta = .18$) and teachers’ years of experience ($\beta = .11$) significantly affected academic achievement, as measured by high schools’ combined average math and verbal Scholastic Aptitude
Test (SAT) scores. Furthermore, the model explained 65% of the variance in school’s average SAT scores.

Ferguson (1991) examined the impact of schooling on student achievement using school districts in Texas and found that the differences in the quality of schooling, as measured by teacher quality, class size, and student characteristics, accounted for between one third and two thirds of the variation in students’ test scores. Using multiple regression techniques, the author found that teacher quality, as measured by teachers’ performances on a statewide recertification exam, explained between 20 and 25% of the variation across school districts’ test scores. In his conclusion, Ferguson suggested that money does matter when it is used on high quality teachers, particularly in schools with lower socioeconomic status.

Knoeppel, Verstegen, and Rinehart (2007) conducted a canonical analysis to discern the effects of school resources on student achievement. Whereas production functions estimate the effects of multiple independent variables on one dependent variable, a canonical analysis accommodates multiple independent variables and multiple dependent variables. The authors used a host of independent variables, including per-pupil expenditures, student-teacher ratio, days of school, average teacher salary, and a measure of local wealth. The dependent variables in the study included student performance on the Iowa Test of Basic Skills (ITBS), schools’ graduation rates, college plans, and voter participation. The analysis yielded average teacher salary ($\beta = .878$) and local wealth ($\beta = .349$) as the two inputs with the largest effects on student achievement.
The authors called for improved measurement of variables that affect student achievement at the classroom level, including teacher practices and the use of technology.

Scholars have also developed models to investigate the effects of single resources on student achievement. Most of the resources that have been examined include teacher quality and characteristics, class size, and school total enrollment. The quality of a school’s teachers have been found to significantly impact student learning outcomes (Archibald, 2006; Kane, Rockoff, & Staiger, 2008; Knoeppe, Verstegen, & Rinehart, 2007; Loeb, Kalogrides, & Béteille, 2012). Researchers often use education attainment, years of teaching experience, and teacher certification as measures of teacher quality. Darling-Hammond (2000) found that measures of teacher preparation are strong correlates of student achievement. Furthermore, Clotfelter, Ladd, and Vigdor (2007a, 2007b) found that teacher credentials, such as years of teaching experience and licensure test scores, systematically affect student achievement—years of teaching experience is associated with student achievement gains in the first two years of their profession. Furthermore, the researchers found that when teacher credentials was related to class size, an increase of five students in each classroom would decrease student achievement by .015-.025 standard deviations in math and .01-.02 standard deviations in reading. In addition to these findings, Rice (2013) synthesized the literature on the effects of teacher experience on student achievement, finding that early-career experience (i.e., two-to-three years of teaching experience) is associated with consistent, positive gains on elementary students’ academic achievement.
Recently, the Bill and Melinda Gates Foundation (2013) released its final report for the Measures of Effective Teaching (MET) Project. In an attempt to better describe teacher effectiveness, the researchers found that multiple measures, such as student achievement indicators from standardized tests, classroom observations by multiple observers (from within the school and from outside of the school), and student perception surveys that measure the learning environment, reliably predict effective classroom teachers. However, most researchers have not had access to schools and sufficient resources to be able to collect that much data. Though years of teaching experience and educational attainment have been found to not fully depict teacher quality, they serve as the best available indicators for which researchers have used in previous studies (Archibald, 2006).

Extensive research has been conducted on the effects of class size on student achievement (Krueger, 2002; Stiefel, Berne, Iatarola, & Fruchter, 2000; Tienken & Achilles, 2009). Though much of the research has highlighted a positive relationship between class size and student achievement, findings remain mixed (Finn & Achilles, 1990; Okpala, 2002). In particular, many studies have documented positive effects of class size reduction in grades K-3 (Blatchford, Bassett, Goldstein, & Martin, 2003; Finn, Gerber, & Boyd-Zaharis, 2005). Finn et al. (2005) examined the cumulative effects of class size reduction and found that students who were enrolled in smaller class sizes for three consecutive years were more likely to graduate from high school, even as class sizes increased in the upper grades. Moreover, Tienken and Achilles (2009) researched
class size effects in the middle grades and found a positive, significant relationship between class size reduction and writing examination scores.

On the other hand, scholars have argued that class size reduction is inefficient; there is not enough evidence to justify the large expenses for implementation (Hanushek & Rivkin, 1997). This is largely because measures of average class size have been known to obscure findings; a school’s average class size does not account for variations across grades and within the school itself (Rubenstein, Schwartz, Stiefel, & Zabel, 2009). In addition, definitions of class size vary, often between the numbers of actual students in a classroom to a school’s student-teacher ratio. Though findings regarding the effects of class size on student achievement remain mixed, the resource represents schools’ instructional conditions because it relates directly to the interactions between teachers and students (Okpala, 2002).

Though school enrollment sizes are difficult to change due to high costs (Rubenstein et al., 2009), research has documented evidence of positive effects on student achievement. Research detailing the effects of school sizes on student achievement is extensive, particularly because school reformers and policymakers have advocated for smaller school sizes as a means for creating effective schools (Stiefel et al., 2000). Andrews, Duncombe, and Yinger (2002) synthesized research on effective school enrollment numbers and found that high schools with 600 to 900 students maximized potential student performance gains. Furthermore, schools that enroll more than 1000 students begin experiencing decreased returns in terms of student achievement.
Critique of Research Methods

Since the 1960s, various researchers have employed quantitative methods to estimate the effects of educational resources on student achievement. Scholars have used methods that range from simple regressions and production functions to multivariate regression statistics (Verstegen & King, 1998). In addition, economists have informed the research on the relationship between resources and student achievement using economic efficiency frontiers like Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) (Rolle, 2005; Ruggeiro, 2001; Ruggeiro, 2007). Despite diverse attempts by scholars in education and economics disciplines to determine the effects of educational resources on student achievement, results remain mixed. Though the general narrative in education finance is that money matters when it is spent on resources that positively affect student achievement and “as long as the resources reach schools, classrooms, teachers and pupils” (Cooper et al., 1994, p. 86), scholars have yet to model a holistic depiction of the direct and indirect links between resources and achievement.

Monk (1990) described some of the limitations of production functions. The author found that production functions produce limited results, particularly because they can only account for a single dependent variable. Conceptually, production functions and other regression models are limited in their abilities to fully depict the effects of resources on student achievement because they account for the variations of student achievement using school and district-level variables. These variables do not measure variations at the classroom-level. Furthermore, researchers have had difficulties in attaining precise measurements of variables. For instance, Rivkin, Hanushek, and Kain (2005) attempted
to estimate the effects of teacher quality and class size on student achievement in Texas. They found that little variation in teacher quality was explained by experience and education; however, even when using experience and education as proxies for teacher quality, they found that teachers affected variations in student achievement more than class size.

Verstegen and King (1998) conducted a review of the literature on production functions used to discern the effects of educational resources on student achievement. Despite concluding that educational resources do significantly affect student achievement, the authors noted limitations of production function methods, stating, “Production equations are limited to the degree that they model only the quantitative contributions of resources while leaving aside more qualitative aspects of how resources are deployed in the classroom” (p. 261). Furthermore, the authors described four methodological approaches that could significantly improve production function research:

if (1) individual children and classrooms were the unit of observation rather than the school, district, or state (if other variables could be specified appropriately at that level); (2) if outputs were expressed in terms of progress or longitudinal growth instead of achievement at one point in time; (3) if resources were identified as those available to a specific child rather than by average resources in a classroom, school or district; and (4) if processes were to include the quality, content, and intensity of student-teacher interactions and time on task (p. 259).
Given these methodological limitations to capturing the deployment of resources in classrooms and their effects on student achievement, Greene et al. (2007) suggested using the actual instructional resources that are purchased with educational dollars rather than expenditure amounts as independent variables to accurately depict their effects on student achievement. The use of actual instructional resources as variables would result in a more accurate depiction of the educational interactions between teachers and students. Cohen, Raudenbush, and Loewenberg Ball (2003) argued "for a model in which the key causal agents are situated in instruction; achievement is their outcome. Conventional resources can enable or constrain the causal agents in instruction, thus moderating their impact on student achievement." (p. 119). The current use of production functions cannot account for moderating variables, such as resources (e.g., class size) that enable causal agents (e.g., teachers) to improve student achievement.

Moreover, whereas production functions assume a direct effect of a combination of independent variables on a single dependent variable, the use of Structural Equation Modeling (SEM) allows the researcher to describe direct and indirect links between independent and dependent variables. SEM allows for particular independent and dependent variables that are similar to be combined into single latent factors using confirmatory factor analysis (Heck & Thomas, 2009; Hox, 2010). Conceptually, the use of latent factors better represents the theoretical models used to discern the effects of educational resources on student performance. For example, production functions typically make use of “vectors” of similar variables that describe teacher and school characteristics. Whereas the use of similar independent variables to measure a single
construct may violate multicollinearity, SEM accounts for those multiple variables by mending them into one single latent factor. Another example is that student performance in reading and mathematics tend to be treated as two separate variables; however, SEM allows for those variables to be combined into a single holistic measure of student achievement. Once combined, the latent factor of student achievement is regressed on the independent variables.

Figure 2.2: Okpala’s (2002) Conceptual Model of the Impact of Educational Resources on Student Achievement.

In particular, Okpala’s (2002) conceptual model of the impact of educational resources on student achievement serves as an appropriate model to adapt to include latent variables. Okpala’s model makes use of the latent variables school characteristics,
teacher characteristics, student/family characteristics, quality of instruction, and student achievement (see Figure 2.2); however, the methods used in her study do not test whether those latent variables are sufficient. SEM can be used to test whether these latent variables are comprised of the variables within the model. For example, SEM allows the researcher to test whether the latent variable school characteristics is comprised of the observed variables fourth grade class size and school size. The new conceptual model of the effects of educational resources on student achievement is shown in Figure 2.3. This model consisted of many of the observed and latent variables that are used in Okpala’s model—the observed variables that predict Okpala’s latent variable titled, quality of instruction, has been included in the new latent variable titled, instructional condition. This model served as the basis for the present study.
Though researchers (Okpala, 2002; Verstegen & King, 1998) have noted the importance of studying variables at the school and classroom-levels to precisely estimate the effects of educational resources on student achievement, few studies have been able to do so. Archibald (2006) conducted a Hierarchical Linear Model (HLM) to investigate the effects of educational resources on student achievement using school, classroom, and student-level data. The author found that student socioeconomic status accounted for most of the variation in student achievement. Additionally, teacher quality was found to be a significant predictor at the classroom level and the school-level. The author measured teacher quality using teacher evaluation scores and educational attainment.
However, much like other forms of production frontiers, HLM cannot make use of latent variables and accounts for a single dependent variable, which may be limited according to some researchers (Fortune & O’Neil, 1994).

**Summary**

Current accountability policies mandate that all students achieve at levels of academic proficiency. Policymakers and educational leaders need substantial evidence to support resource allocation decisions to increase student achievement to meet state and federal accountability policies. Furthermore, an adequate deployment of educational resources is needed in schools to provide sufficient instructional conditions and opportunities for all students to achieve proficiency. Given the demand for the alignment of accountability and school finance resource allocation, a deeper knowledge base is required to discern the effects of educational resources on student achievement. Though scholars have made attempts to estimate the effects of resources on student achievement, findings remain mixed. Thus, further research examining the effects of educational resources on student achievement is needed to fill the gap in research to improve educational practices. Whereas traditional production functions utilize independent variables and not latent variables that are situated at either the school-level or district-level, structural equation modeling may suffice as a method that better accounts for variations in student learning by including latent variables.
CHAPTER THREE

METHODS

The present study used Structural Equation Modeling (SEM) to estimate the effects of school-level resources on elementary school students’ academic achievement. In particular, this study sought to answer the following questions: a) Is the new conceptual model of the effects of educational resources on student achievement a good model fit using elementary school data from South Carolina, and b) What are the estimated effects of the educational resources on students’ academic achievement and how can the findings be used to inform resource allocation practices to meet educational adequacy? The first question is methodological in nature and will require various statistical procedures to test if the conceptual model fits the data. The conceptual model under investigation is shown in Figure 3.1; the latent variables and regression effects were estimated in the present study. The second question is dependent on the results of question one. If the conceptual model fits the data or can be modified to fit the data, then the estimated effects of the independent variables on student achievement will be described using the model.
This chapter presents the research hypotheses, description of the sample, data collection process, and the variables used in the analysis. The data analysis procedures are then described, including tests to determine the adequacy of the dataset, Confirmatory Factor Analysis (CFA), and SEM. Finally, the limitations and delimitations of the study are presented, particularly in relation to the difficulties involved with uncovering the effects of educational resources on students’ academic achievement from a quantitative and macro framework.
Research Hypotheses

The first research question, is the new conceptual model of the effects of educational resources on student achievement a good model fit using elementary school data from South Carolina, was a priori in nature. Due to the confirmatory approach of this study, hypothesis testing was required to examine the research questions, particularly when using CFA and SEM (Byrne, 2012). The following research hypotheses were tested in relation to figure 3.1:

$H_1$: The latent variable, instructional condition, as comprised of schools' total school enrollment, student-teacher ratio, the principal's years in the school, the percentage expenditures for instruction, the percentage prime instructional time, number of professional development days per teacher, average teacher salary, percentage of teachers with advanced degrees, percentage of teachers with continuing contracts, and the percentage of returning teachers, will fit the data.

$H_2$: The latent variable, student characteristics, as comprised of schools’ poverty indices, percentage of students with disabilities other than speech, percentage of students eligible for gifted and talented, percentage of students retained, and the percentage of students older than usual for grade, will fit the data.

$H_3$: The latent variable, student characteristics, will directly and significantly predict the instructional condition latent variable and student achievement dependent variable.

$H_4$: The latent variable, instructional condition, will directly and significantly predict the dependent variable, student achievement.
The second research question, what are the estimated effects of the educational resources on students’ academic achievement and how can the findings be used to inform resource allocation practices to meet educational adequacy, was dependent on the results of the previous hypotheses. Because the conceptual model was modified to fit the data, the estimated effects of the educational resources on student achievement were reported using the model. The procedures to answer the second research question are described later in this chapter.

Data Collection and Sample

The present study was conducted using data from elementary schools in a state located in the southeastern United States. The state consists of 81 public school districts. During the 2012-2013 school year, the state was comprised of over 650 public elementary schools, over 300 public middle schools, and over 215 public high schools. During the 2012-2013 school year, 239 of those schools were designated as Title I schools (South Carolina Department of Education, 2013a). Table 3.1 details the student and teacher descriptors for the state for the 2012-2013 school year. The state was relatively diverse, comprising of over 765,000 students with the highest proportion of students being Black or African American and White (South Carolina Department of Education, 2013a). The elementary schools’ poverty indices ranged from 10.40 to 100, with 68% of the elementary schools having a poverty index over 70. In addition, about 3.6% of the students were designated with Limited English Proficiency (LEP) and over 12% of the students received disabilities services. The state employed over 47,000
teachers for the 2011-2012 school year. Of those teachers, about 57% have greater than 10 years of teaching experience.

Table 3.1. Student and Teacher Descriptors for the State during the 2012-2013 School Year.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Student Descriptors</strong></td>
<td></td>
</tr>
<tr>
<td>% American Indian/Alaskan Native</td>
<td>2.3</td>
</tr>
<tr>
<td>% Asian</td>
<td>1.5</td>
</tr>
<tr>
<td>% Hispanic/Latino</td>
<td>7.2</td>
</tr>
<tr>
<td>% Black or African American</td>
<td>35.5</td>
</tr>
<tr>
<td>% White</td>
<td>57.0</td>
</tr>
<tr>
<td>% Pacific Islander</td>
<td>0.3</td>
</tr>
<tr>
<td>% Multi-Race</td>
<td>3.1</td>
</tr>
<tr>
<td>% Free/Reduced Lunch</td>
<td>58.6</td>
</tr>
<tr>
<td>% Individualized Education Plan</td>
<td>12.2</td>
</tr>
<tr>
<td>% Limited English Proficiency</td>
<td>3.6</td>
</tr>
<tr>
<td><strong>Teacher Descriptors</strong></td>
<td></td>
</tr>
<tr>
<td>Number of Teachers</td>
<td>47,893</td>
</tr>
<tr>
<td>% teachers with &gt; 10 Years of Experience</td>
<td>57.2</td>
</tr>
</tbody>
</table>

Existing data for the 2012-2013 school year was obtained from the state’s Department of Education website. In particular, data was collected from published files including data that was used for elementary schools’ report cards. The initial sample of elementary school districts was over 650; however, that was reduced to 470 in order to maintain some form of uniformity in the sample. Only elementary schools that tested grades three through five were included in the study.
Variables

Various school-level independent variables were used to model and predict the effects of educational resources on student achievement. Consistent with Okpala’s (2002) conceptual model, data included the latent variable, student characteristics, which was comprised of the poverty index, the percentage of students with disabilities other than speech, the percentage of students eligible for gifted and talented, the percentage of students retained, and the percentage of students older than usual for grade. In addition, the data included a second latent variable, instructional condition, comprised of the schools' total school enrollment, student-teacher ratio, the principal's years in the school, the percentage expenditures for instruction, the percentage prime instructional time, number of professional development days per teacher, average teacher salary, percentage of teachers with advanced degrees, percentage of teachers with continuing contracts, and the percentage of returning teachers. The principal’s number of years in the school variable has not been used in previous studies; it served as a proxy for leadership experience. The quality of leadership in schools has been shown to indirectly affect school working conditions, which affects the quality of teaching and learning (Louis, Leithwood, Wahlstrom, & Anderson, 2010).

The student achievement dependent variable was the State’s 2013 Elementary and Secondary Education Act (ESEA) Waiver Index score, which is a composite index score that is calculated for each public school in the state (South Carolina Department of Education, 2013b). The score is comprised of multiple achievement indicators from the state’s standardized tests. In particular, the index score includes weighted measures of
achievement in English Language Arts (ELA), Mathematics, Science, and Social Studies.

In addition, the score is weighted by the percentage of students tested on the assessments. Possible scores range from zero to 100; based on the scores, schools are assigned a grade. Table 3.2 displays the grading scale along with the description for each grade.

Table 3.2. ESEA Waiver Index Score and Grading Scale

<table>
<thead>
<tr>
<th>Weighted Index Score</th>
<th>Grade</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>90-100</td>
<td>A</td>
<td>Performance substantially exceeds the state’s expectations</td>
</tr>
<tr>
<td>80-89.9</td>
<td>B</td>
<td>Performance exceeds the state’s expectations.</td>
</tr>
<tr>
<td>70-79.9</td>
<td>C</td>
<td>Performance meets the state’s expectations.</td>
</tr>
<tr>
<td>60-69.9</td>
<td>D</td>
<td>Performance does not meet the state’s expectations.</td>
</tr>
<tr>
<td>Below 60</td>
<td>F</td>
<td>Performance is substantially below the state’s expectations.</td>
</tr>
</tbody>
</table>

1Table adapted from the South Carolina Department of Education (2013b)

Data Analysis Procedures

The present study advances scholarship on the effects of educational resources on student achievement by using SEM. Whereas past researchers have had to analyze the effects of educational resources on student achievement using multivariate techniques, such as multiple regressions, structural equation modeling allows for the researchers to combine similar independent variables into constructs and test the relationship between each construct and student achievement.

For the present study, data analysis will consist of a three-stage process: a) tests of statistical assumptions and subsequent transformations, b) CFA, and c) SEM. The data analysis process can be used to help researchers determine if the data is adequate to
conduct the CFA and SEM. Furthermore, the use of CFA and SEM allows the researcher to test if the new conceptual model is a good model fit. If the model does not fit the data, then the CFA and SEM statistics provide exploratory, *a posteriori*, suggestions to improve the model. Once the model fits the data, the effects of the independent variables on the dependent variables can be estimated in a reliable manner.

**Tests of Statistical Assumptions**

First, data were entered into the Statistical Package for the Social Sciences (SPSS) version 21 to calculate descriptive statistics on assumptions relevant to CFA and SEM. The statistical assumptions that are pertinent to CFA and SEM are multivariate normality, linearity, and multicollinearity (Vogt, 2007). Multivariate normality “refers to the extent to which all observations in the sample for all combinations of variables are distributed normally” (Mertler & Vannata, 2010, p. 30). This assumption will be assessed by evaluating skewness and kurtosis for each variable as well as statistical tests of multivariate normality. If the data violates the assumption of normality, the appropriate transformations are conducted based on the degree to which the distributions are not normal, as suggested by Mertler and Vannata (2010).

The assumption of linearity posits that a straight-line relationship exists between the independent and dependent variables. Linearity is assessed by evaluating the shape of the scatteplots within the scatterplot matrices. According to Mertler and Vannata (2010), the shape of the scatterplots should be elliptical. The third assumption, multicollinearity, cannot be tested on data for measurement models. Though software does not assess multicollinearity for SEM, researchers have assessed the correlations between latent
variables to determine if the assumption has been violated. If the correlation is approaching the value of one, multicollinearity may exist (Muthén & Muthén, 2012). If multicollinearity appears to be problematic during the analysis of the model, variables that appear to be causing multicollinearity should be removed from the analysis.

In addition to the basic statistical assumptions essential for complex statistical methods, data must be arranged so that the variances of the variables are reasonably homogenous. According to Brown (2006), statistical packages, like Mplus, require “that the indicators submitted to the latent variable analysis be kept on a similar scale” (p. 89). If the observed variables are not kept on a comparable scale, there will be a decreased likelihood of finding a good model fit for each latent variable. Grand mean centering is a viable approach that will rescale each observed variable. Furthermore, grand mean centering reduces the likelihood of multicollinearity (Heck & Thomas, 2009). Grand mean centering should be employed before the CFA.

**CFA and SEM**

Once the relevant statistical assumptions are met, the CFA and SEM can be calculated using Mplus statistical software. Mplus is a statistical modeling program that has the capacity to calculate CFA and SEM using latent variables with missing data (Muthén & Muthén, 2012). CFA is an a priori modeling technique that allows the researcher to test the underlying structure of latent variables. A latent variable “is a construct…a theoretical entity inferred from a pattern of relations among observed variables” (Vogt, 2005, p. 313). Whereas observed variables can be measured, latent variables are non-measurable factors that comprise of multiple observable variables. CFA
tests whether theoretical latent variables, indeed, account for the correlations of the multiple observed variables (Brown, 2006).

Before the CFA or SEM is conducted, the model must be determined to be testable using model identification standards (Byrne, 2012). Model identification refers to whether there is a sufficient number of degrees of freedom in the model, thus, helping the researcher determine “whether or not there is a unique set of parameters consistent with the data” (Byrne, 2012, p. 32). If the model is overidentified, meaning that the number of parameters in the model is less than the number of sample moments, the model is sufficient.

The CFA should be conducted on the new conceptual model before the SEM is calculated. In particular, a Maximum Likelihood (ML) estimation should be undertaken to test the fit of the hypothesized model. ML is appropriate when the variables in the model approximate normality. If the variables are non-normal, a robust maximum likelihood (MLR) estimator should be used to test the model fit (Byrne, 2012). In addition, goodness-of-fit indices, such as the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean square Residual (SRMR), should be used to evaluate whether the model fits the data. Brown (2006) offered guidelines for interpreting these goodness-of-fit indices. He noted that comprehensive evaluations of cutoff criteria for these indices found that adequate model fit is “obtained in instances where (1) SRMR values are close to .08 or below; (2) RMSEA values are close to .06 or below; and (3) CFI and TLI values are close to .95 or greater” (p. 87). However, Brown did note that other scholars have found that
CFI and TLI values between .90 and .95 reflect an adequate model fit. If the latent variables in the model do not fit the data, an exploratory approach is undertaken to improve the model. This is completed by examining the modification indices that are provided in the statistical software, questioning theoretical assumptions, making changes to the model, and testing the model for sufficiency.

After the latent variables have been proven to fit the data, the SEM can be employed to test the overall fit of the conceptual model. SEM is a “sophisticated statistical method for testing complex causal models in which the dependent and independent variables are latent” (Vogt, 2005, p. 313). Because SEM requires an a priori approach to statistical testing, it lends itself well to the analysis of data for inferential purposes (Byrne, 2012). The method is comprised of two aspects that together set it apart from other causal modeling techniques. First, the causal process under examination is represented by a series of regression equations that are simultaneously conducted by the researcher. Second, the regression equations “can be modeled pictorially to enable a clearer conceptualization of the theory under study” (Byrne, 2012, p. 3). In addition to the foundational aspects of SEM, the statistical approach accounts for a multitude of characteristics essential to causal modeling, including endogenous and exogenous variables, recursive and non-recursive models, and reflective and formative models. These aspects allow the researcher to test complex causal models that otherwise cannot be calculated using regression methods or other multivariate techniques (Byrne, 2012).

Causal models are comprised of endogenous and exogenous latent variables. Endogenous variables are influenced or determined by other variables in a causal model.
That is, the values of endogenous variables depend on the values of the predictive variables in the study. The values of exogenous variables are not influenced or determined by other variables; however, they predict the values of endogenous variables. Exogenous variables are independent from variables within the causal model, yet they may be influenced by factors beyond the focus of the model. In the new conceptual model, student characteristics serve as exogenous latent variables and the instructional condition and student achievement latent variables are endogenous.

SEM also allows the researcher to determine the direction of causation in the model. In doing so, the researcher uses existing research to theoretically determine the directions of the regressions within the structural model. Typically, SEM permits the researcher to determine whether the structural model is recursive or non-recursive (Byrne, 2012). Recursive models require that the directions of the regression arrows only move in one direction between two variables. On the other hand, non-recursive models allow the researcher to establish reciprocal effects between variables. The conceptual model under investigation is recursive.

The researcher must distinguish between two types of latent variable models: reflective and formative models (Haenlein & Kaplan, 2004). Reflective latent variables are constructs that are comprised of multiple observable variables that are highly correlated; changes to the value of overall construct causes changes to the values of the observed variables. Formative latent variables are also comprised of multiple observable variables; however, the flow of causality for formative latent variables is from the observable variables to the latent variable. Changes to the values of the observable
variables cause changes to the value of the overall construct for a formative latent variable. Moreover, because observable variables cause variations in a formative latent variable, sufficient observable variables must be selected to determine the meaning of the construct. If all possible causes of the construct cannot be accounted for with the observable variable, then it is better to treat the latent variable as reflective (Hair, Hult, Ringle, & Sarstedt, 2013). The conceptual model under investigation includes three reflective latent variables. Although the student characteristics and instructional condition latent variables appear to be formative, other potential causes of those constructs may have been omitted within the conceptual model. Thus, the constructs must be treated as reflective.

In addition to determining the direction of the regression arrows and the types of latent variables, the sample size is particularly important to the validity of the results in a SEM. According to Brown (2006), many standards exist for determining an adequate sample size for CFA and SEM. Of the many guidelines, two are particularly useful for the present study. First, a general, albeit, limited guideline is that CFA requires a minimum sample size of at least 100 to 200. More stringently, the author noted that another guideline is to use at least five to 10 cases per each freed parameter. The expected sample of 470 elementary schools meets the minimum sample size described by Brown (2006). Additionally, the sample size is adequate if the freed parameters are less than or equal to 47. Therefore, the data for the present study was sufficient for CFA and SEM.
Limitations and Delimitations of the Study

Similar to the previous research studies that have attempted to investigate the relationship between educational resources and student achievement, the present study was limited in its attempt to truly uncover the effects of the selected variables on students’ performance on the state’s standardized test. In particular, this study was restricted due to limited accessibility to data and the quantitative nature of the study. The composition of the conceptual model that will be tested in this study is reliant on the variables that are accessible from the school district. Thus, not every variable that could improve the validity of the study will be used in the analysis.

In addition, the quantitative measures obtained for this study still remain distant from the actual educational interaction between teachers and students. For example, a measure of the percentage of expenditures for instruction may vary by school; however, the effects of those variations may depend on how principals utilize the expenditures to improve teaching and learning and the teachers’ abilities to use those resources effectively in their classrooms. Furthermore, the variables used in this study may not accurately measure the phenomena illustrated in the conceptual model. For instance, teacher salary will be used as a proxy for experience and education, representing a measure of teacher characteristics. Though scholars have noted the inadequacies of using salary, experience, and education as a proxy for teacher characteristics, those variables remain viable because they are the best available measures accessible to researchers.

As for the delimitations of the study, the findings will only be generalizable to elementary schools that tested grades three through five within the state. This
delimitation was chosen for two reasons. First, elementary schools that tested only grades three through five were selected in order to maintain a uniform sample with comparable scores as the dependent variable. Some elementary schools in the state include sixth grade, which could affect the schools’ ESEA waiver score. Therefore, by including schools that tested grades three through five, the effects of the independent variables on the dependent variable could be reliably estimated and compared to each other. Second, the sample for this study was chosen to be within a state in order to maintain some form of regularity in the sample; each school, principal, and teacher in the district is influenced by the same policies that are created by the same policymakers and state leaders. Thus, the reliability of the results will be further strengthened because of the uniformity in policies that affect schooling in the state.

Summary

This chapter detailed the research questions and subsequent hypotheses that were tested for the present study. A description of the method, sample, data collection process, and selected variables were provided for this study. In addition, the methodology and data analysis procedures were justified using relevant literature. The results of the analysis will be presented in chapter four.
CHAPTER FOUR

RESULTS

The purpose of this study was to test the sufficiency of a new conceptual model of the effects of educational resources on student achievement using Structural Equation Modeling (SEM). To discern the effects of resources on achievement, many researchers developed conceptual models and tested them using multiple regression and production function methods. However, findings have been mixed due to methodological limitations, variable selection, and data accessibility. The present study sought to answer the following questions: a) Is the new conceptual model of the effects of educational resources on student achievement a good model fit using elementary school data from South Carolina, and b) What are the estimated effects of the educational resources on students’ academic achievement and how can the findings be used to inform resource allocation practices to meet educational adequacy? The aim of this study was to provide further clarity to the discourse on whether researchers can model how variations in educational resources allocated specifically to schools affect variations in student achievement.

The new conceptual model of the effects of educational resources on student achievement that will be tested is displayed in Figure 4.1. The selection of variables was guided by the review of the literature on the relationship between resources and achievement. The variables were grouped in to two latent variables: student characteristics and instructional condition. In order to investigate the sufficiency of the model and to calculate the estimated effects of resources on achievement, a three-stage
process was undertaken: a) tests of statistical assumptions and subsequent transformations, b) Confirmatory Factor Analysis (CFA), and c) SEM. The tests of statistical assumptions and ensuing transformations were used to determine if the data was adequate to conduct the CFA and SEM. After the appropriate transformations were made, the sufficiency of the conceptual model was analyzed using CFA and SEM. Because the \textit{a priori} conceptual model was not sufficient, the Mplus software provided exploratory, \textit{a posteriori} suggestions to improve model fit. Once the model was altered in response to these suggestions, the effects of the latent variables on schools’ Elementary and Secondary Education Act (ESEA) indices were estimated to answer the research questions.

Figure 4.1: Model of the Effects of Educational Resources on Student Achievement.
The results of this study are presented in this chapter; they are divided into four sections that correspond with the procedures outlined above. The first section displays results from descriptive statistics and tests of statistical assumptions. The second section details the initial CFA on the new conceptual model of the effects of educational resources on student achievement. The third section presents the post hoc CFA and SEM on the modified model of the effects of educational resources on student achievement. Finally, the fourth section provides post hoc descriptive statistics to contextualize the findings of the modified model.

**Descriptive Statistics and Tests of Statistical Assumptions**

In order to determine if the data was adequate to conduct the CFA and SEM, tests of statistical assumptions were conducted on the variables. Basic descriptive statistics were calculated for each variable in the new conceptual model. The variables in the present study included schools’ poverty indices, percentage of students with disabilities other than speech, percentage of students eligible for gifted and talented, percentage of students retained, the percentage of students older than usual for grade, total school enrollment, student-teacher ratio, principal's years in the school, percentage expenditures for instruction, percentage prime instructional time, number of professional development days per teacher, average teacher salary, percentage of teachers with advanced degrees, percentage of teachers with continuing contracts, percentage of returning teachers, and each school’s 2013 ESEA waiver index score. The mean, standard deviation, variance, minimum value, and maximum value for all 16 variables used in the analysis are displayed in Table 4.1. The total sample size for the study was 470 elementary schools.
that tested grades three through five. Six of the variables were missing data as reported by the state Department of Education; however, Mplus accommodates missing data. The software is set to estimate models without imputing values where missing data is present.

The variance of each variable was of particular interest for CFA and SEM. According to Brown (2006), the variance of each variable should be reasonably homogenous. Relatively large variances were found in average teacher salary and total school enrollment. In addition to the large variances of average teacher salary and total school enrollment, the relatively wide-ranging values for each variable’s variance in the present dataset provided justification for the use of grand mean centering.
Table 4.1. Descriptive Statistics for All Variables.

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Variance</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poverty Index</td>
<td>470</td>
<td>74.98</td>
<td>20.41</td>
<td>416.70</td>
<td>14.12</td>
<td>99.79</td>
</tr>
<tr>
<td>% Gifted and Talented</td>
<td>470</td>
<td>8.67</td>
<td>5.66</td>
<td>32.13</td>
<td>0.0</td>
<td>41.90</td>
</tr>
<tr>
<td>% Special Education</td>
<td>470</td>
<td>12.74</td>
<td>3.79</td>
<td>14.40</td>
<td>4.40</td>
<td>28.10</td>
</tr>
<tr>
<td>% Students Retained</td>
<td>470</td>
<td>1.266</td>
<td>1.22</td>
<td>1.49</td>
<td>0.00</td>
<td>7.00</td>
</tr>
<tr>
<td>% Students Older than Grade</td>
<td>470</td>
<td>2.21</td>
<td>1.64</td>
<td>2.7</td>
<td>0.00</td>
<td>10.50</td>
</tr>
<tr>
<td>% Returning Teachers</td>
<td>456</td>
<td>87.65</td>
<td>5.68</td>
<td>32.259</td>
<td>57.40</td>
<td>98.40</td>
</tr>
<tr>
<td>Average Teacher Salary</td>
<td>470</td>
<td>48309.31</td>
<td>3478.15</td>
<td>12097584.84</td>
<td>37629</td>
<td>57928</td>
</tr>
<tr>
<td>% Teachers with Adv. Degree</td>
<td>470</td>
<td>65.56</td>
<td>11.07</td>
<td>122.63</td>
<td>22.20</td>
<td>91.30</td>
</tr>
<tr>
<td>% Teachers with Continuing Contract</td>
<td>470</td>
<td>82.52</td>
<td>10.75</td>
<td>115.59</td>
<td>48.80</td>
<td>100</td>
</tr>
<tr>
<td>Principal’s Years at School</td>
<td>467</td>
<td>5.79</td>
<td>4.83</td>
<td>23.33</td>
<td>0.00</td>
<td>29.00</td>
</tr>
<tr>
<td>Professional Development Days Per Teacher</td>
<td>467</td>
<td>11.63</td>
<td>5.38</td>
<td>28.92</td>
<td>1.00</td>
<td>31.00</td>
</tr>
<tr>
<td>Student-Teacher Ratio</td>
<td>453</td>
<td>19.836</td>
<td>2.95</td>
<td>8.73</td>
<td>2.30</td>
<td>31.20</td>
</tr>
<tr>
<td>% Prime Instruction Time</td>
<td>467</td>
<td>89.86</td>
<td>1.89</td>
<td>3.59</td>
<td>81.00</td>
<td>95.50</td>
</tr>
<tr>
<td>% Expenditures for Instruction</td>
<td>466</td>
<td>68.3</td>
<td>5.48</td>
<td>30.08</td>
<td>48.00</td>
<td>84.00</td>
</tr>
<tr>
<td>Total School Enrollment</td>
<td>470</td>
<td>524.39</td>
<td>203.33</td>
<td>41345.65</td>
<td>88.00</td>
<td>1372.00</td>
</tr>
<tr>
<td>2013 ESEA Waiver Index Score</td>
<td>470</td>
<td>83.54</td>
<td>16.05</td>
<td>257.64</td>
<td>10.5</td>
<td>100.00</td>
</tr>
</tbody>
</table>
Additionally, in order to test for univariate normality, skew and kurtosis statistics were calculated for each variable. The skewness and kurtosis for each variable is presented in Table 4.2. Half of the variables had either a moderate positive skew or a moderate negative skew. Variables with a skewness of an absolute value greater than one were transformed using the appropriate transformations provided by Mertler and Vannatta (2010). A square root transformation was calculated for variables with a moderate positive skew. Variables with a moderate positive skew included schools’ percentage of students eligible for gifted and talented, percentage of students retained, the percentage of students older than usual for grade, the principal's years in the school, and number of professional development days per teacher. In addition, a reflect and square root transformation was calculated for variables with a moderate negative skew. Variables with a moderate negative skew included schools’ percentage of returning teachers, student-teacher ratio, and 2013 ESEA waiver index score. However, the 2013 ESEA waiver index score variable was not transformed to maintain the most accurate depiction of student achievement for each school.
A comparison of the skewness and kurtosis statistics before and after the transformations is presented in Table 4.3. All variables had a skewness that met the
assumption of normality; however, the variables titled professional development days per teacher and student-teacher ratio had kurtosis values greater than one. No additional transformations were conducted on these two variables to maintain a realistic value of both variables.

Table 4.3. Comparison of Skewness and Kurtosis after Transformations.

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>Skewness after Transformation</th>
<th>Kurtosis after Transformation</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Gifted and Talented</td>
<td>470</td>
<td>1.060</td>
<td>2.232</td>
<td>-.102</td>
<td>.189</td>
</tr>
<tr>
<td>% Students Retained</td>
<td>470</td>
<td>1.668</td>
<td>3.532</td>
<td>.192</td>
<td>-.081</td>
</tr>
<tr>
<td>% Students Older than Grade</td>
<td>470</td>
<td>1.791</td>
<td>4.548</td>
<td>.462</td>
<td>.886</td>
</tr>
<tr>
<td>% Returning Teachers</td>
<td>456</td>
<td>-1.292</td>
<td>2.866</td>
<td>.497</td>
<td>.530</td>
</tr>
<tr>
<td>Principal’s Years at School</td>
<td>467</td>
<td>1.867</td>
<td>5.902</td>
<td>.663</td>
<td>.330</td>
</tr>
<tr>
<td>Professional Development Days Per Teacher</td>
<td>467</td>
<td>1.177</td>
<td>3.324</td>
<td>-.025</td>
<td>1.431</td>
</tr>
<tr>
<td>Student-Teacher Ratio</td>
<td>453</td>
<td>-1.392</td>
<td>5.798</td>
<td>.319</td>
<td>5.007</td>
</tr>
<tr>
<td>2013 ESEA Waiver Index Score</td>
<td>470</td>
<td>-1.535</td>
<td>2.302</td>
<td>.610</td>
<td>-.150</td>
</tr>
</tbody>
</table>

Tests for multivariate normality were conducted on all variables using a research-validated SPSS syntax macro (DeCarlo, 1997). The macro calculated tests of multivariate skewness and kurtosis developed by Small (1980) and Srivastava (1984) on all variables. In addition, the macro calculated an omnibus test of multivariate normality that is based
on Small’s test. The p-values for each test are detailed in Table 4.4. All tests reported significant p-values ($p < .001$); therefore, the data violated the assumption of multivariate normality. Due to this violation, a robust maximum likelihood (MLR) estimator will be used because it accommodates data non-normal data for the CFA and SEM calculations.

Table 4.4. Tests of Multivariate Skewness, Kurtosis, and Normality.

<table>
<thead>
<tr>
<th>Test and Description</th>
<th>Value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small’s Test of Multivariate Skew</td>
<td>260.29</td>
<td>$p &lt; .001$</td>
</tr>
<tr>
<td>Srivastava’s Test of Multivariate Skew</td>
<td>145.29</td>
<td>$p &lt; .001$</td>
</tr>
<tr>
<td>Small’s Test of Multivariate Kurtosis</td>
<td>129.66</td>
<td>$p &lt; .001$</td>
</tr>
<tr>
<td>Srivastava’s Test of Multivariate Kurtosis</td>
<td>4.16</td>
<td>$p &lt; .001$</td>
</tr>
<tr>
<td>Omnibus Test of Multivariate Normality</td>
<td>389.95</td>
<td>$p &lt; .001$</td>
</tr>
</tbody>
</table>

The assumption of linearity was tested by evaluating the scatterplot matrices (see Figure 4.2). The majority of the scatterplots appeared to approach elliptical shapes. However, linearity may be problematic for the total school enrollment variable because of its non-linear relationship with student achievement. After the tests of statistical assumptions were conducted, it was concluded that the data were appropriate for the CFA and subsequent SEM as long as a MLR estimator was used and the data was transformed using grand mean centering.
Confirmatory Factor Analysis Using the New Conceptual Model

Once the appropriate transformations were made to the variables, the sufficiency of the new conceptual model could be tested by the researcher using CFA. In order to answer the first research question, is the new conceptual model of the effects of educational resources on student achievement a good model fit using elementary school data from South Carolina, a series of hypotheses were created to test whether the theoretical latent variables, indeed, account for the correlations of the multiple observed variables.
variables in the model (Brown, 2006). A visual representation of the model that was tested using CFA is displayed in Figure 4.3. The model was created based on the following hypotheses:

H1: The latent variable, instructional condition, as comprised of schools' total school enrollment, student-teacher ratio, the principal's years in the school, the percentage expenditures for instruction, the percentage prime instructional time, number of professional development days per teacher, average teacher salary, percentage of teachers with advanced degrees, percentage of teachers with continuing contracts, and the percentage of returning teachers, will fit the data.

H2: The latent variable, student characteristics, as comprised of schools’ poverty indices, percentage of students with disabilities other than speech, percentage of students eligible for gifted and talented, percentage of students retained, and the percentage of students older than usual for grade, will fit the data.

Figure 4.3: Visual Representation of the Conceptual Model for CFA.
The CFA was conducted using Mplus statistical software. The model was overidentified, with 89 degrees of freedom and 46 free parameters, suggesting that the number of sample moments were sufficient for the analysis. After using a MLR estimator, model fit indices were examined and were found to be below the standards identified in the literature. The Comparative Fit Index (CFI) was .639 and the Tucker-Lewis Index (TLI) was .575, well below the .90 standard. In addition, the Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean square Residual (SRMR) were greater than the standards of .06 and .08, at .11 and .09, respectively.

Modification indices serve as evaluative statistics used to identify areas of misfit within CFA models. The Mplus software provides modification indices to improve model fit; the researcher judges whether the suggestions provided by the software are appropriate for the analysis. For the post hoc CFA, 23 modification suggestions for correlations between observed variables were provided to improve model fit. Of those 23 suggestions, eight were added to the model through a series of three iterations. After the addition of eight correlations, the model remained sufficient for the CFA because it was overidentified, with 81 degrees of freedom and 54 free parameters. However, model fit indices yielded a poor fit. The CFI was .80 and the TLI was .752. Furthermore, The RMSEA and SRMR were both found to be .08. Due to the poor model fit, the SEM was not conducted on the model. Therefore, the two hypotheses were rejected by the researcher; the new conceptual model was not a good model fit. As a result, a reconceptualization of the model and post hoc analyses was required to discern an
adequate model fit in order to calculate the estimated effects of educational resources on students’ academic achievement.

**Post Hoc Confirmatory Factor Analysis and Structural Equation Modeling**

Of the many reasons for the poor model fit for the new conceptual model, the large number of observed variables that contributed to the instructional condition latent variable may have been problematic. In the tested model, the latent variable was comprised of 10 observed variables. During the post hoc analysis, the instructional condition was separated into two latent variables. One latent variable remained as the instructional condition. This variable represented the conditions that enable or constrain the interaction between teachers and students. Furthermore, the type and amounts of variables that represented the instructional conditions of schools are determined by education leaders and policymakers. The observed variables within the instructional condition were hypothesized to be schools’ student-teacher ratio, percentage expenditures for instruction, percentage prime instructional time, and number of professional development days per teacher. The total school enrollment observed variable was removed from the model because the residual variance was significantly greater than the residual variances of the rest of the variables. Even with grand mean centering, the unstandardized residual variance was 37912.41, much larger than the 116.57 residual variance of the poverty index, the second largest residual variance (see Table 4.5).
Table 4.5. Unstandardized Residual Variances for Variables from Initial Model Test.

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poverty Index</td>
<td>116.57</td>
<td>53.28</td>
</tr>
<tr>
<td>% Gifted and Talented</td>
<td>0.62</td>
<td>0.12</td>
</tr>
<tr>
<td>% Special Education</td>
<td>12.45</td>
<td>1.12</td>
</tr>
<tr>
<td>% Students Retained</td>
<td>0.28</td>
<td>0.02</td>
</tr>
<tr>
<td>% Students Older than Grade</td>
<td>0.16</td>
<td>0.02</td>
</tr>
<tr>
<td>% Returning Teachers</td>
<td>0.30</td>
<td>0.03</td>
</tr>
<tr>
<td>Average Teacher Salary</td>
<td>6.43</td>
<td>0.66</td>
</tr>
<tr>
<td>% Teachers with Adv. Degree</td>
<td>97.93</td>
<td>7.40</td>
</tr>
<tr>
<td>% Teachers with Continuing Contract</td>
<td>48.44</td>
<td>6.34</td>
</tr>
<tr>
<td>Principal’s Years at School</td>
<td>0.80</td>
<td>0.06</td>
</tr>
<tr>
<td>Professional Development Days Per Teacher</td>
<td>0.63</td>
<td>0.05</td>
</tr>
<tr>
<td>Student-Teacher Ratio</td>
<td>0.16</td>
<td>0.02</td>
</tr>
<tr>
<td>% Prime Instruction Time</td>
<td>3.58</td>
<td>0.31</td>
</tr>
<tr>
<td>% Expenditures for Instruction</td>
<td>26.93</td>
<td>2.34</td>
</tr>
<tr>
<td>Total School Enrollment</td>
<td>37912.41</td>
<td>2411.92</td>
</tr>
</tbody>
</table>

The second new latent variable in the model was titled personnel. The personnel variable represented characteristics of the people who either interact with students or teachers to deliver effective instruction to meet students’ learning needs. The observed
variables that were hypothesized to be part of the personnel latent variable were the percentage of teachers with advanced degrees, average teacher salary, percentage of teachers with continuing contracts, percentage of returning teachers, and the principal's years in the school. The new latent variables and their corresponding observed variables that served as the basis for the post hoc CFA are shown in Figure 4.4.

![Diagram](image)

Figure 4.4: Post Hoc Conceptual Model for CFA.

**CFA Results**

The post hoc model was overidentified, with 74 degrees of freedom and 45 free parameters, indicating that the model was sufficient for analysis. Model fit indices were examined and were found to be below the standards. The CFI and TLI were below the .90 standard at .73 and .66, respectively. Additionally, RMSEA was .10 and the SRMR was
.07, greater than the .06 and .08 standards. Similar to the CFA for the initial model, modification indices were provided by the statistical software. Of the 20 suggestions provided by the software, 11 correlation modifications were included in the model. After the modifications were made, there was still more sample moments than free parameters, suggesting that the model was overidentified, with 62 degrees of freedom and 57 free parameters. Thus, the data was appropriate for the CFA. In addition, the model fit indices yielded confirming results. The CFI and TLI were either greater than or equal to the .90 standard, at .93 and .90, respectively. The RMSEA and SRMR were both found to be .05. Because the model fit indices indicated confirming results, the post hoc model was deemed appropriate for the SEM.

The standardized estimates for the model are detailed in Table 4.6. For the student characteristics latent variable, schools’ poverty indices and percentage of students eligible for gifted and talented had the largest loadings of .961 and -.771, respectively. Schools’ percentage of students older than usual for grade had a moderate loading of .539. In addition, three of the observed variables within the personnel latent variable had moderate to large loadings. Schools’ percentage of teachers on continuing contracts, average teacher salary, percentage of returning teachers had loadings of .642, .800, and -.551, respectively. Higher absolute values of loadings suggest that those variables are the distinguishing features of the latent variables.
Table 4.6. Standardized Estimates from the CFA for the Post Hoc Conceptual Model.

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>Standard Error</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Student Characteristics BY</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poverty Index</td>
<td>.961</td>
<td>.02</td>
<td>$p &lt; .001$</td>
</tr>
<tr>
<td>% Gifted and Talented</td>
<td>-.771</td>
<td>.03</td>
<td>$p &lt; .001$</td>
</tr>
<tr>
<td>% Special Education</td>
<td>.296</td>
<td>.04</td>
<td>$p &lt; .001$</td>
</tr>
<tr>
<td>% Students Retained</td>
<td>.264</td>
<td>.04</td>
<td>$p &lt; .001$</td>
</tr>
<tr>
<td>% Students Older than Grade</td>
<td>.539</td>
<td>.03</td>
<td>$p &lt; .001$</td>
</tr>
<tr>
<td><strong>Personnel BY</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Returning Teachers</td>
<td>-.551</td>
<td>.06</td>
<td>$p &lt; .001$</td>
</tr>
<tr>
<td>Average Teacher Salary</td>
<td>.800</td>
<td>.06</td>
<td>$p &lt; .001$</td>
</tr>
<tr>
<td>% Teachers with Adv. Degree</td>
<td>.510</td>
<td>.06</td>
<td>$p &lt; .001$</td>
</tr>
<tr>
<td>% Teachers with Continuing Contract</td>
<td>.642</td>
<td>.05</td>
<td>$p &lt; .001$</td>
</tr>
<tr>
<td>Principal’s Years at School</td>
<td>.188</td>
<td>.05</td>
<td>$p &lt; .001$</td>
</tr>
<tr>
<td><strong>Instructional Condition BY</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Professional Development Days Per Teacher</td>
<td>.096</td>
<td>.09</td>
<td>$p = .325$</td>
</tr>
<tr>
<td>Student-Teacher Ratio</td>
<td>.424</td>
<td>.15</td>
<td>$p = .007$</td>
</tr>
<tr>
<td>% Prime Instructional Time</td>
<td>-.632</td>
<td>.29</td>
<td>$p = .030$</td>
</tr>
<tr>
<td>% Expenditures for Instruction</td>
<td>-.164</td>
<td>.10</td>
<td>$p = .103$</td>
</tr>
</tbody>
</table>
All observed variables loaded significantly on the latent variables student characteristics and personnel. However, only student-teacher ratio and percentage prime instructional time loaded significantly on the instructional condition latent variable. Because two non-significant loadings were found, the latent variable was determined to be weak; thus, results that centered on the instructional conditions of the schools should be interpreted with caution. In addition to the loadings of the observed variables, the correlations between the latent variables are of interest (see Table 4.7). None of the correlations were greater than .85, suggesting that multicollinearity among the latent variables was not a problem (Brown, 2006). Therefore, the SEM was calculated with caution given to the instructional condition latent variable.

Table 4.7. Correlations between Latent Variables.

<table>
<thead>
<tr>
<th></th>
<th>Student Characteristics</th>
<th>Instructional Condition</th>
<th>Personnel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Student Characteristics</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Instructional Condition</td>
<td>.631</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Personnel</td>
<td>-.399</td>
<td>-.049</td>
<td></td>
</tr>
</tbody>
</table>

SEM Results

The structural model was added to the post hoc conceptual model and calculated using the MLR estimator. The model that was tested using SEM is displayed in Figure 4.5. The model was overidentified, with 78 degrees of freedom and 58 free parameters, and found to be sufficient to examine the model fit indices. Model fit indices suggested a
model that was approaching an adequate fit. The CFI and TLI were below the .90 standard, at .88 and .85, respectively. The RMSEA was .06 and the SRMR was .05, representing a sufficient model fit. In addition, four correlation modification indices were suggested from the analysis.

![Post Hoc Conceptual Model for SEM](image)

Figure 4.5: Post Hoc Conceptual Model for SEM.
A near adequate model fit was obtained after the modification indices were added to the analysis. The model remained overidentified, with 75 degrees of freedom and 60 free parameters. Furthermore, the CFI was found to be .91 and the TLI was .87. The RMSEA was .06 and the SRMR was .05. In addition, the model was moderately parsimonious, with 11 correlations added from the initial CFA modification indices. Therefore, the model was determined to be sufficient and the standardized estimates and r-squares were deemed interpretable.

The post hoc conceptual model predicted 34.3% of the variation in the schools’ 2013 waiver index score and 18.1% of the variation in the personnel latent variable. Similar to the CFA results, the student characteristics and personnel latent variables had the strongest loadings (see Table 4.8). For the student characteristics latent variable, schools’ poverty indices and percentage of students eligible for gifted and talented had the largest loadings of .853 and -.867, respectively. Schools’ percentage of students older than usual for grade had a moderate loading of .595. Additionally, schools’ percentage of students with disabilities other than speech and the percentage of students retained had the smallest loadings of .363 and .259, respectively.

For the personnel latent variable, schools’ percentage of teachers on continuing contracts, average teacher salary, percentage of returning teachers had moderate to large loadings of .720, .705, and -.610, respectively. Schools’ percentage of teachers with advanced degrees and principals' years in the schools had the smallest loadings of .430 and .209. None of the observed variables loaded significantly on the instructional condition latent variable; however, schools’ percentage of prime instructional time and
student-teacher ratio had large loadings of -.812 and .771, respectively. Although two of
the loadings were large, the insignificant loadings confirm the results of the CFA; the
instructional condition is not a significant latent variable and should be interpreted with
cautions.
Table 4.8. Standardized Estimates from the Post Hoc Structural Equation Model.

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>Standard Error</th>
<th>p-value</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013 Waiver Index Score</td>
<td></td>
<td></td>
<td></td>
<td>.343</td>
</tr>
<tr>
<td><strong>Student Characteristics BY</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poverty Index</td>
<td>.853</td>
<td>.02</td>
<td>$p &lt; .001$</td>
<td>.728</td>
</tr>
<tr>
<td>% Gifted and Talented</td>
<td>-.867</td>
<td>.03</td>
<td>$p &lt; .001$</td>
<td>.752</td>
</tr>
<tr>
<td>% Special Education</td>
<td>.363</td>
<td>.05</td>
<td>$p &lt; .001$</td>
<td>.132</td>
</tr>
<tr>
<td>% Students Retained</td>
<td>.259</td>
<td>.04</td>
<td>$p &lt; .001$</td>
<td>.067</td>
</tr>
<tr>
<td>% Students Older than Grade</td>
<td>.595</td>
<td>.03</td>
<td>$p &lt; .001$</td>
<td>.354</td>
</tr>
<tr>
<td><strong>Personnel BY</strong></td>
<td></td>
<td></td>
<td></td>
<td>.181</td>
</tr>
<tr>
<td>% Returning Teachers</td>
<td>-.610</td>
<td>.05</td>
<td>$p &lt; .001$</td>
<td>.372</td>
</tr>
<tr>
<td>Average Teacher Salary</td>
<td>.705</td>
<td>.06</td>
<td>$p &lt; .001$</td>
<td>.497</td>
</tr>
<tr>
<td>% Teachers with Adv. Degree</td>
<td>.430</td>
<td>.06</td>
<td>$p &lt; .001$</td>
<td>.185</td>
</tr>
<tr>
<td>% Teachers with Continuing Contract</td>
<td>.720</td>
<td>.05</td>
<td>$p &lt; .001$</td>
<td>.519</td>
</tr>
<tr>
<td>Principal’s Years at School</td>
<td>.209</td>
<td>.05</td>
<td>$p &lt; .001$</td>
<td>.044</td>
</tr>
<tr>
<td><strong>Instructional Condition BY</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Professional Development Days Per Teacher</td>
<td>.083</td>
<td>.04</td>
<td>$p = .058$</td>
<td></td>
</tr>
<tr>
<td>Student-Teacher Ratio</td>
<td>.771</td>
<td>1.04</td>
<td>$p = .461$</td>
<td></td>
</tr>
<tr>
<td>% Prime Instruction Time</td>
<td>-.812</td>
<td>1.30</td>
<td>$p = .532$</td>
<td></td>
</tr>
<tr>
<td>% Expenditures for Instruction</td>
<td>-.113</td>
<td>.28</td>
<td>$p = .685$</td>
<td></td>
</tr>
</tbody>
</table>

$R^2$ is reported for variables with $p$-values less than .05.
A visual representation of the regression estimates for the post hoc SEM can be viewed in Figure 4.6. Significant weightings were marked with an asterisk. For the direct effects between the latent variables, student characteristics ($\beta = -0.431$) and personnel ($\beta = 0.246$) significantly predicted schools’ achievement as measured by their 2013 ESEA waiver index score ($R^2 = 0.343$). The instructional condition latent variable was not a significant predictor of the waiver index score. In addition, the personnel latent variable served as a moderating variable between student characteristics and the ESEA waiver index score. Student characteristics negatively predicted ($\beta = -0.426$) personnel which positively predicted ($\beta = -0.246$) the schools’ ESEA waiver score. The total indirect effect of student characteristics on schools’ ESEA waiver score was -0.10. This was determined by multiplying the regression coefficient for personnel on student characteristics and the ESEA waiver score on personnel. The standardized regression coefficients also serve as measures of effect size. When compared to standards in the social sciences (Cohen, 1988), the effect sizes for student characteristics on achievement and student characteristics on personnel were moderate and the effect size for personnel on student achievement was small. However, the size of the effect of personnel on student achievement was relatively large relative to the findings of studies within the does money matter debate.
Figure 4.6: Regression Estimates for the Post Hoc SEM.

**Post Hoc Descriptive Statistics**

Post hoc descriptive statistics were calculated to contextualize the non-significant effects of the instructional condition latent variable on students’ academic achievement. In particular, descriptive statistics were calculated for the observed variables within the instructional condition to assess the degree of variation within each variable. A prerequisite to assess whether variations in resources affect variations in achievement is that variation must exist within the independent variables. In addition, the literature suggested that variables like student-teacher ratio are related to student achievement
(Blatchford, Bassett, Goldstein, & Martin, 2003; Finn, Gerber, & Boyd-Zaharis, 2005). However, the degree to which these resources are allocated differently to schools serving students with different circumstances within the state may affect whether those resources are significant predictors of student achievement.

The degree to which the instructional condition observed variables were allocated differently was assessed by analyzing the variations of the observed variables across the state. Means of each observed variable within the instructional conditions of schools were compared based on their poverty index. The poverty index was chosen as the grouping variable because it had a strong loading within the student characteristics latent variable and is a significant predictor of student achievement. Group means were calculated based on whether schools’ poverty indices were within the ranges of 0.00-20.00, 20.01-40.00, 40.01-60.00, 60.01-80.00, and 80.01-100. The statistics can be viewed in Table 4.9.
Table 4.9. Means for Observed Variables in the Instructional Condition Latent Variable.

<table>
<thead>
<tr>
<th>Group with poverty Index between</th>
<th>N</th>
<th>Professional Development Days Per Teacher</th>
<th>Student-Teacher Ratio</th>
<th>% Prime Instructional Time</th>
<th>% Expenditures for Instruction</th>
</tr>
</thead>
<tbody>
<tr>
<td>between 80.01 and 100</td>
<td>229</td>
<td>11.65</td>
<td>18.95</td>
<td>89.37</td>
<td>67.82</td>
</tr>
<tr>
<td>between 60.01 and 80.00</td>
<td>144</td>
<td>12.00</td>
<td>20.51</td>
<td>89.96</td>
<td>68.11</td>
</tr>
<tr>
<td>between 40.01 and 60.00</td>
<td>57</td>
<td>11.11</td>
<td>21.13</td>
<td>90.66</td>
<td>69.29</td>
</tr>
<tr>
<td>between 20.01 and 40.00</td>
<td>33</td>
<td>10.76</td>
<td>20.28</td>
<td>90.88</td>
<td>70.45</td>
</tr>
<tr>
<td>between 0.00 and 20.00</td>
<td>7</td>
<td>11.41</td>
<td>21.83</td>
<td>92.07</td>
<td>70.00</td>
</tr>
</tbody>
</table>

After reviewing the means for each observed variable within the instructional condition latent variable, there were few noticeable differences and little variation based on schools’ poverty indices. The majority of elementary schools in the state had a poverty index greater than 80.00. For the schools with a poverty index greater than 80.00, the mean student-teacher ratio was less than 19. For the schools with a poverty index less than 20.00, the mean student-teacher ratio was less than 22. Little variation was also found with the percentage of prime instructional time and the percentage of expenditures for instruction. No difference was found between high and low poverty schools with the number of professional development days per teacher. The relatively low variation in the observed variables provided insight as to why the instructional condition latent variable was a poor fit and, therefore, was a non-significant predictor of student achievement.
Summary

This chapter detailed the analysis and findings of the present study as they relate to the two research questions. Descriptive statistics were calculated on the variables in order to make the appropriate transformations for the CFA and SEM. The new conceptual model was tested using Confirmatory Factor Analysis (CFA) and was found to have a poor model fit. After subsequent modifications to the model, the fit remained insufficient to the data. As a result, a post hoc reconceptualization of the model was required to discern an adequate model fit. The instructional condition latent variable was divided into two separate latent variables: personnel and instructional condition. This change yielded a model with a total of three latent variables and was found to be a good model fit. Student characteristics and personnel were found to be significant predictors of student achievement, explaining 34.3% of the variation in the latent variable. The instructional condition latent variable was found to be a poor latent variable and a non-significant predictor of student achievement. Post hoc descriptive were calculated to assess variation of the observed variables within the instructional condition. Little difference was found within the observed variables when schools were grouped by their poverty index. Chapter five describes implications for research and practice as they relate to the findings of the present study.
CHAPTER FIVE
SUMMARY AND IMPLICATIONS

The present study sought to discern the effects of school-level resources on elementary school students’ academic achievement. Research investigating the relationship between educational resources and student achievement garnered substantial attention from the 1960s into the early 2000s, fueling scholarly and political debates. Yet, findings of these research studies remain mixed due to variations in research designs, limitations of statistical approaches, and data accessibility. With the increase of educational policies centered on improving students’ academic achievement toward proficiency goals, the ability for researchers to confidently define the relationship between educational resources and student achievement becomes even more important; results may be used to inform resource allocation practices to improve student learning. Using Structural Equation Modeling (SEM) and data from elementary schools in South Carolina, the following research questions were answered in this study: a) Is the new conceptual model of the effects of educational resources on student achievement a good model fit using elementary school data from South Carolina (see Figure 5.1), and b) What are the estimated effects of the educational resources on students’ academic achievement and how can the findings be used to inform resource allocation practices to meet educational adequacy?

This chapter is divided into two sections. In section one, the two research questions are addressed and findings are compared to the literature that guided this study.
In addition, methodological implications are offered to improve future research studies that attempt to discern the effects of educational resources on student achievement. In section two, the findings are used to guide a discussion about how the present model may be used to inform resource allocation practices to meet demands for educational adequacy.

**Findings and Methodological Implications**

The initial conceptual model was tested using Confirmatory Factor Analysis (CFA) and was found to have a poor model fit. After subsequent modifications to the model, the fit remained insufficient to the data. As a result, a post hoc reconceptualization of the model was required to discern an adequate model fit. The instructional condition latent variable was divided into two separate latent variables: personnel and instructional condition. This change yielded a model with a total of three latent variables (see Figure 5.1). The post hoc conceptual model was tested using CFA and the goodness-of-fit indices yielded a good model fit ($CFI = .91$, $TLI = .87$, $RMSEA = .06$, $SRMR = .05$). Therefore, the post hoc conceptual model was sufficient to analyze the effects of educational resources on student achievement.
Figure 5.1: Post Hoc Conceptual Model for SEM.

**Findings from the Model**

Since the 1960s, researchers have investigated the relationship between educational resources and student achievement and have found mixed results (Archibald, 2006; Coleman et al., 1966; Cooper et al., 1994; Fortune & O’Neill, 1994; Greene, Huerta, & Richards, 2007; Greenwald, Hedges, & Laine, 1994; Hanushek, 1981, 1989, 1991, 1997; Knoeppe, Verstegen, & Rinehart, 2007; Okpala, 2002). Whereas some researchers have found significant relationships between variations in resources, such as teacher qualifications and per-pupil expenditures, and variations in student achievement (Archibald, 2006; Cooper et al., 1994; Fortune & O’Nei, 1994; Greenwald et al., 1994; Knope, Verstegen, & Rinehart, 2007), other researchers have found non-significant
effects (Coleman et al., 1966; Hanushek, 1981, 1989, 1991; Okpala, 2002). As a result of differences in these findings, scholars have yet to model a holistic representation of the relationship between resources and achievement.

In the present study, a post hoc conceptual model of the effects of educational resources on student achievement was developed, tested, and validated using elementary school data from South Carolina. For the most part, the analysis yielded results that confirmed previous findings. Yet, SEM was also found to be a plausible method that improved the reliability of the findings when modeling of the effects of educational resources on student achievement. In particular, the use of SEM, comprised of multiple latent variables and direct and indirect effects between those variables, allowed for more precise estimated effects to be extracted in a reliable manner. Moreover, the findings of the present study suggest that traditional economic analytical frameworks that represent “inputs and outputs” may limit the potential for researchers to account for unique effects of educational resources on student achievement because they do not accommodate mediating and moderating variables.

The regression coefficients from the SEM for the post hoc conceptual model can be viewed in figure 5.2. The model explained 34.3 percent of the variation in the schools’ measure of student achievement and 18.1 percent of the variation in the schools’ measure of personnel. A finding consistent with the literature was a significant negative direct effect between the student characteristics of the school ($\beta = -.431$) and the schools’ achievement. In addition, a key finding of the study was that it provided empirical evidence that confirms Sanders’ (1998) suggestion that after controlling for student
demographics, “the single largest factor affecting academic growth of populations of students is differences in effectiveness of individual classroom teachers” (p. 27). The present study yielded a significant positive effect between measures of schools’ personnel ($\beta = .246$) and the schools’ achievement. The personnel latent variable also served as a unique, moderating variable between student characteristics and the 2013 Elementary and Secondary Education Act (ESEA) waiver index score. Student characteristics negatively predicted ($\beta = -.426$) personnel which positively predicted ($\beta = .246$) the schools’ ESEA waiver score. The total indirect effect of student characteristics on the schools’ ESEA waiver score was -.10.

![Figure 5.2: Regression Estimates for the Post Hoc SEM.](image)
The instructional condition latent variable was not a significant predictor of the waiver index score. In addition, the observed variables within the instructional condition latent variable had non-significant loadings. The fact that the latent variable was comprised of non-significant loadings may be a contributing factor that explains the lack of a relationship between the instructional conditions of schools and their achievement on the ESEA waiver index score. Methodological implications related to the instructional condition latent variable are detailed later in this chapter.

Results from the present study were compared to findings from the literature. Because some of the prominent research in the “Does Money Matter?” debate was conducted using meta-analytic methods, the actual weightings from the present study will not be comparable to those findings. However, researchers who used meta-analyses studies did report significant and non-significant relationships between resources and achievement, including the direction of each relationship. These findings will be compared to the results of the post hoc conceptual model. In addition to the meta-analysis findings, the results from studies that used regression or production function methods were compared to the results of the present study.

A summary of the comparison between the significant predictors of the present study and the related literature can be viewed in Table 5.1. For the most part, the findings of the present study are consistent with findings in the literature. Four of the eleven studies found that students’ characteristics, whether measures of wealth or other characteristics, were significant and negative predictors of achievement. Findings from
the present study confirm the notion that students’ characteristics, even when considering
gifted and talented and retention rates, negatively affect student achievement.

The present study yielded the largest estimated effect of student characteristics on
student achievement, at -.431. The second largest effect between student characteristics
and student achievement was found by Okpala (2002), at -.377. The difference in effect
sizes between the present study and previous inquiries may be due to the inclusion of a
latent variable that comprises of multiple measures of student characteristics. Previous
studies have made use of measures of poverty as a proxy for socioeconomic status;
however, the present study offered a comprehensive measures of socioeconomic status,
comprised of variables like poverty, Medicaid, retention, special education, and gifted
and talented. The holistic measure of socioeconomic status in the present study provided
further evidence of the significant association between measures of student characteristics
and their achievement on standardized tests. Moreover, the student characteristics latent
variable was found to have a negative indirect effect on student achievement, as
moderated by the personnel latent variable, suggesting that students’ characteristics affect
student achievement through other variables within schools.

Five of the studies yielded findings that measures of personnel, such as teachers
and administrators, were significant predictors of student achievement. The present study
confirmed these findings, indicating a significant and positive relationship between
personnel and student achievement. The largest effect of school personnel-related
variables on student achievement was found in the present study at .246. This effect is
substantially larger than the significant effects found in Archibald’s (2006) and Cooper’s
et al. (1994) investigations, at .04 and .11, respectively. In addition, a noteworthy finding of the present study is that a positive significant relationship was found between personnel and student achievement after holding constant the relatively large -.431 effect of student characteristics on achievement. Typically, the effect sizes of variables that represent personnel-related characteristics are minimal due to the presence of measures of schools’ socioeconomic status.

A relatively large amount of variance in student achievement was also explained (34.3%) in the present study. Although the variance in student achievement explained by the present study was less than the variance explained in the studies by Okpala (2002) and Cooper et al. (1994), the amount is still large as compared to standards in the social sciences. Archibald’s (2006) use of Hierarchical Linear Modeling (HLM) yielded the largest amount of variance explained in student achievement. In her multi-level analysis, 82% of the student-level variation and 16% of the school-level variation was explained by the independent variables.
**Table 5.1.** Comparison of Significant Predictors of Student Achievement in Related Literature.

<table>
<thead>
<tr>
<th>Author(s) and Year(s)</th>
<th>Method</th>
<th>Significant Predictors of student achievement ($\beta$)</th>
<th>Variance Explained</th>
</tr>
</thead>
</table>
| **Present Study**     | Structural Equation Modeling | • Student characteristics  
Direct: (-.431)  
Indirect: (-.10)  
• Schools’ personnel (.246) | 34.3% |
| Archibald (2006)      | Hierarchical Linear Modeling | • Student socioeconomic Status: (-.13)  
• Teacher quality: (.04) | School-level: 16%-19%  
Student-level: 74%-82% |
| Cooper et al. (1994)  | Multiple Regression | • Per-pupil expenditures: (.18)  
• Teachers’ Years of Experience: (.11) | 65% |
| Greenwald, Hedges, & Laine (1994, 1996) | Combined Significance Test (meta-analysis) | • Teacher education, teacher salary, administrative inputs, and teacher-pupil ratio have statistically reliable and positive relationships | N/A |
| Knoeppel, Verstegen, & Rinehart (2007) | Canonical Analysis | • Average teacher salary and local wealth had the largest loadings on the effects. | 18% |
| Okpala (2002)         | Multiple Regression | • % of students FRL: (-.377)  
• % of parents with post-high school education: (.35) | 59.07%-81.06% |

Another important comparison for the present study is the kinds of educational resources that were found to be non-significant predictors of student achievement.

Hanushek’s (1981, 1989, 1991) synthesis of 152 production function studies yielded results suggesting that expenditures per-pupil, teacher quality indicators, and student-teacher ratio measures had little power in significantly predicting student achievement.
Furthermore, after updating his research and including 96 studies that incorporated value-added modeling in their methods, Hanushek (1997) still concluded that teacher-pupil ratio, teacher education, salary, and experience, and per-pupil expenditures were not strong predictors of student achievement. Okpala (2002) also found that measures of teacher quality, class size, and expenditures per-pupil were found to be insignificant predictors of student achievement.

The present study yielded non-significant findings that were somewhat consistent with the findings of Hanushek (1981, 1989, 1991, 1997) and Okpala (2002). The instructional condition latent variable, which is comprised of each school’s student-teacher ratio, expenditures for instruction, percentage of prime instructional time, and professional development days per teacher, was found to be a non-significant predictor of student achievement. Research on the effects of educational resources on student achievement has demonstrated that resources do matter for achievement if those resources are applied appropriately to promote learning based on students’ differential needs (Adams, 2008; Alexander, 1998; Baker, 2005). In order to examine the effects of schools’ instructional conditions on student achievement, variation in the distribution of resources must exist. Contributing factors as to why some of these variables were found to be non-significant predictors of student achievement are discussed in the following implications sections. The only finding from the present study that contradicts Hanushek’s and Okpala’s findings is that teacher-related variables were positive and significant predictors of achievement.
Implications for Model Improvement and Future Research

Three implications for model improvement emerged from the findings of the present study. The first implication relates to the improvement of the measurement of the observed variables. Many of the variables used in this study may not be the best available measures of the intended phenomena. For example, the personnel latent variable was comprised of the schools’ average teacher salary, percentage of teachers with advanced degrees, percentage of returning teachers, percentage of teachers on continuing contracts, and the principals’ number of years in their schools. Although these variables served as proxies for the quality or experience of personnel, school districts may be able to collect better measures of teacher impact in their schools. For instance, teacher evaluation scores or value-added scores may serve as improved measures of the quality of instruction in each school.

Recently, the Bill and Melinda Gates Foundation (2013) released findings from their Measures of Effective Teaching (MET) Project. The project aimed to enhance the measurement of teacher effectiveness. Researchers found that multiple measures, such as student achievement indicators from standardized tests, classroom observations by multiple observers (from within the school and from outside of the school), and student perception surveys that measure the learning environment, reliably predicted effective classroom teachers. Future iterations of the present study should include these three variables to improve the personnel latent variable.

In addition to the personnel latent variable, observed variables within the instructional condition latent variable could be improved significantly to enhance the
measurement of teachers’ work conditions. For instance, the student-teacher ratio is a proxy for class size; however, scholars have found that it is not necessarily an adequate measure because it is calculated by dividing each school’s enrollment by the number of teachers in the school (Hanushek & Rivkin, 1997). The actual average class size for each school may serve as a stronger observed variable. In addition, limitations were prevalent for the percentage of prime instructional time observed variable. The variable only measures how much time teachers spend teaching the main content areas to students, but not how teachers make use of their prime instructional time to effectively teach their students.

The same limitations for the percentage of prime instructional time observed variable apply to the professional development days per teacher observed variable. Professional development for teachers can positively affect students’ academic achievement. However, research on the characteristics that make professional development effective vary depending on the type of content and pedagogical knowledge learned, the amount of time and resources that teachers have to use the knowledge learned through their professional development, and the types of evaluations that are conducted by leaders to assess whether the content and pedagogical knowledge learned has improved instruction (Guskey, 2003). The school-level variable in the present study only reports the number of professional development days per teacher, not the content area, amount of time and resources for teachers, or types of evaluations used to assess the effectiveness of the professional development activities. Perhaps future research could include variables that better measure the particularities of the observed variables, like
professional development, within the instructional condition latent variable. Then, more variation regarding how those particularities are used in each school would exist.

The second implication for model improvement relates to scholars’ calls for the use of value-added modeling in educational research. Value-added modeling is used by researchers as an attempt to isolate and estimate the contributions to student test scores made by factors other than student, family, social, or economic characteristics (Harris, 2011). In other words, value-added modeling is used to estimate the effects of independent variables on student achievement after controlling for demographic characteristics. Control variables often used in value-added modeling studies include measures of socioeconomic status and students’ previous achievement scores.

While the present study included many measures of students’ characteristics, such as poverty, special education, gifted and talented, and retention, the present study did not make use of students’ previous achievement scores. This is due to limitations in the dataset. The present study used each school’s 2013 ESEA waiver index score, which is a combined score that includes grades 3-5. If each school’s 2012 ESEA score was used as a measure of student’s previous achievement, then students who were in the fifth grade in 2012 would not be included in the 2013 ESEA score. Similarly, students who were in the third grade for the 2013 ESEA score would not be included in the 2012 ESEA score because they would have been in the second grade.

Another reason that students’ previous scores were not included in the analysis is because the current dataset did not allow for the researcher to control for transiency. It is plausible that certain elementary schools have higher transiency rates than others. The
2013 ESEA waiver index score would not have been able to account for students who were tested in 2012 but moved to a new school in 2013. Lastly, because the present study used variables that were situated at the school-level, much of the variation in the 2013 ESEA waiver index score would have been accounted for by the 2012 index score. The significant amount of variance explained by the 2012 index score may result in type II errors for other predictors. That is, non-significant estimates for other independent variables may have been confounded by the 2012 waiver index score.

While the measurement of the specific observed variables and the use of student’s previous achievement scores are critical to the validity of the findings, the emphasis of the third implication is on the particular units of analysis. Recently, multi-level analysis has become a viable method to garner more precise measurements of the effects of independent variables on dependent variables. Whereas current and past researchers have had to either aggregate or disaggregate variables to a single level of analysis, multi-level analyses allow researchers to examine phenomena within a hierarchical structure (Byrne, 2012; Hox, 2010). For example, researchers may disaggregate school-level student achievement scores into classroom-level achievement means. The disaggregation of school-level data will allow researchers to examine the effects variations in class size and teacher quality on variations in student achievement within schools.

According to methodologists (Byrne, 2012; Heck & Thomas, 2009; Hox, 2010; Muthén & Muthén, 2012), multi-level analyses avoids two methodological problems. First, statistical methods lose power when variables are aggregated and disaggregated to different levels, often leading to type I or type II errors. If data were to be disaggregated
to a lower level, then the sample size would become much larger. For instance, if all
students in a school were assigned a variable that indicates the denomination of the
school, then the sample size would increase from one school to the total number of
students in that school. This would increase the likelihood that “investigators come up
with many ‘significant’ results that are totally spurious” (Hox, 2010, p. 3).

Second, there is the potential for researchers to commit what Hox termed an
*ecological fallacy*, where conclusions are formulated by interpreting aggregated data at
the individual level. For example, in education research, conclusions are often drawn
about the effects of programs on student learning using student achievement variables
that are situated at the school-level (i.e., percentage of students proficient in math). In
order to truly uncover the effects of a particular educational program on student learning,
data would need to be collected at the student-level to formulate reliable conclusions.

To date, Archibald (2006) was the only scholar who used HLM to investigate the
effects of educational resources on student achievement at the student level, classroom
level, and school level. At the school level, the models accounted for 16% of the variation
in reading and 19% of the variation in mathematics. However, at the student level, the
models accounted for 82% of the variation in reading and 74% of the variation in
mathematics. Other scholars, including Okpala (2002), have called for further research on
the effects of educational resources on student achievement using multi-level analyses.
Perhaps future research could examine the estimates of the post hoc conceptual model
presented in the current study by modifying it into a multi-level model. The student
characteristics, personnel, and instructional condition latent variables could be
disaggregated into classroom-level variables and the multi-level analysis may explain more variation at the school-level or classroom-level.

**Implications for Resource Allocation and Educational Adequacy**

Beyond methodological implications, the findings from the present study serve as a basis for recommendations for educational policy. In order to meet student learning goals as mandated by accountability policies, states must deploy resources strategically to maximize student achievement. To date, courts in Colorado, North Carolina, and Ohio have adopted the notion that student performance outcomes may be traced to resource allocation patterns across their respective states. In addition to an analysis of the degree to which students’ achievement levels met states’ goals, states may consider whether resources are deployed to schools based on the their students’ circumstances and the degree to which those resources affected students’ achievement on standardized tests.

To some degree, the strategic deployment of resources based on students’ circumstances and needs would partially fulfill states’ obligations to provide equality of educational opportunity. Specifically, the strategic deployment of resources based on students’ differential needs would also serve as an attempt to achieve Rawls’ (1971) theory of justice. Resource allocation policies premised on adequacy serve attempts to ensure that the distribution of resources is arranged so that all citizens are provided with similar opportunities to achieve specified goals and that those who are least favored are provided with enhanced opportunities to enable them to compete fairly within those structures.
Many education finance scholars have studied the adequacy of state finance systems in providing sufficient resources to all students so that they have fair opportunities to be successful in school (Alexander, 2004; Baker, 2005; King, Swanson, & Sweetland, 2005; Ladd, 2008; Toutkoushian & Michael, 2007; Verstegen, 2002). Alexander’s (2004) conceptualization of educational adequacy was used to make sense of the findings from the post hoc conceptual model. As noted by the author, determining educational adequacy entails identifying relationships between resources and the different phases of the schooling process. These phases include adequacy of inputs, process, and outputs. Not only must an adequate funding for education be inputted into the school system, but adequacy also entails that the appropriate type and amount of resources provide sufficient classroom conditions to enable all students to learn the content necessary for achievement of proficiency goals.

The emphasis of the present study, though, is on whether researchers can quantify the relationship between the types and amount of resources and students’ academic achievement to inform education policy. To some degree, the interaction between resources (e.g., teachers, class size, time spent on instruction) and students depicted in the post hoc conceptual model represents the inputs and process aspects of Alexander’s (2004) conceptualization of adequacy (see Figure 5.3). Additionally, process may be interpreted as the way personnel make use of their instructional conditions to improve student learning. The ESEA waiver index score represents the outputs phase of Alexander’s conceptualization of adequacy. The personnel and instructional condition latent variables might be significant predictors of the outputs if they were allocated
differently across a state to meet students’ differential needs. Because the post hoc conceptual model was sufficient, the findings from the analysis may be used to inform state-level resource allocation practices to support educational adequacy goals.

Figure 5.3. Alexander’s (2004) Conceptualization of Educational Adequacy and the Post Hoc Model of the Effects of Educational Resources on Student Achievement.

Can results from the model inform resource allocation practices?

School finance scholars have called for the alignment of accountability policies with state finance formulae to allocate adequate resources to meet students’ specific
learning goals (Adams, 2008; Ryan, 2008; Superfine, 2009; Verstegen, 2002). Findings from the conceptual model in the present study are useful to inform resource allocation practices to meet the demands of educational adequacy. In particular, two policy implications emerged from the analysis: (a) a redistribution of resources within the instructional condition based on students’ needs to test the effects of the variables on student achievement and (b) modifications to the current state finance formula to include additional weightings based on schools’ poverty indices to improve the state’s attempt to provide equality of educational opportunity.

The fact that the instructional condition is a non-significant and weak predictor of student achievement may indicate that schools were not using their instructional conditions effectively to improve student achievement. However, another reason that the instructional condition does not explain variations in student achievement may be that the instructional conditions are not allocated differently across the state. Research on the effects of educational resources on student achievement has demonstrated that resources do matter for achievement if those resources are applied appropriately to promote learning based on students’ differential needs (Adams, 2008; Alexander, 1998; Baker, 2005). In order to truly examine the effects of schools’ instructional conditions on student achievement, two conditions may need to be met. First, researchers, educators, and policymakers would have to ensure that the variables used to capture schools’ instructional conditions are the best possible measures. As stated earlier in this chapter, variables such as the percentage of prime instructional time and professional development days per teacher do not adequately measure the educational process that
occurs on a day-to-day basis in schools. Second, once an adequate measure for variables within the instructional condition is conceived, then a redistribution of those resources to schools based on students’ needs would need to occur in order to discern whether those resources are significant predictors of student achievement. Researchers would then be able to draw conclusions about the effects of those resources on student achievement in order to make policy recommendations to meet the demands of educational adequacy.

In addition to the fact that the instructional condition does not vary depending on students’ circumstances, the findings of the present study may be used to inform how the state can further its attempts to adequately fund education through its finance formula. Currently, South Carolina finances the operations of public schools using a foundation program. The foundation program includes three major components that determine how much money a district will receive: (a) the base student cost per pupil, (b) weighted pupil units, and (c) the local contribution. Implications for resource allocation based on the findings of the present study may be applied to how the state calculated weighted pupil units. Weighted pupil units are computed by multiplying the average daily membership (the number of students in school divided by the number of days in session) and student weightings that are determined by the cost of educating different student populations based on their specific learning needs. In South Carolina, additional weightings are established for students depending on grade level, degree of special education services, and the existence of vocational education programs. However, the state does not distribute additional funds to schools based on their poverty index. The findings of the present study suggest that modifications may be made to the foundation program in order
to create services that lessen the effects of students’ characteristics on student achievement.

In the present study, the schools’ poverty index was found to have a large loading for the student characteristics latent variable, which was a significant and negative predictor of personnel and student achievement. Because the state does not distribute additional funds to schools based on each school’s poverty index, a weighting could be established that provides additional funds for schools to invest in school personnel. As of 2011, 37 states included weightings for low-income or compensatory education (Verstegen, 2011); however, there is no mandated program or service that those funds must support. In South Carolina, the funds generated from the additional weighting could be allocated to schools for them to devise programs or structures that have been proven to help students from low socioeconomic backgrounds achieve proficiency. For instance, funds could be allocated specifically to schools for them to use to incentivize teachers and administrators to work in schools with higher poverty indices.

The post hoc conceptual model could serve as a tool to evaluate the effectiveness of the new student weighting policy. If the redistribution of funds based on schools’ poverty indices were to be effective in providing adequate educational services, then the estimated effects of student’s characteristics on achievement should decrease and the effects of personnel and the instructional condition on achievement should increase. Judgments could then be made about whether the state is furthering its attempts to provide a just system of education premised on the notions of adequacy and equality of educational opportunity.
Summary

This chapter detailed the summary and conclusions of the present study. The new conceptual model of the effects of educational resources on student achievement was tested and found to be a poor model fit. As a result, a post hoc conceptual model of the effects of educational resources on student achievement was devised and findings were used to inform implications for methodological improvement. While the post hoc model yielded confirming results about the effects of resources on achievement, implications included enhanced measures of the observed variables, the use of students’ previous achievement scores, and the use of multi-level analyses to analyze the effects of variations simultaneously between schools and within schools.

In addition, two policy implications emerged from the findings to inform state allocation practices to meet the demands of educational adequacy. First, the instructional condition may not be a predictor of variations in student achievement because there is little variation of the resources within the latent variable. As such, policymakers may need to develop better measures of the resources within the instructional condition to capture the educational process and then redistribute those resources to schools based on students’ needs. Then, more resources would reach schools with larger percentages of students with higher needs to meet their learning goals. Second, modifications may be made to the current state finance formula to include an additional weighting for poverty. The funds generated from the additional weighting in this state could then be allocated to schools for them to devise programs or structures that have been proven to help students from low socioeconomic backgrounds achieve proficiency on accountability exams. The
post hoc conceptual model could then be used as a tool to evaluate whether the 
modification to the funding formula resulted in increased student achievement. With 
these two policies in place, the state may further its efforts to provide an adequate 
education for all students, ensuring that they have fair opportunities to be successful in 
school.


Mplus (Version 7) [Computer software]. Los Angeles, CA.


Statistical Package for the Social Sciences (Version 21) [Computer software]. Chicago, IL: IBM.


