ABSTRACT

Title of Document: WHO GETS WHAT: A WITHIN-SCHOOL EQUITY ANALYSIS OF RESOURCE ALLOCATION

Rebecca Elizabeth James Wolf
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Directed By: Assistant Professor Dr. Thomas Davis
Department of Teaching, Learning, Policy, and Leadership

This study analyzes resource allocation *within* schools, and it is one of the first in the literature to analyze the equity of monetary resources at the individual student level. The study calculates teacher resource expenditures (TREs) per pupil by allocating teacher salaries to individual students for each high school student in a large urban public school district. Next, the study compares the degree of within-school variation in per-pupil TREs to the variation between schools and concludes that the variation within schools is much larger than the variation between schools. The study then uses Berne and Stiefel's (1984) equity evaluation framework and develops an analytic approach that is appropriate for conducting a within-school equity analysis of per-pupil TREs. The findings indicate that inequities in the allocation of teacher salaries at the student level do exist. Specifically, the study finds violations of horizontal equity, vertical equity for low-income students, and equal opportunity for students of differing achievement levels.

These findings also suggest that district leaders may be unaware of how resources are ultimately allocated to students.

This study also evaluates the equity of the within-school allocation of specific resources to identify if resources are equitably allocated in academic courses that are critical for academic success. This study evaluates the equity of the allocation of class size, teacher experience, and social capital in students' English and math courses only as well as the number of advanced placement (AP) courses taken by students, which indicates access to rigorous curricula. In analyzing the equity of these specific resources within each school in the district, this study determines if multiple resource advantages or disadvantages exist for some students.

Findings indicate that multiple resource inequities may exist for low-performing, low-income, and minority students. Further, the study finds that schools with greater socioeconomic and racial diversity have more occurrences of within-school resource inequities for low-income and minority students than schools with homogeneous student populations. The study is among the first to analyze the equity of the within-school allocation of multiple resources simultaneously to gain a better understanding of whether students in the same school receive equitable resources.

WHO GETS WHAT: A WITHIN-SCHOOL EQUITY ANALYSIS OF RESOURCE ALLOCATION.

By

Rebecca Elizabeth James Wolf.

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Advisory Committee:
Dr. Robert Croninger, Associate Professor
Dr. Thomas Davis, Assistant Professor, Chair
Dr. Steven Klees, Professor
Dr. Jennifer Rice, Professor
Dr. Laura Stapleton, Associate Professor

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Table of Contents

List of Tables

List of Figures

List of Equations

Chapter 1: Introduction

Federal, state, and local governments collectively spend hundreds of billions of dollars every year on public elementary and secondary education, yet we know "remarkably little" about how these funds are allocated to individual students (Picus, 2000, p. 75). One structural impediment to tracking expenditures to the individual student level is the collective–federal, state, and local–nature of K-12 public education funding itself; as Roza (2010) noted, "No one governmental level takes full responsibility for funding" (p. 33). As a result, district leaders may be unaware of spending differences between schools (Roza, Hill, Sclafani, & Speakman, 2004), as well as between individual students within a school. Roza, Guin, and Davis (2008) conclude: "A straightforward answer to the question of how much is spent on different student types" is needed (p. 2).

This lack of knowledge regarding student-specific expenditures is troubling, because–to put it bluntly–money matters. If allocated effectively, money can help improve student achievement through purchasing resources that promote student learning (Rice & Schwartz, 2008; Slavin, 1999). The most important of these resources are teachers (Rice, 2003), and research has shown that higher salaries can attract and retain more effective teachers (Slavin, 1999; Theobald & Gritz, 1996). Both class sizes (Krueger, 2002) as well as access to academically rigorous courses are also known to affect student achievement (Gamoran, 1987; Madigan, 1997; Muller, Stage, & Kinzie, 2001; Tyson, 2013), but these resources are costly. Thus, it is not surprising that numerous studies establish the positive association between money spent on instruction and student outcomes (Archibald, 2006; Deke, 2003; Fortune & O'Neil, 1994; Hogrebe, Kyei-Blankson, & Zou, 2008; Knoeppel, Verstegen, & Rinehart, 2007).

Because money can matter, education leaders should ensure that money spent on public education is equitably allocated. Equity is defined in the literature as the "fair distribution of goods, services, and burdens" (Rice, 2004, p. 136), and it is one of the three public goals of education finance: equity, efficiency, and liberty (Springer, Houck, & Guthrie, 2008). Yet it is one of the "most compelling, consistent, and complicated issues related to K-12 public school finance in the United States" (Rice, 2004, p. 134). Equity in education is "compelling" in part because it is a national value. The idea that every child should receive equitable educational opportunities "lies at the core of American schooling" (Welner & Carter, 2013, p. 5). Education has been referred to as the "central engine" for achieving equal opportunity and realizing the "American Dream" (Koski & Reich, 2006, p. 607). When inequities in access to educational opportunities exist, American scholars have described these inequities as being "un-American" (Carter & Welner, 2013; Ladson-Billings, 2013).

Not only is equity in education an American value, it can implicate legal rights as well. While the U.S. Supreme Court has held that education is not a fundamental right under the federal Constitution (*San Antonio Independent School District v. Rodriguez,* 1973), every state constitution contains at least one provision regarding education, and courts in a majority of states have held the applicable state constitutional language to provide some form of a right to education (Friedman & Solow, 2013). In turn, in the landmark U.S. Supreme Court decision in *Brown v. Board of Education*, Chief Justice Earl Warren stated that education, "where the state has undertaken to provide it, is a right which must be made available to all on equal terms" (1954, p. 493). While subsequent lawsuits raising state law claims with regard to funding equity have met with mixed results (National Education Access Network, 2014), some state courts–including, for example, the high courts of California (*Serrano v. Priest*, 1976), New Jersey (*Abbott v. Burke*, 1994), and Vermont (*Brigham v. State*, 1997)–have held that large interdistrict disparities in the state's public education funding system violated the state constitution (Friedman & Solow, 2013).

These judicial rulings are perhaps unsurprising, as education quality and attainment have economic as well as non-monetary implications for both individuals and society. Regarding economic matters, education quality and attainment can increase workers' employability and productivity and ultimately, national economic growth (Hanushek & Woessmann, 2006), while dropping out of high school is associated with lower earnings and income tax payments; greater dependency on Medicaid and unemployment programs; and increased criminal activity and spending on incarceration (Belfield & Levin, 2013; H. Levin, 2009). One study estimated that preventing one high school student from dropping out would result in a cost savings to society of $129,230 over the lifetime of the student (Belfield & Levin, 2013).

Education quality and attainment are also associated with non-monetary benefits to individuals and society. Education attainment is correlated with better overall health for individuals and their families, improved child cognitive development, increased happiness, and more civic engagement (Brewer & McEwan, 2010). Further, greater inequality in education quality and attainment are associated with "lower levels of social cohesion and trust" (B. Levin, 2003, p. 5), which are necessary components for successful governance. Finally, B. Levin (2003) notes, "Inasfar as opportunity is not distributed fairly there will be an underutilization of talent; some people will not develop their skills and abilities with consequent loss not only to them but to society generally" (p. 5). Thus, it is critical that all individuals experience equitable opportunities in education.

In their book, *Closing the Opportunity Gap,* Welner and Carter (2013) argue that current inequities in student education outcomes are the result of cumulative inequitable educational resources and opportunities and that the effects of differential educational experiences for students of different races are already evident. As of 2010, the high school graduation rates were 93.5% for White students, 83% for Asian students. 71.4% for Latino students, and 66.1% for African American students, and the dropout rates for minority students were more than double the national average (Welner & Carter, 2013). Furthermore, in large urban areas, at least half of high school students did not graduate from high school (Welner & Carter, 2013).

Yet despite the knowledge that large discrepancies in student educational outcomes exist in the U.S., inequities in resources are commonplace. Inequities in per-pupil expenditures (PPEs) exist at every organizational level–in states, in districts, and in schools (Ladd, Chalk, & Hansen, 1999). Until relatively recently, education researchers examined the equity of PPEs using district-level averages (Odden & Picus, 2008), but district-level averages do not inform the variation in resources between and within schools. As school-level data have become more widely available over the past two decades, a growing body of research has investigated the equitable distribution of monetary resources between schools in the same district. In many cases, PPEs are lower in schools enrolling large proportions of low-income, minority, and/or low-performing students compared to other schools in the same district (Berne & Stiefel, 1994; Condron & Roscigno, 2003; Heuer & Stullich, 2011; Klein, 2008; Owens & Maiden, 1999;

Rubenstein, 1998; Spatig-Amerikaner, 2012). Even when studies found that PPEs were higher in schools with larger proportions of low-income and minority students, researchers found that these schools employed less experienced and less well-paid teachers and therefore had lower *instructional* PPEs–or PPEs dedicated to instructional purposes only–than schools serving middle-class and White student populations (Baker, 2012; Iatarola & Stiefel, 2003; Stiefel, Schwartz, Portas, & Kim, 2003).

In addition to inequities in PPEs across schools, researchers have found inequities in the allocation of certain resources among individual students within the same school. For example, studies have already shown that, within schools, low-income, minority, and low-performing students are assigned to less qualified teachers (Feng, 2010; Kalogrides & Loeb, 2013; Koedel & Betts, 2009; Player, 2010; Rothstein, 2008), have larger class sizes (Boozer & Rouse, 1995; Roza, 2009), take fewer academic courses (Darling-Hammond, 2007; Gamoran, 1987) and more low-track academic courses (Brent, Roellke, & Monk, 1997; Buckley, 2010; Carter, 2013; Ingersoll, 1999; Lee et al., 1997; Tyson, 2013), and have lower-achieving peers than their middle-class, White, and high-achieving counterparts (Conger, 2005; Kalogrides, Loeb, & Beteille, 2013). Given that such inequities exist with respect to certain resources within schools, we can conclude that inequities in real instructional expenditures exist for individual students within the same school. This conclusion is bolstered by research that analyzes program and course level resource allocation. Marguerite Roza has argued that inequities and efficiencies in resource allocation exist for various curricula and extracurricular programs: She found that schools spend more money in terms of teacher salaries per student on advanced courses than on regular or remedial track courses (Roza, 2009).

Little research, however, has examined the equity of the allocation of student-specific expenditures despite the knowledge that student-level resource inequities exist. The sole published study to date to calculate student-specific PPEs descriptively found considerable variation in student-level expenditures for students within the same school. After analyzing the data from a single high school, the authors found that individual student PPEs ranged from $3,615 to $16,734 and thus concluded that there may be "considerable" differences in PPEs for students in the same school (Picus, McCroskey, Robillard, Yoo, & Marsenich, 2002, p. 200).

This gap in the literature regarding the equity of the allocation of student-specific expenditures stems from the limited availability of student-level data, the complexity of cleaning and combining raw district and school datasets, and the challenges of calculating student-level expenditures. Detailed student-level data that allow for analyses of resource equity at the student level are generally not available. Until 2009, federal legislation only required districts to report district-wide average teacher salary, as opposed to actual individual or school-level average teacher salaries, and districts did not typically keep track of resources at the school level (Spatig-Amerikaner, 2012). Further, individual schools do not record differences in instructional resources across classrooms, let alone merge such records for each resource (Cooper et al., 1994). Detailed, comprehensive data that link individual students with their courses and teachers, are needed in order to analyze the equity of student-level expenditures, yet data are rarely collected and organized in this manner. Accordingly, the research community has noted the need not only for more analyses using student-level data (Burke & White, 2001; Picus, 2000; Verstegen & King, 1998), but specifically for studies that examine the relationships between student-level expenditures, student achievement, and demographic characteristics (Goertz & Stiefel, 1998).

In addition to the lack of research employing student-level expenditure data, few studies evaluate how the equity of one resource relates to the existence or non-existence of other resources. Students may experience multiple simultaneous resource advantages or disadvantages, yet Rodriguez (2004) remarks that the missing link in the literature is a study that develops a "deeper understanding of the workings of schools" by integrating all of the elements of the schooling process–"highly qualified teachers, school and class sizes, allocation of time and dollars toward specific curricular areas, investments in professional development, and so on" (p. 20). Similarly, Odden and Borman (2004) have noted, "Too much previous research has tended to assess the effects of student, classroom, and school variables in isolation from other variables" (p. 4). Clearly, more research that examines the equity of the interplay of various educational resources is needed.

This study seeks to address these gaps in the literature by analyzing the equity of the results of the within-school allocation process for all high school students in a large urban school district. The study first defines teacher resource expenditures (TREs) as the amount spent per pupil on teacher salaries and then allocates teacher salaries to individual students accounting for class sizes and length and duration of courses, among other factors. In doing so, the study calculates a pair of student-specific expenditures–one for instruction in all classes and one for instruction in core-academic subjects only–for each high school student in the district. To determine if a thorough investigation of the equity of the allocation of per-pupil TREs within schools is warranted, the study then investigates whether the variation in per-pupil TREs is practically significant compared to the variation between schools. This analysis clarifies whether most of the variation in per-pupil TREs is due to resource allocation differences between schools or within schools in one district.

The study then conducts an equity analysis of per-pupil TREs. Specifically, it builds on Berne and Stiefel's (1984) widely used framework as well as Toutkoushian and Michael's (2007) modification thereof to develop an analytic approach appropriate for evaluating the within-school equity of per-pupil TREs. Berne and Stiefel's framework involves three principles of equity: horizontal equity, vertical equity, and equal opportunity. The presence of horizontal equity indicates that students with similar characteristics get the same amount of resources; in other words, for similar students, there should be little to no variation in their per-pupil TREs. Vertical equity is achieved if students with greater educational needs actually receive more resources, and this study examines vertical equity for certain student subgroups who are widely recognized as requiring greater educational resources. The study investigates equal opportunity by evaluating whether per-pupil TREs are associated with student characteristics that should not be predictive of funding such as student gender or race. The study then turns to an analysis of whether within-school allocation patterns of per-pupil TREs are similar or different across schools, particularly across schools with different characteristics. If within-school allocation patterns remain relatively constant, particularly across different types of schools, then school and district leaders may attempt to address any inequities differently than if such patterns vary.

Lastly, the study assesses the equity of the within-school allocation of a specific set of resources. Though an equity analysis of per-pupil TREs is informative, it does not inform resource tradeoffs. For example, per-pupil TREs may not highlight resource differentiation for students who have higher paid teachers and larger class sizes if the higher costs of teachers balance the lower costs of large class sizes. In addition, some courses are likely to affect student educational outcomes more than others, and per-pupil TREs do not reflect resource differences across individual courses. For these reasons, the study analyzes the equity of the within-school allocation of a set of specific resources–class sizes, teacher experience, and social capital–in students' English and math classes because graduating from high school and post-secondary opportunities depend on mastering content in these courses. Further, though class size and teacher experience in students' English and math courses are related to each student's per-pupil TRE, they may vary in ways not captured by the variation in per-pupil TREs, and an examination of the allocation of these resources may shed light into resource equity. Finally, this study examines the number of advanced placement (AP) courses taken by each student, which reveals at least to some extent students' access to academically rigorous curricula, which is known to impact student success (Gamoran, 1987; Madigan, 1997; Muller, Stage, & Kinzie, 2001; Tyson, 2013).

By evaluating the equity of the within-school allocation of multiple resources–including per-pupil TREs; class sizes, teacher experience, and social capital in students' English and math classes; and number of AP courses taken by each student–the study assesses whether the results of the within-school resource allocation process are equitable for high schools students in one district. The study also demonstrates whether certain students have multiple resource advantages or disadvantages compared to others and how the equity of the allocation of one resource relates to the existence or non-existence of other resources. Accordingly, the study may help school and district leaders better understand not only "who gets what" but also how to reduce inequity in within-school resource allocation.

Research Purposes

This study has four main purposes. The first purpose is to compare the variation in per-pupil TREs within schools to the variation between schools. Next, the study seeks to evaluate the equity of per-pupil TREs within schools and at the student level. The third purpose is to analyze whether within-school allocation patterns of per-pupil TREs vary across schools. Finally, the study seeks to evaluate the equity of the allocation of class size, teacher experience, and peer achievement in students' English and math courses as well as the number of AP courses taken by each student.

Research Questions

To address these purposes, this study poses four research questions:

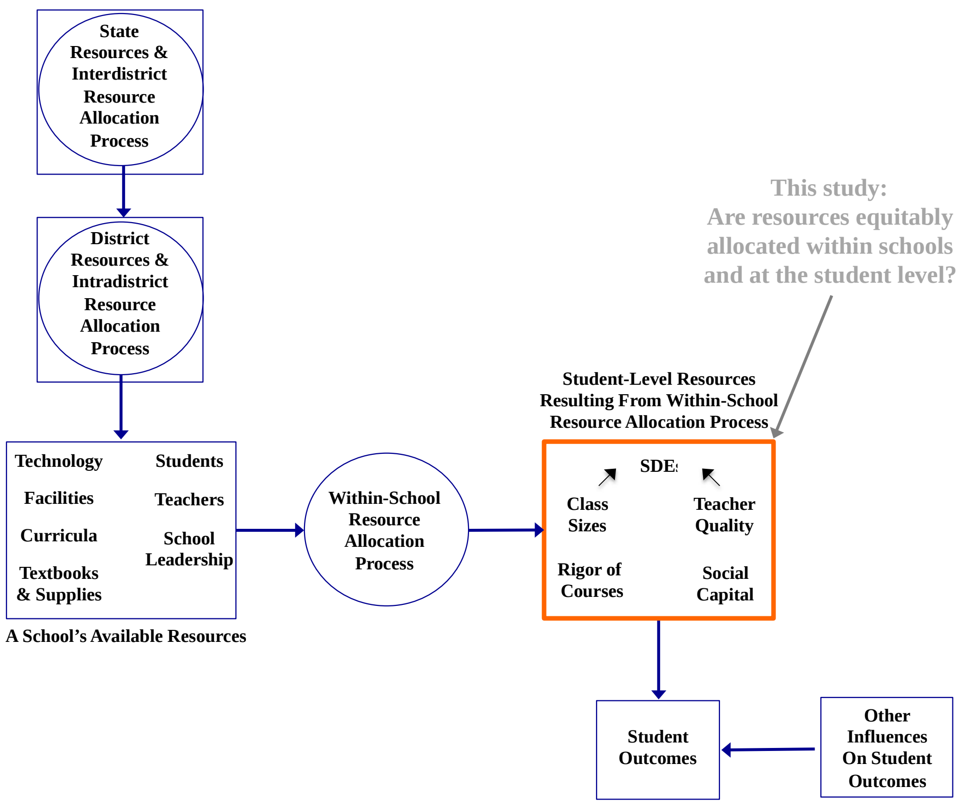
1. How does the within-school variation in teacher resource expenditures per pupil compare to the variation between schools?
2. Are teacher resource expenditures per pupil equitably distributed within schools?
3. Do within-school allocation patterns of teacher resource expenditures per pupil vary across schools?
4. Are specific resources equitably allocated within schools, and do multiple resource advantages or disadvantages exist for some students?

Conceptual Framework

The conceptual framework for this study draws from three bodies of literature. First, using the logic of education production functions from the economics of education literature, the author argues that the levels of certain inputs are related to student outcomes. Second, this study draws on school finance literature to explain how monetary resources are allocated to both districts and schools and why inequity in monetary resources may exist between districts, schools, or even students. Finally, this study draws from the equity in education literature to account for the equity of the allocation of other resources–class sizes, teacher experience, number of AP courses, and peer achievement–between and within schools.

Illustrated in the following conceptual model, this study assumes that interdistrict and intradistrict fiscal resource allocation processes affect the quality of a school’s available resources. Educational leaders and administrators allocate resources to districts, schools, and classrooms. Within a classroom, students benefit from monetary resources that fund teachers’ salaries and class sizes. In addition, there are non-monetary resources like the experience of the teacher, the rigor of the curriculum, and the academic ability of a student’s peers. This study analyzes whether the results of the within-school allocation process for these resources are equitable.

Figure 1: Conceptual Model



Notes: In the model above, rectangles represent things (e.g., resources, outcomes) and circles represent resource allocation processes.

As described in the next chapter, states allocate funding for public education to districts, and inequities in funding among districts may exist due to state legislation or differences in local funding, which is generally tied to property wealth (Odden & Picus, 2008). Districts then allocate resources to schools, primarily through teacher salaries, and inequities in funding may exist across schools with different teacher populations. At the school level, who gets what is primarily determined by how teachers and students sort into classes. This study examines the equity of the results of the within-school allocation process by analyzing the equity in the allocation of the following resources: teacher resource expenditures (TREs) per pupil; class sizes, teacher experience, and peer achievement in students' English and math classes; and the number of AP courses taken by each student. This study uses peer achievement as a proxy for social capital, teacher experience as a proxy for teacher quality, and the number of AP courses taken by each student as a proxy for exposure to rigorous curricula. Taken together, these resources can impact student learning and outcomes.

Significance

While there is ample research on the equity of the allocation of per-pupil expenditures (PPEs) across districts and schools, there is very little research on the equity of student-level expenditures within schools. Therefore, the study contributes to school finance literature by conducting an equity analysis of student-level TREs. The study also contributes to school finance literature by documenting the degree of the variation in per-pupil TREs within schools relative to the variation between schools. Finally, the study adds to literature on equity in education because it explores within-school allocation of specific resources and herein provides an in-depth equity analysis of resources allocated to students within the same school. Though past studies have investigated the equity of the allocation of certain resources within schools, few studies have examined the interplay of multiple resources with regard to equity.

This study may also have practical implications for educational leaders and policymakers as well. State, district, and school officials make numerous decisions affecting resource allocation, and studies, such as this one, that examine resource allocation at the student level may enable educational leaders at all levels to better target their resources to attain state, district, or school funding goals and to improve the equity of resource allocation for students in their jurisdictions.

Chapter 2: Literature Review

This chapter summarizes the research on equity in education and shows that more research is needed to understand the equity of the allocation of resources within schools, particularly the equity of per-pupil TREs. First, this chapter summarizes Berne and Stiefel's (1984) framework, which is a widely used tool to evaluate equity in education. Next, it summarizes the existing research on the efficacy and equity of resources that are known to matter for student success, including teachers, class sizes, rigorous academic courses, peers, and per-pupil expenditures (PPEs). There is evidence that these resources are often inequitably distributed between districts and schools, and research even suggests that some resources are inequitably distributed within schools. Finally, this chapter discusses the factors that influence the within-school resource allocation process and whether students within the same school receive equitable resources.

How Should Equity in Education Be Evaluated?

Scholars have noted that defining "what, specifically, constitutes equity [in education] has been an evolving process" (Rice, Monk, & Zhang, 2010, p. 217). Decades ago, scholars in various fields, including tax policy and legal theory as well as education, debated the definition of equity in education (Baker & Green, 2008). In 1984, Berne and Stiefel, reviewed and synthesized much of this literature into what is now the most widely used framework for evaluating equity in education (Baker & Green, 2008), and this study employs their framework to develop an approach to determine within-school resource equity.

Overview. Berne and Stiefel (1984) pose four questions for defining and evaluating equity–Who? What? How? and How Much?–and the "How" question involves three principals of equity–horizontal equity, vertical equity, and equal opportunity. With "who," Berne and Stiefel refer to whom should be treated equitably–the taxpayer or the child–and what should be the level of organization (e.g., district, school, or child) in which equity should be evaluated (Baker & Green, 2008). School finance literature has generally focused on equity for children, because children are the "customers" of schools (Odden & Picus, 2008, p. 63). Equity has "historically and traditionally" been analyzed at the district level (Odden & Picus, 2008), and only more recently at the school level (Berne & Stiefel, 1994; Condron & Roscigno, 2003; Klein, 2008; R. Miller, 2010; Odden, Archibald, Fermanich, & Gross, 2003b; Owens & Maiden, 1999; Rubenstein, Schwartz, Stiefel, & Amor, 2007; Rubenstein, 1998; Spatig-Amerikaner, 2012; Stiefel, Rubenstein, & Berne, 1998; The Education Trust, 2008). However, Baker and Green (2008) note that, "ideally, equity [should] be measured across each individual child or taxpayer using precise measures of the educational inputs available to each child" (p. 204).

Berne and Stiefel's framework then seeks to define the "what," or the object that is to be distributed equitably. For example, researchers may investigate whether fiscal and physical inputs or student outcomes are equitably distributed. The equity of fiscal resources, which are usually denominated in terms of district-level average PPEs, can be analyzed "on a total basis (current operating expenditures per pupil), by function (expenditures on administration, instruction, operation and maintenance, transportation, etc.), or by program (regular, special education, compensatory education, bilingual education, etc.)" and are ideally analyzed separately for elementary, middle, and high school students because some districts spend more money on high schools than elementary schools (Odden & Picus, 2008, p. 60). School finance research has mainly employed district-level averages of PPEs because these data are typically available (Odden & Picus, 2008).

Other fiscal and physical inputs may also be used as the object of equity. These inputs may include student-level resources (number of courses a student takes or participation in special courses), classroom-level resources (class sizes and quality of teacher and curriculum), and school-level resources (professional development, instructional leadership, textbooks, and facilities), among others (Baker & Green, 2008; Odden & Picus, 2008). Finally, the "what" may refer to student outcome variables, including high school graduation rates, number of academic courses taken, college attendance rate, and student achievement on standardized tests (Odden & Picus, 2008).

Once the object of equity and the resource that is to be equitably distributed are selected, the "how" question in Berne and Stiefel's framework asks which type of equity is the goal: horizontal equity, vertical equity, or equal opportunity. Finally, Berne and Stiefel's "how much" inquiry refers to the degree of inequity that is permissible before equity is violated. The next three subsections address these related concepts.

Horizontal equity. Horizontal equity is the equal treatment of equals, which means that students with equal needs receive the same amount of resources (Baker & Green, 2008). However, Odden and Picus (2008) point out that not "all children are alike;" hence, horizontal equity analyses are "best applied to subgroups of students" (p. 66). Children differ in grade level, prior performance level, disability status, socioeconomic background, and English proficiency, and "care must be taken to create a legitimate subgroup of students, for which homogeneity claims are valid" (Odden & Picus, 2008, p. 67). Coupled with the fact that districts target funds for a number of reasons (Education Week, 2005), there could potentially be a large number of student subgroups when analyzing horizontal equity.

After a subgroup of "like" students is identified, there are a number of available statistics to gauge horizontal equity for these students. Horizontal equity statistics are calculated and then compared to pre-determined criteria to ascertain if horizontal equity is achieved (Berne & Stiefel, 1984; Odden & Picus, 2008).

Common horizontal equity statistics include the federal range ratio, coefficient of variation, McLoone index, and the Gini coefficient, though some of these are better for capturing variation than others[1] (Odden & Picus, 2008). The federal range ratio is a good range statistic, is not sensitive to outliers, but it is only based on two values in the data. The McLoone index is best for determining the equity of the bottom half of the distribution of values. The Gini coefficient and the coefficient of variation (CV) are good measures to assess the overall equity and take into account all values. Other studies employ descriptive statistics, such as the range, restricted range, mean, and standard deviation, to assess the degree of variation.

[1] Other less commonly used equity statistics include Theil's measure and Atkinson's index (Berne & Stiefel, 1984).

Table 1: Common Horizontal Equity Statistics and Criterions (Berne & Stiefel, 1984; Goertz & Stiefel, 1998; Odden & Picus, 2008)

Statistic	Calculation	Range	Criterion
Federal range ratio	Difference between the value at the 95th percentile and the value at the 5th percentile, divided by the value at the 5th percentile	0 to infinity, 0 for perfect equity	NA
Coefficient of variation	Standard deviation divided by the mean	0 for perfect equity, 1 for maximum inequity	< .1 or < .15 for cross-state and district comparisons but < .05 for intradistrict studies
McLoone index	Ratio of the sum of all values below the median to the sum if all values were the median	1 for perfect equity, 0 for maximum inequity	> .9 or > .95
Gini coefficient	Area of the graph between the Lorenze curve and the 45-degree line divided by the area under the 45-degree line	0 for perfect equity, 1 for maximum inequity	< .05 though most values in school finance literature are between .1 and .2

The coefficient of variation (CV) is an easily-understood statistic employed to evaluate horizontal equity of PPEs (Baird, 2008; Baker, 2001; Berne & Stiefel, 1984; Hirth & Eiler, 2005; Iatarola & Stiefel, 2003; Klein, 2008; Maiden & Evans, 2009; Rubenstein, Doering, & Gess, 2000), and it is calculated by dividing the standard deviation of PPEs by the mean PPE. The CV is a good overall measure of variation because it takes into account all values (Odden & Picus, 2008). One limitation of employing CVs to gauge horizontal equity, however, is that the researcher must determine an appropriate criterion on which to compare the value of the CV, and this process is subjective. A common criterion for achieving horizontal equity of PPEs in studies of interdistrict equity is a CV of less than 0.10, though several scholars argue that this criterion is too large for studies of intradistrict spending (Goertz & Stiefel, 1998; Odden & Picus, 2008). For example, if the average PPE is $10,000, a CV of 0.10 would be obtained if PPEs differ by $2,000 for two-thirds of students and by $4,000 for one third of students. These amounts are large differences for variation in PPEs within districts, and for studies of intradistrict equity, Odden and Picus (2008) suggest using 0.05 as the CV criterion. If the average PPE is $10,000, a CV of 0.05 would be obtained if PPEs differ by $1,000 for two-thirds of students and by $2,000 for one third of students. However, due to limited research on within-school horizontal equity of PPEs, there is no commonly accepted criterion for determining within-school horizontal equity of PPEs. This issue is addressed in subsequent chapters.

Vertical equity. Vertical equity is the unequal treatment of unequals (Odden & Picus, 2008) and is based on the assumption that, "Students who bring certain educational needs to the classroom require additional resources to address those needs within the educational process" (Rodriguez, 2004, p. 7-8). This idea stems from Rawl's (1971) concept of redress: "Society must give more attention to those with fewer native assets and to those born into the less favorable social positions. The idea is to redress the bias of contingencies in the direction of equality" (p. 17).

Vertical equity may be determined based on characteristics of children, districts, or programs (Odden & Picus, 2008). Districts that serve large numbers of low-income, special education, or English language learner students need additional resources to achieve the same outcomes (Taylor, Alexander, Gronberg, Jansen, & Keller, 2002). For example, Baltimore City Public Schools must dedicate 23% of its budget to special education services compared to the average 14% dedicated by other districts in Maryland (Slavin, 1999). In addition, some programs cost more than others; vocational education and magnet schools cost more than traditional education programs, and science labs are more costly to provide than English or math courses (Odden & Picus, 2008). There may be legitimate reasons for providing some of these programs or courses.

Costs also vary across geographic regions, and districts may pay different amounts for equivalent items due to variations in transportation, energy, property, and labor market costs (Liu, 2006; Odden & Picus, 2008). One study found that in eight states, costs varied as much as 40% from one part of the state to another (Taylor, 2006). Further, in an evaluation of Texas districts, one study determined that teachers required higher salaries for teaching in rural districts and in districts with higher housing costs (Taylor, Alexander, Gronberg, Jansen, & Keller, 2002). Districts located in rural areas may also enroll a small number of students and may not be able to benefit from economies of scale, resulting in higher PPEs for the same educational resources (Odden & Picus, 2008).

Vertical equity, though simple in theory, is difficult to implement due to controversy on the reasons why some students, districts, or programs should receive additional resources. However, some of the widely agreed-upon reasons for unequal treatment of children include disabilities, physical or mental handicaps, low-income backgrounds, and limited English language proficiency (Baker & Duncombe, 2004; Berne & Stiefel, 1984; Carey, 2002; Education Week, 2005). Many state policymakers have agreed that special eduation, low-income, and English language learner (ELL) students need additional resources to achieve the intended outcomes (Education Week, 2005). More controversial reasons for unequal treatment of students include age, grade level, and gifted status (Berne & Stiefel, 1984; Odden & Picus, 2008).

There are two ways to gauge vertical inequity. First, weights are applied to students, districts, or programs according to legitimate needs or variations in costs, and then a horizontal equity analysis is conducted once again (Berne & Stiefel, 1984; Odden

& Picus, 2008). However, just as there is no consensus on characteristics of students, districts, and programs that necessitate additional funding, there is also no consensus on what these weights should be. Berne and Stiefel (1984) note that determining these weights is the most difficult aspect of vertical equity analysis. Another approach to assessing vertical equity is to employ multiple linear regression (MLR) to test the direction and magnitude of the relationship between PPEs and a student or district characteristic that warrants additional funding (Berne & Stiefel, 1984); recent research primarily employs this method (Baker, 2012; Berne & Stiefel, 1994; Bundt & Leland, 2001; Iatarola & Stiefel, 2003; L. Miller & Rubenstein, 2008; Owens & Maiden, 1999; Rubenstein, 1998; Stiefel et al., 1998). However, Goertz and Stiefel (1998) point out a limitation to studies using this approach: Most studies only assess the direction of the linear relationship between PPEs and the student or district characteristic and do not further analyze the magnitude of the regression coefficients, i.e. the implicit funding weights. Odden and Picus (2008) thus remark that this method "essentially skirts analysis of vertical equity" (p. 74). Therefore, vertical equity analyses should compare implicit funding weights to pre-determined criteria.

The greatest challenge of vertical equity analyses is selecting criteria on which to base vertical equity analyses (Berne & Stiefel, 1984). Researchers can look to prior studies for guidance on how much more districts should spend on students with various characteristics to achieve a specific outcome; however, prior research suffers from some inconsistencies. For example, Odden & Picus (2008) find that studies that estimate the cost of providing bilingual education produce results that range from no additional costs to an additional 100 percent per student compared to traditional education (Odden &

Picus, 2008). In addition, Duncombe and Yinger (2004) found that a weight of at least 185% is needed for special education students, but Odden and Picus (2008) remark that a weight of 230% is generally accepted for the average special education student, but costs for special education students vary depending on the type of disability (Duncombe & Yinger, 2004; Odden & Picus, 2008).

An alternative approach for selecting criteria on which to assess vertical equity is to compare actual funding weights for students with categorical needs to funding weights specified in state funding plans (Odden & Picus, 2008). State funding plans may assign funding weights for allocating dollars to districts based on the categorical needs of the student populations. Twenty-eight states allocate additional funds for special education students, 25 states do so for English language learners, and 23 states do so for low-income students (Education Week, 2005). Though state weights may not reflect the true cost differentials in educating students with different needs (Duncombe & Yinger, 2004), they do provide one benchmark for categorical funding. Some states also differentiate funding to districts based on other district characteristics, such as district size, number of students in each grade level, geographic isolation, teacher qualifications, gifted programs, prior student achievement test scores, and cost of living (Education Week, 2005; Huang, 2004). Thus, when evaluating vertical equity, multiple dimensions of student and district need must be considered.

Equal opportunity. Equal opportunity occurs when "there is an absence of a relationship between the object [of equity]" and a student, district, or program characteristic that should not be associated with the object of equity (Berne & Stiefel, 1984, p. 26). For example, access to educational inputs should not be "a function of the wealth of the community in which a child happens to live" (Baker & Green, 2008, p. 204). In addition, student race, ethnicity, and gender should not be related to resources received (Odden & Picus, 2008). There are exceptions, however; additional funds may be provided to minorities or to female students to spur participation in science, technology, engineering, and math (STEM) programs (Odden & Picus, 2008).

Traditionally, equal opportunity is calculated by the Pearson correlation coefficient, which assesses "the degree to which there is a linear relationship between the two variables" (Odden & Picus, 2008, p. 65). Pearson correlation coefficients range from negative one to positive one. A Pearson correlation coefficient of negative one indicates a perfect and negative linear relationship between the object of equity and the illegitimate district or student characteristic. A Pearson correlation coefficient of positive one indicates a perfect and positive linear relationship between the object of equity and the illegitimate district or student characteristic. A Pearson correlation coefficient of zero indicates no relationship between the object of equity and the illegitimate district and student characteristic. To test for equal opportunity, both the direction and magnitude of the Pearson correlation coefficient should be examined (Berne & Stiefel, 1984; Odden & Picus, 2008).

Summary. Berne and Stiefel (1984) provide a useful framework for analyzing equity in education. However, equity analyses are complex and based on assumptions about which students require extra resources and how much more students who need extra resources should receive. Horizontal equity analyses should account for multiple dimensions of student and district need, and vertical equity should be analyzed against clearly articulated funding goals. Measures of equal opportunity should reflect both direction and magnitude of the relationship between the object of equity and the district or student characteristic.

Are Key Educational Resources Equitably Distributed?

There is convincing evidence that certain educational resources are critical for the academic success of students. This section summarizes the research on the efficacy and equity of these key resources, which include teachers, class sizes, academically rigorous courses, peers, and per-pupil expenditures. Each subsection first discusses the efficacy and then the equity of each resource.

Teachers. It is commonly accepted that teachers are the most important school-based factor impacting student achievement (Rice, 2003). In his landmark study, Hanushek (1992) estimated that having a good teacher (compared to having a bad teacher) increases student achievement by “more than one grade-level equivalent in test performance” (p. 107). Similarly, Goldhaber (2009) reported that a one standard deviation increase in teacher quality results in student achievement that is 30-40% higher than the average yearly gain. Teacher quality is often determined by gains in student achievement scores, and research consistently finds that there is substantial variation in teacher quality (Goldhaber, 2009; Hanushek, 1992).

Though it is clear that teachers impact student achievement, teacher quality may not be associated with observable characteristics of teachers, such as teachers’ educational attainment. There is evidence, however, that teacher salary and experience are associated with student achievement. A number of studies have found that average salary in a district is positively associated with average student achievement (Darling-Hammond, 2007; Hogrebe et al., 2008; Luca, Takano, Hinshaw, & Raisch, 2010).

Further, two studies found that the average starting salary, at either the school or district level, is also associated with higher student performance (Figlio, 1999; Grubb, 2006). Teacher salary may be associated with student achievement because higher salaries can help attract and retain effective teachers (Slavin, 1999; Theobald & Gritz, 1996). Teacher salary may also be positively related to student achievement because teacher salary may be partially determined by years of experience, and teachers tend to improve with experience (Clotfelter, Ladd, & Vigdor, 2007; Elliott, 1998; Hogrebe et al., 2008; Ludwig & Bassi, 1999; Okpala, 2002; Perez & Socias, 2008; Stiefel et al., 2003; Wayne & Youngs, 2003). However, the relationship between teacher experience and student achievement is not linear. Teachers improve the most during their first few years of teaching (Rice, 2003), and some researchers estimate that gains from teacher experience level off after six to ten years (Boyd, Lankford, Loeb, Rockoff, & Wyckoff, 2007). Teacher education, particularly in math and science fields, has also been shown to be associated with student achievement (Elliott, 1998; Ferguson & Ladd, 1996; Goldhaber & Brewer, 1997; Hogrebe et al., 2008; Okpala, 2002; Raudenbush, Fotiu, & Cheong, 1998; Stiefel et al., 2003; Wayne & Youngs, 2003). Thus, teacher salary, experience, and education are potentially related to student achievement, and due to collective bargaining agreements that determine teacher salary, teacher salary is often related to teacher experience and education.

As teachers are arguably the most important school-based instructional resource, effective teachers should be equitably distributed. Most studies that examine the equity of the distribution of teachers employ district and school aggregates of teacher quality; in these studies, teacher salary and experience are often used as proxies for teacher quality.

Numerous studies indicate that the average teacher salary in schools serving large proportions of low-income students is substantially less than in other schools (Berne & Stiefel, 1994; Rubenstein et al., 2007; Stiefel et al., 1998; The Education Trust, 2008). A study of California schools found that a 10% increase in the school-wide student poverty rate is associated with a $411 decrease in average teacher salary for that particular school, controlling for other school and district characteristics; the study also estimated that a low-poverty school could spend $76,000 more on teacher salaries than a high-poverty school (Miller, 2010). Though highly paid teachers are not necessarily more effective than comparably less well-paid teachers, these "salary gaps" are noteworthy because teacher salary may reflect teacher quality to some extent.

Teacher mobility patterns also contribute to the inequitable distribution of effective and experienced teachers across schools. Teachers tend to leave low-performing, low-income, and high-minority schools (Boyd, Lankford, Loeb, & Wyckoff, 2005; Hanushek, Kain, & Rivkin, 2004; Hanushek & Rivkin, 2006; Ingersoll, 2001; Rivkin, Hanushek, & Kain, 2005; Scafidi, Sjoquist, & Stinebrickner, 2007) and move to schools with "real or perceived" differences in the quality of students and/or resources (Condron & Roscigno, 2003, p. 22). Teachers also move to schools where "average teacher quality is like their own" (Feng & Sass, 2011). Many teachers move from one school to another within the same district. For example, in 1994-95, 23% of teachers who left their schools moved to another school within the same district (Condron & Roscigno, 2003).

Substantial teacher turnover is problematic for a number of reasons. Effective schools require cohesion and community among students, teachers, and parents, and high levels of turnover can be disruptive and lower the quality of education (Ingersoll, 2001). Research has shown that high turnover rates can cause a lack of continuity in instruction as well as lack of teaching expertise necessary to make good curriculum decisions and to provide support and mentoring to struggling or new teachers (Loeb, Darling-Hammond, & Luczak, 2005). Barnes, Crowe, and Schaefer (2007) note that, "Low performing schools rarely close the student achievement gap because they never close the teaching quality gap – they are constantly rebuilding their staff" (p. 2). Further, given that low-income and low-performing schools have higher rates of turnover, these schools do not benefit from their investments in professional development if teachers continue to leave (Darling-Hammond, 2007).

Teacher mobility patterns also result in qualified and effective teachers concentrated in some schools and unqualified and ineffective teachers in others. Schools with large numbers of low-income, high-minority, and low-performing students employ less-qualified teachers compared to their counterparts (Berne & Stiefel, 1994; Darling-Hammond, 2007; Koski & Horng, 2007; Lankford, Loeb, & Wyckoff, 2002; Rice, 2010; Rubenstein et al., 2007). One study found that schools serving low-income students employed two to three times the rate of inexperienced teachers as schools serving middle-class students (The Education Trust, 2008). Another study found that teachers with at least six years of experience were more likely to be teaching in schools with fewer English language learner, low-income, and minority students than teachers with less experience (Feng, 2010); the same study found that teachers with less than two years of experience were more likely to teach in low-performing schools and in schools with a higher number of disciplinary incidents compared to more experienced teachers (Feng, 2010).

Despite these inequities, many districts provide few incentives for experienced teachers to remain in low-income, low-achieving, and/or high-poverty schools (Rubenstein et al., 2007). In fact, district policies may incentivize teachers to transfer to schools with fewer proportions of low-income and minority students, if teacher salary and evaluation policies remain stagnant across schools in the district and/or if effective school leaders are not present in low-income and high-minority schools.

Though most of the literature analyzes the equitable distribution of teachers across districts and schools, a growing body of research suggests that inequity in teacher quality exists for students within the same school. Recent studies suggest that within a school, low-performing students are the most likely to be taught by novice teachers and the highest performing students are the least likely to be taught by novice teachers (Clotfelter, Ladd, & Vigdor, 2006; Feng, 2010; Kalogrides & Loeb, 2013; Kelly, 2004; Player, 2010). Further, studies of teacher quality for elementary school teachers find that high-achieving students are systematically assigned to teachers who are more effective (Koedel & Betts, 2009; Rothstein, 2008). Finally, studies have also found that minority, low-income, special education, and ELL students and students with more disciplinary incidents are more likely to be taught by novice teachers than other students in the same school (Feng, 2010; Kalogrides & Loeb, 2013). All of this research supports the claim that there are "considerable" differences in "teacher and classroom characteristics within schools" (Goldhaber and Brewer, 1997b, p. 201), and these differences are likely to be related to the substantial variation in student achievement for students within the same school. In fact, one study found that there is six times more variation in student achievement across classrooms in the same school than across schools in the same district (Demeuse, Crahay, & Monseur, 2001).

Access to effective teachers is also mediated by track and/or course assignments. Studies indicate that high-track courses are more likely to be taught by teachers with higher qualifications (Brent, Roellke, & Monk, 1997; Clotfelter et al., 2006; Ingersoll, 1999; Kelly, 2004; Lee, Croninger, & Smith, 1997; Player, 2010; Roza, 2009; Talbert & Ennis, 1990), which means that low-performing students may not have equitable access to qualified teachers (Clotfelter et al., 2006; Kelly, 2004; Player, 2010). Further, students are generally not equitably distributed across academic tracks or courses as student race and socioeconomic status are statistically significantly associated with assignment to advanced, remedial, college preparatory, or vocational tracks (Darling-Hammond, 2007; Gamoran, 1987; Lee et al., 1997).

Even within the same academic track, however, students of different races may be assigned to teachers with different qualifications. For example, in one study, Black students were 57% more likely than White students to be assigned to a novice teacher in math and 37% more likely to be assigned to a novice teacher in English (Lee et al., 1997). In summary, as Darling-Hammond (2007) explains, teachers are scarce resources that are "allocated to the students whose parents, advocates, or representatives have the most political clout," which results in "the most highly qualified teachers offering the most enriched curricula to the most advantaged students" (p. 324).

Class sizes. The impact of class sizes on student achievement has been hotly contested over the years. Hanushek initially fueled the debate on the implications of class size by arguing that class size does not matter for student performance (Hanushek, 1981; Rice, 2002). However, today, there is some consensus on the issue, and even Hanushek agreed that class size matters in certain scenarios (Hanushek, 2006; Rice & Schwartz, 2008): in grades K–3, if there are no more than 15 students per class (Krueger, 2002), and for low-income and minority students (Odden & Picus, 2008).

Class size indicates the number of students per instructional class, and classroom-level data are needed to understand the direct impact of class size on achievement. Studies that employ pupil-teacher ratios, or the proportion of the number of students to the number of teachers in the school or district, may be misleading because pupil-teacher ratios are not good proxies of class size (Odden & Picus, 2008). For example, special education and reading specialist teachers are included in pupil-teacher ratios, though they often do not affect actual class sizes. For this reason, pupil-teacher ratios are most often found not to be correlated with student achievement even though class sizes are (Figlio, 1999; Greene, Huerta, & Richards, 2007; Grubb, 2006; Hogrebe et al., 2008; Okpala, 2002).

Most of the research on class sizes has estimated the impact of class sizes on student achievement for elementary school students. Few studies employ classroom-level data to investigate the impact of class size at the middle and high school levels, though available research indicates that class sizes in middle and high schools may be related to student achievement. Three studies examine the impact of class size using the National Education Longitudinal Study of 1988 (NELS88), which contains data on middle and high school students in the U.S. Elliott (1998) found that class size predicted achievement in science but not in math and only in high-poverty schools. Ludwig and

Bassi (1999) found that class size predicted achievement for both reading and math but that the effect was larger for reading than for math. Finally, Boozer and Rouse (1995) found that smaller classes in the 8th grade were associated with increased gains in student performance in history, math, reading, and science; Boozer and Rouse (1995) also found that differences in class size partially explain the Black-White racial achievement gap. Discrepancies in these findings may be partially explained by the use of different methods, outcome variables, and use of additional data sources (See Table 2).

In addition to the studies employing NELS data, one study employed classroom-level data of New Jersey public high schools to estimate the impact of class sizes on gains in student achievement; the authors found no effect of class size on student achievement in multiple subjects (Greene, Huerta, & Richards, 2007). While it is not yet clear the extent to which class size is related to student achievement in middle and high schools, three out of the these four studies in this review indicate that class sizes in middle and high schools are related to student achievement.

Table 2: Descriptions and Summaries of Studies on the Impact of Class Size in Middle and High Schools

Author & Year of Study	Data	Years of Data	Method & Outcome Variables	Findings
(Boozer & Rouse, 1995)	NELS88 and surveys of teachers in New Jersey; classroom-level data	1988 & 1990 (8th & 10th grade data)	Regression analysis; student-level gain scores in history, math, reading, science	Smaller classes in 8th grade linked to larger test score gains; differences in class size explain 15% of racial achievement gap in test score gains between White and Black students
(Elliott, 1998)	US Census data and NELS88; SES-based weighted district- and classroom-level data (equipment & class size)	1988 & 1990 (8th & 10th grade data)	HLM; math and science scores	Class size has a negative association with math scores; class size has positive association with science scores, but only in high-poverty schools
(Greene et al., 2007)	New Jersey public high schools; classroom-level data	1999-2002	Regression analysis; student-level gain scores in multiple subjects	Class sizes were not statistically significant
(Ludwig & Bassi, 1999)	NELS88; classroom-level data	1988 & 1990 (8th & 10th grade data)	Value-added model; also instrumental variables to address omitted variable bias found in value-added models; reading and math test scores	Class size predicts test scores with larger effect in reading than in math

Several studies use school-level data to analyze the equity of pupil-teacher ratios (Berne & Stiefel, 1994; Iatarola & Stiefel, 2003; Miller & Rubenstein, 2008; Rubenstein et al., 2007), but as previously stated, pupil-teacher ratios are not good proxies for actual class sizes. Few studies examine the equity of class sizes using classroom-level data, though existing research suggests that class sizes may be an inequitably distributed resource. For example, Boozer and Rouse (1995) found that Black students, compared to White students, are more likely to be in schools with larger than average class sizes and are more likely to be in larger classes within schools, controlling for prior achievement. In addition, a study of high schools in two districts found that AP courses had smaller than average class sizes by five students than other courses (Roza, 2009). More research employing classroom-level data is needed to further analyze the equity of class sizes.

Academically rigorous courses. Students have higher achievement when they are exposed to academically rigorous content (Carter, 2013; Darling-Hammond, 2007; Gamoran, 1987; Madigan, 1997; Muller et al., 2001; Tyson, 2013), and the effect of academically rigorous coursework on student achievement may be large. Gamoran (1987) estimated that when academic track, course taking, and dropout rates were held constant, the effect of socioeconomic status on student achievement was not statistically significant. Further, placement in the low academic track with non-challenging courses has been associated with students' lack of motivation, higher rates of misconduct and absenteeism, and lower rates of completing college (Carter, 2013; Kao & Thompson, 2003).

There are three primary reasons why academically rigorous courses impact student achievement. First, students may opt or be encouraged to take different numbers of academic courses. Numerous studies have found that number of academic courses taken is related to student achievement (Darling-Hammond, 2007; Gamoran, 1987; Madigan, 1997; Muller et al., 2001). For example, Muller et al. (2001) found that the number of science courses taken in high school was the only consistent predictor of gains in science test scores across all racial/ethnic by gender subgroups; they also found that high school science attainment is associated with college coursework and holding careers in science, math, and engineering fields, especially for female students. Similarly, Madigan (1997) found that taking eight or more semesters of science is positively associated with an increase in science test scores, even after controlling for socioeconomic status, prior achievement, gender, and race.

Second, the curricula and skills emphasized vary across high-track, regular, and remedial courses. For this reason, tracking "exacerbates differential access to knowledge" because remedial courses often focus on basic skills while advanced courses emphasize higher-order thinking (Darling-Hammond, 2007, p. 324). The result is that students who are initially placed in low tracks have difficulty switching tracks later and successfully competing with other students who have been exposed to better learning environments (Tyson, 2013). In addition, students in low tracks are sometimes restricted from taking more advanced courses because these courses require teacher approval and/or high grades in subsequent courses (Buckley, 2010). Further, some tracks are "dead-end" tracks, and in one study, students in the lowest math track did not have a math course option after completing geometry (Buckley, 2010), which is typically offered as a 9^{th} or 10^{th} grade math course.

Third, students in different tracks and courses are exposed to teachers with different levels of effectiveness. Low-track courses are often taught by the least experienced teachers (Brent et al., 1997; Lee et al., 1997), and as noted previously, teacher experience is associated with increased student achievement. Lee et al. (1997) remark, "The probability that a student is exposed to an experienced teacher falls monotonically across the remedial, standard, and advanced courses" (1997, p. 389). Relatedly, Ingersoll (1999), using a national survey, found that, in every subject, students in low-track classes were more likely to be taught by teachers who were teaching out of their field: in English, 24.7% of low-track teachers were not certified to teach in English compared to 11.2% of high-track teachers, and in math, 33.5% of low-track teachers were not certified to teach in math compared to 20.4% of high-track teachers. Finally, Talbert and Ennis (1990) found that teachers themselves were tracked and that low-track students were primarily taught by low-track teachers. Compared to other teachers, low-track teachers had less administrative and organizational support, less influence over school policies, less classroom autonomy, and lower self-efficacy, and were less able to improve student achievement.

Academically rigorous courses are an inequitably distributed resource because minorities and low-income students are disproportionately represented in lower academic tracks than their White and middle-class counterparts (Darling-Hammond, 2007; Gamoran, 1987; Lee et al., 1997). The National Center for Education Statistics (NCES) reported that 40% of Asian, 31% of White, 19% of Black, 15% of Latino, and 11% of Native American high school seniors are engaged in “high-level academic, college preparatory coursework” (Carter, 2013, p. 150). This phenomenon is true even after controlling for prior student achievement (Buckley, 2010; Conger, 2005; Darling-Hammond, 2007; Tyson, 2013). For example, for students who scored in the 99th percentile on the California achievement test, 72% of White students were in the most advanced English course compared to only 19% of Black students (Mickelson, 2005). Similarly, another study found that 50% of Latino students who scored in the 90th percentile on state standardized tests were in the college preparatory track compared to 90% of White students (Darling-Hammond, 2007).

Further, inequities in academically rigorous courses caused by within-school tracking may be exacerbated by across-school differences in curricula because schools serving more high-minority and low-income students offer more remedial and vocational courses, on average, than other schools (Darling-Hammond, 2007). Alternatively, there may be a “crowding out” effect where “increasing school racial diversity increases the chances that White students will be in the college preparatory track and decreases the chances that Blacks will be in that track” (Lucas & Berends, 2007; Tyson, 2013). Academic tracks may become associated with student race, and minority students do not always feel comfortable being placed in the top academic track if White students are overrepresented in this track (Carter, 2013; Tyson, 2013). For all of these reasons, some scholars argue that tracking is one of the main reasons for inequity in educational opportunity and outcomes in the United States (Tyson, 2013). Academically rigorous courses, academic tracks, and teacher quality are all related, and taken together, these variables “account for much of the school-related contribution to achievement” (Darling-Hammond, 2007, p. 322).

Peer effects. Research has found that peer effects–defined in several ways–relate to student outcomes. Peer effects may be defined as mean achievement or IQ of a student’s peers (Boucher, Bramoulle, Djebbari, & Fortin, 2010; Burke & Sass, 2008; Hanushek, Kain, Markman, & Rivkin, 2003; Hoxby, 2000; Lefgren, 2004; Levin, 2001), educational or college attainment of a student’s peers (Palardy, 2013; Patacchini, Rainone, & Zenou, 2011), or disruptive behaviors of a student’s peers (Figlio, 2005). Peer effects may also be defined in terms of concentrations of minority and low-income students (Caldas & Bankston, 1997; Ewijk & Sleegers, 2010; Konstantopoulos & Borman, 2011; Mickelson, 2005; Raitano & Vona, 2013). Peer effects may be determined at the school or classroom levels.

The general consensus is that peers who have higher achievement and educational attainment and less disruptive behaviors positively impact student achievement and educational attainment, and this is true for students in all grades. Effect sizes of peer effects differ across studies, ranging from very small to moderate, which is not surprising given that peer effects are defined differently across studies. There is also disagreement whether peer effects impact students of all abilities equally.

Levin (2001), using data of Dutch students in grades two through eight, found that peer effects–defined as peer mean IQ–have the largest positive impact on the lowest ability students. He concludes, “Students towards the lower end of the conditional achievement distribution are ‘dependent’ learners, relying more heavily on the number of similar peers relative to their higher achieving counterparts that learn more ‘independently’” (p. 241). Burke and Sass (2008) also found that the lowest ability students benefit the most from being grouped with the highest ability students. However, they also found that combining the highest and lowest ability students may damper the achievement of the highest ability students; the highest ability students benefit from having peers that are of middle ability. Burke and Sass (2008) recommend combining high and middle achieving students in classrooms for the best possible results. These findings are consistent with Raitano and Vona’s (2013) conclusion that, in the U.S., some heterogeneity of peer effects has a positive relationship with student achievement. While research is less clear on the most efficient strategy for re-distributing higher achieving peers to maximize student outcomes, studies consistently find that having higher achieving peers is positively correlated to students’ educational outcomes.

Peer effects in terms of concentrations of minority and low-income students have been shown to have a negative impact on student achievement (Caldas & Bankston, 1997; Ewijk & Sleegers, 2010; Konstantopoulos & Borman, 2011; Mickelson, 2005;

Raitano & Vona, 2013). Compared to middle-class students, low-income students are more likely to have worse health, more school-to-school mobility, and less educated parents, which translate into more disruptions to student learning, a more limited vocabulary, and fewer critical thinking skills (Rothstein, 2013). For these reasons, even when school-based resources are equivalent, low-income students have worse achievement than middle-class students, on average (Rothstein, 2013). Further, in schools with large numbers of low-income students, the negative effects of poverty are exacerbated, and schools often spend time and resources addressing issues of poverty at the expense of providing high quality education (Rothstein, 2013). To the extent that race is related to poverty, the same findings occur. Harris (2006) explains, "It is not race per se that affects learning, but the conditions under which minority students are raised and the characteristics of their classmates" (p. 18).

Coupled with the fact that schools and classes with larger proportions of low-income and minority students may also have lower quality teachers and less rigorous curricula (Kalogrides & Loeb, 2013; Southworth, 2010), racial and socioeconomic peer effects may have a "profound" impact on student achievement. For example, one study found that "both the racial/ethnic and social class composition of a student's school are 175% times more important than a student's individual race/ethnicity or social class for understanding educational outcomes" (Borman & Dowling, 2010, p. 1202).

A small but growing body of research has investigated the equity of peer effects among classrooms in the same school, and three recent studies analyzed this issue. The first study found that schools sorted students into classes primarily based on student ability, which was associated with student race and socioeconomic status and resulted in concentrations of low-achieving, minority, and low-income students grouped in certain classrooms (Kalogrides, Loeb, & Beteille, 2013). Another study found that within-school sorting of students across classes resulted in segregated classrooms for minority students but that differences in student ability did not fully explain student sorting (Conger, 2005); in other words, even after controlling for student achievement, minority students were more likely to be grouped with low-achieving and minority peers than their non-minority counterparts. A third study found that within-school sorting of students across classes resulted in racially and socioeconomically segregated classrooms, which resulted in negative peer effects for minority and low-income students (Clotfelter, Ladd, & Vigdor, 2003). This study also found that within-school racial segregation of classes is most problematic in middle and high schools where between 50 and 70% of the student population is African American (Clotfelter et al., 2003). In summary, research suggests that peer effects–as defined by peer achievement, race, or socioeconomic status–impact student achievement and are, in many cases, inequitably distributed across classrooms in the same school.

Per-pupil expenditures. This section discusses the efficacy of per-pupil expenditures (PPEs) and equity of the allocation of PPEs. One scholar notes that PPEs are "typically used as a proxy measure for the whole package of school inputs available in a school" (Ladd, 2008, p. 406). Total PPEs include instructional expenditures as well as expenditures not related to instruction–such as facilities, transportation, and food services. Instructional PPEs are those related to the instruction of students, and around 60% of district budgets are spent on instructional resources including teacher salaries and benefits, teaching aides, textbooks, and supplies (Odden & Picus, 2008). The majority of instructional expenditures are spent on teachers' salaries and benefits (Odden, 2000). Class size, which determines the number of teachers needed, is also a large component of instructional expenditures (Odden & Picus, 2008).

In 1981, in his journal article entitled "Throwing Money at Schools," Hanushek released a synthesis of 130 school finance studies and concluded that money spent on K-12 education is not associated with improved student outcomes. Since then, many have disputed his finding. Krueger (2002) pointed out that Hanushek equally weighted each finding in each study and therefore did not take into account the studies' sample sizes or power, the grades or subjects sampled, or the methodological strengths and weaknesses of each study. Krueger conducted his own analysis of the studies and concluded that when the studies are given equal weight–as opposed to the findings in the studies–money spent on public education is related student performance. Further, Hedges, Laine, and Greenwald (1994) conducted a meta-analysis of the same set of studies, taking into account the sample sizes and power of each study, and reached the opposite conclusion: money matters.

Ten more recent studies have investigated the association between total and instructional PPEs and student achievement (See Table 3).[2] All but one found at least one statistically significant positive effect of PPEs on a student outcome in a specific year and/or for a specific grade-level (Archibald, 2006; Deke, 2003; Elliott, 1998; Fortune &

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[2] To conduct a fair synthesis on the research on the direct impact of expenditures on student outcomes, I conducted a literature review for the years 1994 to 2012, commencing with articles in the *Journal of Education Finance* and *Education Finance and Policy* and then cross-referencing the citations. I also searched the databases *Education Research Complete* and the *Web of Science* using the search terms "per-pupil expenditure" (PPE) and "expenditure." Studies were included in this literature review if they: a) examined the impact of instruction-related or total PPEs on student outcomes, b) employed data aggregated to the district, school, or classroom levels, c) were conducted in the U.S. and d) concerned grades K-12.

O'Neil, 1994; Grubb, 2006; Hogrebe et al., 2008; Nyhan & Alkadry, 1999; Roy, 2011; Stiefel, Schwartz, Portas, & Kim, 2003). The studies, however, did not find associations between PPEs and all student outcomes or for students in every grade. The only study that did not observe an effect of PPEs on any student outcome was a study conducted by Wenglinsky in 1998; however, Wenglisky did find that instructional PPEs were associated with the size of the socioeconomic-related achievement gap and that districts with higher per-pupil spending had less of a socioeconomic-related achievement gap than districts with lower per-pupil spending.

Table 3: Research on Impact of PPEs on Student Outcomes

Author & Year of Study	Data	Years of Data	Method & Outcome Variables	Findings
(Archibald, 2006)	3rd–6th graders in Washoe County School District in Reno, NV; classroom-level data for teachers and school-level expenditure data	2002/03	HLM; reading & math test scores	Small effect (.06 standard deviations) of instructional PPEs and instructional support PPEs on reading achievement (but not math)
(Deke, 2003)	Kansas school districts; district-level data	1989/90 to 1991/92	Fixed-effect panel regression with two time periods (conservative estimates due to method); likelihood of pursuing post-secondary education	20% increase in total PPEs results in additional 5% likelihood of pursuing post-secondary education
(Elliott, 1998)	US Census data and NELS88; SES-based weighted district- and classroom-level data (equipment & class size)	1988 & 1990 (8th & 10th grade data)	HLM; math and science test scores	Total PPEs (even when controlling for teacher salary) are associated with math and science test scores with small standardized effect sizes (.07-.11)
(Fortune & O'Neil, 1994)	9th and 11th graders in Ohio; district-level data	1992/93	Regression analysis with threshold; % of students passing writing, math, reading, and citizenship tests	Instructional PPEs are positively associated with all test scores after threshold has been met with small effect (.24-.32 standard deviations)
(Hogrebe et al., 2008)	3rd, 7th, and 10th graders in 30 St. Louis area public school districts; district-level data	2000-2005	Pearson correlation; % of students proficient or advanced on science test	Modest positive correlations for 10th grade science achievement and instructional PPEs (.55)
(Knoeppel et al., 2007)	A cohort of students in VA; 4th and 11th graders; district-level data	1989 and 1996 (cohort)	Canonical correlation; outcome variables: cohort scores on tests, students plan to attend 2 or 4-year colleges, and voter participation	Linear combinations of variables are related: total variance explained was 76.6%; average teacher salary is the most significant contributor to input variables; input variables: adjusted PPEs (excluding special education and transportation expenditures), student-teacher ratio, measure of local wealth, average teacher salary, administrative expenditures per pupil, and facility expenditures per pupil

Author & Year of Study	Data	Years of Data	Method & Outcome Variables	Findings
(Nyhan & Alkadry, 1999)	4th, 8th and 10th or 11th graders 3 counties in South Florida; school-level data	1993/94	Regression analysis; average of math, reading, and writing scores on different tests	Total PPEs do not predict achievement except in middle schools with a small standardized effect (.18)
(Roy, 2011)	Michigan district data; district-level data	1990-2001	Regression analysis examining trends over time & cohort gains and instrumental variables method; reading and math scores, ACT scores and participation	Total increased PPEs improved achievement for lowest-spending districts and in highest-spending districts where spending froze, student achievement decreased; for cohort, improvement in performance from 4th to 7th grade, effect stronger in math; decrease in performance for highest-spending districts, effect stronger in reading; for IVs: increased performance on test scores but no effect on participation and ACT scores
(Stiefel et al., 2003)	4th and 5th graders in New York City elementary schools; school-level data	1995/96 through 1998/99	Logistic regression including fixed school effects; reading and math scores	Total PPEs do not predict achievement except for reading in the 5th grade (standardized effect size of .12)
(Wenglinsky, 1998)	Nationally representative sample of 12th graders using NAEP and Common Core Data; district-level data	1997	HLM; math test scores	No effect of instruction and capital expenditures on mean achievement but more spending is associated with weakening of SES-related achievement gaps with small effect

According to all but two of these studies, the effect size of total or instructional PPEs in predicting student achievement is small or negligible. Some researchers have noted, however, that effect sizes of PPEs on student outcomes may be underestimated for five potential reasons. First, some studies examine the association between total PPEs and student outcomes, and because total PPEs include expenditures that are not related to instruction, they may potentially cloud the relationship between instructional PPEs and student outcomes (Fortune & O'Neil, 1994). Second, weak relationships between money and student outcomes may exist due to resource substitution in which a school or district may receive more of one resource and less of another. For example, in their study of New York City schools, Berne and Stiefel (1994) found that high-poverty schools had smaller class sizes but employed lower-paid teachers. Thus, the higher expenditures due to small class sizes were offset by the lower expenditures due to lower paid teachers. Relatedly, Rubenstein et al. (2007) found that while schools with large numbers of low-income students had higher overall PPEs and fewer pupils per teacher than other schools, they also employed less educated and less well-paid staff. Several studies have found that schools with large proportions of low-income students have smaller class sizes but employ lower quality teachers than other schools (Baker, 2012; Iatarola & Stiefel, 2003; Stiefel et al., 1998).

Third, not all resources are efficiently allocated. For example, Ilon and Normore (2006) show that investments in teacher quality are likely to produce, at a lower cost, greater student achievement gains than decreasing class sizes. In other words, the effect of a small monetary investment in class sizes may not be identified if class size is not a cost effective variable to influence student achievement. Fourth, a certain amount of resources may be necessary to observe an effect on student achievement. Fortune & O'Neil (1994) found a threshold effect for fiscal resources and estimated that a $700 increase in PPEs is necessary to observe an effect on student outcomes. For example, reducing a class size by one student may not result in improved student performance because studies suggest that class sizes of between 12 and 15 students are needed to produce positive results in student achievement (Krueger, 2002).

Finally, the use of aggregated data may hinder researchers' ability to correctly determine the effect of fiscal resources on student outcomes. Traditionally, school finance research has employed district-level data (Berne & Stiefel, 1994; Odden & Picus, 2008), which aggregate expenditures and student achievement to the district level. However, the most "critical" activities occur at the school or program level, and data aggregation to the district level ignores any variation in resources within or between schools (Berne & Stiefel, 1994, p. 405). At least 80% of district budgets are spent at the school level (Odden & Archibald, 2001); thus, the assumption that all students within a district get the same resources is "bold" (Odden & Picus, 2008, p. 58). Researchers have noted that studies that examine associations between expenditures and student achievement would be improved if students–not districts, schools, or classrooms–were the unit of observation and if the effect of fiscal resources was analyzed at the student level (Jefferson, 2005; Verstegen & King, 1998).

Nevertheless, given the small effect sizes of PPEs on student outcomes, some scholars argue that money does not matter. However, there is ample evidence that statistically significant relationships do exist between dollars spent and student outcomes. Card and Krueger (1998) note that:

> To some extent, interpreting the literature depends on the strength of one's expectations. If one starts from the position that school resources do not make a difference, then one can point to the bulk of the evidence on the lack of a statistically significant connection between school resources and test scores, and a handful of studies on economic outcomes, to support that view. On the other hand, if one starts from the view that resources do make a difference, then the available evidence on school quality and economic outcomes may be interpreted as generally supportive. (p. 50)

Yet, as Slavin (1999) remarks:

> It is clear (and obvious) that increased dollars do not magically transform themselves into greater learning. But it is just as clear (and just as obvious) that money can make a difference if spent on specific programs or other investments known to be effective. (p. 522)

Additional spending can improve student performance if the dollars are invested in instructional resources that matter for student outcomes, and without money, schools and districts are unable to obtain key resources necessary to promote student learning.

Given the importance of school funding, equity in PPEs is worth investigating. Research has shown that inequities in PPEs can exist at every organizational level–between states, districts, and schools (Ladd et al., 1999). For students within the same state, the equity in the allocation of student-level PPEs depends on interdistrict, intradistrict, and intraschool equity.

Interdistrict equity. Property wealth is the primary cause of interdistrict inequity in PPEs because districts with greater property wealth have a larger tax base with which to raise local money for education (Odden & Picus, 2008). In the early 1900s, districts were primarily responsible for raising funding for education; however, as interdistrict inequities in funding became more apparent around 1920, states responded by providing additional financial support to districts with lower property wealth (Odden & Picus, 2008). However, vast inequities in interdistrict spending have persisted.

In the 1960s, school finance litigation began to play a large role in defining and addressing interdistrict equity (Odden & Picus, 2008). Most notably, in the case of *Serrano v. Priest II* in 1976, the California Supreme Court found the degree of interdistrict inequity in PPEs to be in violation of the California Constitution, which held that education is a fundamental right and that PPEs may not depend on local property wealth (Odden & Picus, 2008). Since then, lawsuits in a number of other states have challenged the equity and adequacy of state school finance systems. Plaintiffs argued that resources were not equitably distributed and/or that adequate funding was not provided for all students to achieve a basic education, as defined by the individual state constitution. In approximately half of the cases, the state school finance systems were overturned and declared to be unconstitutional according to the individual state constitutions (Odden & Picus, 2008). Even when litigation was not pursued, some states responded to the threat of litigation by re-designing their school finance systems to ensure greater interdistrict equity (Odden & Picus, 2008).

Today, states provide roughly half of the funding for public K-12 education: 50.7% of district funding is provided by the state, 6.9% by the federal government, and 42.4% by local municipalities. Further, in 80% of states, states allocate funding to districts according to formulas that ensure a minimum per-pupil spending level for all districts and provide additional aid to districts with low property wealth; this funding structure is called a foundation plan (Odden & Picus, 2008; Park, 2004; Verstegen, 2002).[3]

State foundation plans have not, however, substantially reduced interdistrict inequities in PPEs for three reasons. First, creating a formula that adequately captures district need is difficult. Foundation plans may not adequately account for differences in student need (Slavin, 1999), purchasing power across districts in different geographic

[3] Other states employ modified versions of foundation plans, and seven states allocate funds based on student enrollment (Roza, 2010).

locations (Liu, 2006; Odden & Picus, 2008; Taylor, 2006), rising costs of resources, or economies of scale (Odden & Picus, 2008). Second, the process of creating a state foundation plan is inherently political and therefore may impede equity. State formulas that provide no aid to wealthy districts are often not politically popular, and politicians may push for political compromises that provide some level of funding to all districts; in addition, politicians may create funding "loopholes" to promote the interests of their constituents (Bundt & Leland, 2001; Timar, 1994; Toutkoushian & Michael, 2008; Verstegen, 2002). These practices maintain and exacerbate interdistrict inequities (Bundt & Leland, 2001; Toutkoushian & Michael, 2008; Verstegen, 2002). For example, Toutkoushian and Michael (2008) found that loopholes regarding school facilities provided no additional resources to districts with the lowest PPEs and provided an addition $2,700 to districts with the highest PPEs for districts in Indiana. Third, some poor districts responded to increased state support by decreasing local funding while other wealthier districts continued to raise additional revenue, resulting in higher PPEs in wealthier districts than in poor districts (Driscoll & Salmon, 2008; Odden & Picus, 2008; Verstegen, 2002). Thus, despite their purposes, state foundation plans do not resolve interdistrict inequities in many cases (Odden & Picus, 2008).

In addition, studies that find that increased state involvement in school finance decreased interdistrict inequity come with caveats. For example, Hussar and Sonnenberg (2000) found that nationwide, while interdistrict equity of PPEs improved across districts within the same state due to state involvement in school finance, interdistrict disparity in instructional PPEs persisted. Another study employing a national database found that while interdistrict inequity in PPEs declined from 1972 to 1992, other resources continued to be inequitably distributed; specifically, schools serving larger percentages of poor or minority students were more likely to report lower quality facilities, less experienced teachers, fewer AP course offerings, and fewer Internet connections than other schools (Corcoran, Evans, Godwin, Murray, & Schwab, 2003).

Numerous studies have investigated the equity of interdistrict PPEs and found inequities in monetary resources. Hartman (1999) studied a sample of districts in Pennsylvania and grouped them into low, middle, and high spending categories. The average difference in PPEs between the low and middle spending districts was $845, between the middle and high spending districts was $2,707, and between the low and high spending districts was $3,552. The high spending districts had larger tax capacities in terms of personal income and property wealth and spent considerably more per-pupil than low-spending districts. Similarly, Rolle and Liu (2007) examined interdistrict equity in Florida and found that, in 2003, even with state dollars, the more affluent and high-spending districts outspent the low-spending districts by more than 50%. Finally, using a national sample of districts, Spatig-Amerikaner (2012) found that across all districts, an increase of 10% in non-White students is associated with a decrease of $75 of spending per student. In some states, the differential amounts are more substantial; in Vermont, for example, a 10% increase in non-White students is associated with a decrease of $762 per student. In 12 states, the percentage of non-White students is positively associated with PPEs.

Slavin (1999) argues, however, that student need should be considered in analyzing interdistrict equity because districts with more low-income and minority students may have greater student need and higher educational costs. For example, Bifulco (2005) found that nationwide, the average African American student's district faces costs 30% higher than the average White student's district. He notes that at first glance, districts with larger percentages of African American students appear to have larger PPEs, but controlling for poverty, PPEs are 15% less than those in districts with fewer than 20% African American students. Similarly, other studies employing national data and controlling for the proportion of special education students found that in high-poverty districts, average district PPEs were 5.4% to 15.3% less than in low-poverty districts (Wilson, Lambright, & Smeeding, 2006), and in high-minority districts, average district PPEs were 13% to 25% less than in low-minority districts (Wilson et al., 2006). These findings indicate that interdistrict inequities in monetary resources persist.

Intradistrict equity*.* In 1998, the *Journal of Education Finance* dedicated an entire issue to *intradistrict* equity of PPEs and offered two criticisms of studies that investigate *interdistrict* equity: that studies employing data aggregated to the district level mask considerable variation in school-level resources and that district-level financial resource data do not necessarily inform available instructional resources (Odden, Archibald, Fermanich, & Gross, 2003a). Schools "are the units primarily responsible for producing educational outcomes" (Stiefel et al., 1998, p. 447), yet studies employing district-level data do not account for variations in resources across schools. In fact, studies have shown that there is more variation in intradistrict PPEs than in interdistrict PPEs (Owens & Maiden, 1999; Speakman et al., 1997).[4]

Intradistrict inequity in PPEs results from a number of factors, including teacher preferences and collective bargaining agreements (CBAs). Much of the variation in

[4] Owens and Maiden (1999) did not include funding for compensatory education in their study; they examined all other expenditures.

across-school spending stems from differences in teacher salaries, which comprise the majority of school budgets (Miller, 2010; Rubenstein, 1998; Spatig-Amerikaner, 2012; The Education Trust, 2008). As previously discussed, experienced teachers tend to leave low-performing, high-poverty, and high-minority schools (Boyd et al., 2005; Hanushek et al., 2004; Hanushek & Rivkin, 2006; Ingersoll, 2001; Rivkin et al., 2005; Scafidi et al., 2007). Because teacher salary is correlated to years of experience, schools with large numbers of low-income, minority, and low-performing students employ a disproportionate percentage of inexperienced teachers and therefore spend less on teacher salaries than other schools. CBAs often include clauses that give experienced teachers preferential treatment in transferring to schools of their choice (Miller, 2010), which may exacerbate the inequitable distribution of experienced teachers as well as affect total spending differences across schools.

CBAs may also influence school-level average PPEs by dictating maximum class sizes (National Council on Teacher Quality, 2013), which ultimately affect the number of teachers at each school and thus average spending per student. In exceptional cases, an additional teacher may be assigned to the school even though the class size is too large by one student. Class size may also be affected by staff-based budgeting policies, which determine the number of teachers per grade or school based on benchmarks of student enrollment (Roza & Miles, 2002; Roza, 2008). Thus, between-school differences in spending on instruction result from teacher choices, CBAs, and staff allocation policies.

The degree of fiscal intradistrict inequity has been difficult to determine due to the lack of reliable school-level data (Spatig-Amerikaner, 2012). Until 2009, federal legislation did not require districts to track actual teacher salaries–only district averages of teacher salaries–and districts did not typically keep track of resources allocated to each school; the Department of Education now requires reporting of school-level expenditure data (Heuer & Stullich, 2011). Further, when districts attempted to report school-level resource data, the data were often coded inconsistently, rendering data analysis difficult (Stiefel et al., 1998).

Despite these limitations, several studies have researched intradistrict equity in PPEs and reported findings regarding the horizontal equity, vertical equity, and equal opportunity of PPEs within districts (See Table 4).[5] Existing research indicates that intradistrict inequity exists. There are inconsistent findings, mainly because the criteria for determining equity and the expenditures included to gauge equity vary across studies. However, common findings of this literature include that inequity exists for low-income and minority students and that the degree of inequity is more severe for expenditures related to classroom instruction.

Concerning intradistrict horizontal equity, two studies concluded that intradistrict horizontal equity of PPEs was satisfied because the coefficient of variation (CV) was less than .15 (Klein, 2008; Stiefel et al., 2003). However, Goertz and Stiefel (1998) argue that a CV of .15 is too high for studies of intradistrict equity. An additional two studies found violations of horizontal equity–determined by CVs larger than .15–and the degree of inequity varied depending on the school grade level type (elementary, middle, or high) and type of expenditures examined (total, instructional, including special education, excluding special education, including compensatory education, and excluding

[5] I attempted to conduct a comprehensive literature review for this section. I commenced with articles in the *Journal of Education Finance* and *Education Finance and Policy* and then cross-referenced the citations. I also searched the databases *Education Research Complete* and the *Web of Science* using the search terms “intradistrict” or “school-level” and “PPE” or “expenditure.”

compensatory education) (Iatarola & Stiefel, 2003; Rubenstein, 1998). Thus, whether horizontal intradistrict equity was achieved depended on the author's criterion for achieving horizontal equity and which expenditures were included in the analysis.

Other studies examined intradistrict vertical equity and equal opportunity, and, as previously discussed, most studies do not differentiate between the concepts of vertical equity and equal opportunity; in evaluating vertical equity, most studies only examine the existence and direction of the relationship between PPEs and student characteristics as opposed to comparing the magnitude of the relationship to a pre-determined criterion. Most of these studies found some evidence of vertical inequity or unequal opportunity in PPEs between schools in the same district. A common finding of these studies is that total and instructional PPEs are higher in schools with lower proportions of low-income and minority students (Baker, 2012; Berne & Stiefel, 1994; Condron & Roscigno, 2003; Heuer & Stullich, 2011; Iatarola & Stiefel, 2003; Klein, 2008; Owens & Maiden, 1999; Spatig-Amerikaner, 2012). The degree of vertical inequity or unequal opportunity may be considerable in some cases. Using national data, Spatig-Amerikaner (2012) found that across the U.S., predominantly non-White schools spend $733 less per pupil on average than predominantly White schools. Similarly, Condron and Roscigno (2003), who examined the allocation of district dollars raised by a local municipality, found that high-poverty schools received $800 less per pupil than low-poverty schools.

A second common finding of these studies is that when the percentage of low-income or minority students is positively associated with total PPEs, it is negatively associated with instructional PPEs or PPEs that exclude funding for special education (Berne & Stiefel, 1994; Owens & Maiden, 1999; Rubenstein, 1998; Stiefel et al., 2003).

Therefore, though high-poverty and/or high-minority schools may have higher total PPEs than other schools, these schools may still be underfunded compared to other schools in terms of expenditures dedicated to classroom instruction because these schools must spend a larger portion of their budget on special education services. This finding is consistent with research that shows that schools enrolling large percentages of low-income and/or minority students almost always have lower school-level averages of teacher salaries (Berne & Stiefel, 1994; R. Miller, 2010; Roza & Miles, 2002; Rubenstein et al., 2007; Rubenstein, 1998; Stiefel et al., 1998; The Education Trust, 2008), even though they may have higher averages of total PPEs than schools enrolling few low-income and minority students. These studies indicate that intradistrict inequity in instructional PPEs is commonplace.

Table 4: Summaries of Studies of Intradistrict Equity in PPEs

Study	Data	Horizontal Equity	Vertical Equity & Equal Opportunity
(Baker, 2012)	Elementary schools in five urban districts in Texas	NA[6]	PPEs in schools with 100% poverty are 25% more than in schools with 0% poverty, on average.
(Berne & Stiefel, 1994)	Schools in New York City, NY	NA	Instructional PPEs are negatively associated with number of students in poverty, and non-instructional PPEs are positively associated.
(Condron & Roscigno, 2003)	Schools in Columbus, Ohio	NA	Students in high-poverty schools receive roughly $800 less than students in more affluent schools of local dollars (not state or federal).
(Heuer & Stullich, 2011)	U.S. Department of Education School-Level Expenditure Data	Almost 50% of schools had PPEs that were more than 10 percent above or below their district's average.	Lower PPEs in more than one third of schools serving greater percentages of low-income students than the district average compared to schools with fewer low-income students, for the same grade level.
(Iatarola & Stiefel, 2003)	Elementary and Middle schools in New York City, NY	Elementary schools: CV is .126 for PPEs for regular program and .191 for regular and special education programs. Middle schools: CV is .156 for PPEs for regular program and .195 for regular and special education programs.	PPEs are negatively associated with percent low-income and minority in elementary schools only. Negative relationship between PPEs and percent of immigrant students.
(Klein, 2008)	Elementary Schools in Nashville, TN	CV is 14.9% for PPEs.	PPEs decrease as percent of low-income students increases.
(Owens & Maiden, 1999)	Elementary schools in Florida	When remove compensatory expenditures, PPEs at some schools were more than double those at other schools.	Negative association between PPEs (excluding compensatory education) and percent African-American and low-income students; positive association between PPEs and percent Hispanic; positive association between PPEs and percent low-income when compensatory funds are included.
(Rubenstein et al., 2007)	Schools in New York City, NY, and Cleveland & Columbus, OH	NA	Overall: higher PPEs for special education and ELL students. Elementary schools: PPEs are positively associated with percent low-income. Middle schools: lower PPEs for immigrants; PPEs are negatively associated with percent minority and low-income.

[6] NA indicates that the study did not investigate the particular aspect of equity.

Study	Data	Horizontal Equity	Vertical Equity & Equal Opportunity
(Rubenstein, 1998)	Schools in Chicago, IL	(1) For school-level PPEs, CV is .27 in elementary schools and .14 in high schools; (2) removing special education funds, CV is .22 in elementary schools and .13 in high schools; and (3) removing special education and desegregation funds, CV is 12 in elementary schools and .13 in high schools.	Positive relationship between PPEs and percent low-income but negative relationship between "general fund" PPEs and percent low-income. (General fund includes state and local money to provide general and special education.)
(Stiefel et al., 1998)	Schools in New York City and Rochester, NY, Chicago, IL, & Forth Worth, TX	CVs are close to .15 and are within horizontal equity range.	In New York and Rochester, general education PPEs are positively correlated with percent low-income, and effect is stronger in middle schools. In Chicago, negative relationship between general education PPEs and percent low-income but positive relationship between total PPEs (including special education funding) and percent low-income.
(Spatig-Amerikaner, 2012)	U.S. Department of Education school-level expenditure data	NA	On average, students attending predominantly non-White schools receive $733 less than students attending predominantly White schools.

Intraschool equity. While there is ample research on interdistrict equity and a growing body of research on intradistrict equity of PPEs, research on intraschool equity of PPEs is almost nonexistent. Three dissertations descriptively analyzed how much money was spent on individual students in a large urban high school and did not find noteworthy inequities in student-level PPEs (Kimball, 2009; Robillard, 2001; Young, 2003); however, each of these studies examined student-level expenditures at only one school in California, and each school primarily enrolled low-income and minority students. Since the student populations were not racially, ethnically, or socioeconomically diverse, there may not have been adequate variation in student characteristics to identify student characteristics that are associated with PPEs.

Another dissertation conducted an equity analysis of student-level expenditures (in terms of teacher salaries) at two high schools in the same district with dissimilar characteristics (Holmes, 2001). The author found that although there was little variation across the two schools in teacher expenditures per student and that there was large within-school variation; as a result, horizontal equity was not achieved in either school. The author also found tradeoffs in resource allocation: High-achieving students were assigned to the highest paid teachers but had larger class sizes than low-achieving students. Finally, the author found that, out of a number of student characteristics, prior student achievement and placement in academic track were the most explanatory factors in differential resource allocation.

The one published study that calculated student-level PPEs did so for students within one large urban high school and found that student-level PPEs ranged from $3,615 to $16,734 and varied according to grade level and academic track (Picus et al., 2002). The authors concluded that there were "considerable" differences in PPEs for students in the same school (Picus et al., 2002, p. 200).

Three studies have examined differences in expenditures per course for courses within the same school. Though these studies do not calculate student-specific expenditures, they provide evidence that substantial variation in within-school resource allocation exists and that inequites and inefficiences of course expenditures may exist. In their case study of six high schools in New York, Brent et al. (1997) found that in terms of teacher salary expenditures, the most expensive courses per student across the six schools were the foreign language and science courses followed by music and special education courses. Concerning academic track, they found that the remedial core-academic courses were more costly per student than regular or advanced core-academic courses. Finally, they also found evidence of an inequitable distribution of experienced teachers across courses: Experienced teachers competed to teach the advanced courses, and novice teachers taught a disproportionate number of low-track courses and courses outside of their areas of certification. Second, in his study of resource allocation for all students attending public schools in Ohio, Chambers (1999) found similar results: Foreign language courses were more costly per student than regular core-academic courses, and that special education courses were among the most costly program offerings in terms of expenditures per student.

Lastly and more recently, Roza (2009) analyzed resource allocation in terms of per-pupil costs and found that schools spend more in terms of teacher salary expenditures on advanced courses than on regular or low-track courses due to higher teacher salaries. For example, while high schools in her study averaged $1,660 per pupil per advanced course, the schools averaged $739 per pupil per regular course and $713 per pupil per remedial course. Advanced placement (AP) courses were more costly per student than regular-track courses due to higher teacher salaries ($16,656 more on average than other teachers) as well as smaller class sizes (five students less on average than other courses).

These studies suggest that inequities in resources at the individual student level exist. However, one shortcoming of the studies that examine course expenditures per student–as opposed to student-specific expenditures–is that they do not link course expenditures to certain student characteristics. For example, they do not inform which students are enrolled in the remedial, regular, and advanced track courses. Further, these studies do not account for all of a particular student's courses, and it is possible that some students take multiple advanced and foreign language courses and that the spending differentials compound for certain students. Thus, these studies do not inform the degree of variation or inequity in student-specific expenditures for students within the same school. To date, the only studies that calculated student-specific expenditures include three dissertations and one published study by Picus and his colleagues. However, the available evidence suggests that variation and inequities in resources may exist for students within the same school, and more research is needed to understand the within-school variation and equity of student-level PPEs.

What Are the Dynamics of the Within-School Resource Allocation Process?

This section describes the factors that influence the within-school resource allocation process and discusses why schools may spend more to educate some students than others. Within-school resource allocation is primarily determined by teacher and student sorting into classes. This sorting ultimately affects how instructional resources are allocated to individual students within schools. Teacher and student sorting into classes has two components: teacher assignment to courses and students and student course-taking behaviors

School leaders influence teacher assignment (Brent et al., 1997; Koski & Horng, 2007; Leithwood et al., 2004), though how much discretion school leaders have is debated. Some studies indicate that school leaders are limited in assigning teachers to courses due to teacher seniority clauses in CBAs, which allow senior teachers to select the courses that they teach (Brent et al., 1997). A recent study finds that even if CBAs do not restrict school leaders in assigning teachers per se, school cultural norms regarding teacher seniority may still present barriers to school leaders in allocating teachers as they see fit (Donaldson, 2013). However, another study found that effective school leaders are not hindered by provisions in CBAs in assigning teachers to courses (Koski & Horng, 2007). In addition, when school leaders do have influence over teacher assignment, they may choose to reward and help retain effective teachers by assigning them to more desirable courses or students (Player, 2010), and teachers generally prefer to teach higher-income and more advanced students (Ingersoll, 2004). As teacher salary structures are largely static, this is one way that school leaders can influence teacher satisfaction and retention. Thus, teacher assignment may produce inequities in access to effective and experienced teachers for some students.

Student course-taking behaviors also affect within-school resource allocation and access to high-quality teachers because high track courses are more likely to be taught by high-quality teachers than low-track courses. School policies, parent and student preferences, and teacher expectations may all potentially influence student course-taking behaviors. Further, school policies regarding course taking may preclude some students from participating in certain courses. For example, one study by the National Center for Education Statistics (NCES) found that the most powerful influence on student course-taking is prerequisite requirements; teacher recommendations and student grades were the second greatest factors influencing student participation in courses, and suprisingly, only 14% of schools placed students in courses based on student achievement scores (Tyson, 2013). An additional study that reviewed the literature on student course-taking behaviors concuded that school policies leave little room for students to select courses (Tyson, 2013).

Other research indicates that parents play large roles in student course-taking behaviors. For example, Oakes and Guiton (1995) found that middle-class parents are more likely to push their children to take advantage of “open access” course policies for advanced courses, while low-income and minority students often opt out of these advanced courses. Student preferences also influence student participation in courses. Brent et al. (1997) note that, in addition to parents, “students themselves play an important role in terms of actual utilization of teaching resources,” because, “it is students who have ultimate control over the availability of their time, interest, and commitment to various educational activities” (p. 225). In addition, studies show that students may select courses attended by students of similar race, and minority students may opt out of advanced courses if White students are overrepresented in those courses (Tyson, 2013). However, one study found that student and parent preferences did not fully account for differential course-taking (Oakes & Guiton, 1995); instead, they found that differential course-taking was also related to teacher perceptions regarding “race and social class differences in [students’] academic abilities and motivation” and that school staff did not encourage low-income and minority students to take advanced courses (p. 28).

In summary, there are a number of reasons why students within the same school may receive different instructional resources. As Kalogrides, Loeb, and Beteille (2013) remarked, “The allocation of teachers to students is likely to result from a complex process whereby principals and other school leaders attempt to balance short and long term goals while responding to pressures to meet the preferences of teachers, students, and parents” (p. 105). Given the complexity and non-transparency of this process, it is possible that teacher and student sorting into classes results in inequitable resources for students within the same school.

This chapter highlights that there is a lack of knowledge on the equity of the allocation of resources within schools and at the student level. There is virtually no research on the equity of the allocation of instructional expenditures within schools, and few studies investigate the equity of the interplay of the allocation of multiple resources. This study seeks to address this gap in the literature by conducting a within-school equity analysis of a number of resources and determining if the results of the within-school resource allocation process are equitable.

Chapter 3: Data Source, District Context, & Variables

This chapter describes the data source, district context, and variables used in this study. The first section identifies the data source and provides the sample size. The second section describes the context of the district, including demographic characteristics, financial considerations, and goals and values. The final section of this chapter defines and explains the variables used in this study.

Data Source

Education Resource Strategies (ERS) originally collected the data analyzed in this study. ERS is a non-profit organization dedicated to transforming how urban school systems organize resources–people, time, technology, and money–so that every school succeeds for every student. This study employs ERS's data collected from one large urban public school district for the 2009-10 academic year. To preserve confidentiality, this study does not identify the name or location of the district. The raw data files contain information on student demographics, achievement, and course enrollment; special education services; and staff qualifications, salaries, and courses taught. The author cleaned and merged the raw data files to create a flat file linking individual high school students to allocated resources. The sample contains 41,537 high school students in more than 20 schools; sample selection is further discussed in Appendix I. The following table outlines documents that were collected and reviewed to more fully understand the district context and the raw data files.

Table 5: Data Documents

Source	Type of Document
Board of Education	Annual report
	Operating budget
	Policies
	Mission
District	Course guide handbook
	Promotion & retention policies
	Collective bargaining agreement
	Description of staff positions
State Department of Education	Annual report
	List of Title 1 schools

District Context

This section describes aspects of the district's context that are relevant to this study. The first subsection shows that this district serves a racially and ethnically diverse student population, whose racial and socioeconomic diversity allows this study to explore resource allocation patterns for students with different characteristics, and that the district employs an atypically larger proportion of minority teachers than other urban school districts. The second subsection discusses financial considerations, which inform what percentage of the district's total budget this study investigates and funding weights provided to certain student groups in the state foundation plan. The final subsection discusses district values and goals in order to determine if the district resource investment is consistent with their stated priorities.

Student and school demographics. The district is located in a major mid-Atlantic metropolitan area. The district is chosen because it is a large, urban district with a diverse student population. A sufficient number of schools are needed to analyze resource allocation patterns across schools, and a diverse student population is needed to analyze whether groups of students receive more or fewer resources. Districts with homogenous student populations may still have practically significant within-school variation in the allocation of resources; however, if all students are similar, student characteristics cannot be associated with differences in resource allocation. This district has a diverse student population in terms of both race and socio-economic status, and it is historically recognized as a being a middle-class African American community.

Across the district, 79% of high school students are African American, 12% are Latino, and 8% are White or Asian; 40% of students qualify for free and reduced priced meals (FARMS); and 3% are English language learners (ELLs). Examining further the relationship between student race and socioeconomic status in this district, 40% of African American students qualify for FARMS, 68% of Latino students qualify for FARMS, 33% of Asian students qualify for FARMS, and 0% of White students qualify for FARMS. None of these high schools receive federal Title 1 funds, though Title 1 funds are provided to some elementary and middle schools in the district.

Table 6: High School Student Demographics

		All Students %	**School-Level Minimum %**	**School-Level Maximum %**
Special Education		9	6	15
FARMS		40	22	62
ELL		3	< 1	18
Race	African-American	79	42	98
	Latino	12	1	49
	White or Asian	8	1	27
	Other	< 1	< 1	< 1
Gender	Male	49	55	46
	Female	51	45	54
Math Achievement	Below Proficient	29	19	55
	Proficient	56	37	60
	Advanced	15	3	44
English Achievement	Below Proficient	32	15	51
	Proficient	53	41	59
	Advanced	15	4	45

The high schools in the sample differ in terms of student characteristics. African American students are the majority racial group in almost every school, and White, Asian, and Latino students are concentrated in certain schools. Two schools have substantial proportions of White and Asian students (27% and 24%), and four schools have substantial proportions of Latino students (49%, 47%, 41%, and 39%). Schools also differ in terms of proportions of low-income students: In a few schools, fewer than 30% of students qualify for FARMS; in approximately half of the schools, between 30 and 50% of students qualify for FARMS; and in a number of schools, 50% or more students qualify for FARMS. Finally, schools differ in student performance. In a few schools, more than 70% of students have passed the state English and math tests; in a few schools, between 60 and 70% of students have passed the state tests; in the majority of schools, between 50 and 60% of students have passed the state tests; and in a number of schools, less than 50% of students have passed the state tests.[7]

School-level values of student race distribution, mean achievement, and average socioeconomic status are related in this district. Schools with the largest proportions of Latino students have the largest proportions of low-income students. The two schools with substantial White and Asian populations are among the schools with the lowest proportions of low-income students and have the highest average student achievement. Characteristics of the high schools are outlined in the following tables. Table 7 categorizes the number of schools in the sample by racial composition, socioeconomic status, and achievement level. All schools have relatively large enrollments, and the

[7] These percentages are calculated for 10th–12th graders only, as student achievement data are mostly missing for 9th grade students.

median school size is 1,841 students, the minimum school size is 918 students, and the maximum school size is 3,106 students.[8]

[8] Descriptives for each school are provided in Appendix II.

Table 7: High School Types By Racial Composition, Socioeconomic Status, and Achievement

Substantial White/Asian Population	Substantial Latino Population	Predominantly African American Population	Low-Poverty	Mid-Poverty	High-Poverty	Low-Achieving	Low- to Mid-Achieving	Mid- to High-Achieving	High-Achieving
X			X						X
X				X					X
	X				X	X			
	X				X		X		
		X	X					X	
		X		X				X	
		X		X					X
		X		X			X		
		X			X		X		
		X			X	X			

Tables Notes:

(a) In the two schools with substantial White/Asian populations, White and Asian students comprise 24% and 27% of the student population.

(b) In the schools with substantial Latino populations, Latino students comprise 41%, 47%, 39%, and 49% of the student population.

(c) Low-poverty in this table is defined as less than 30% of students qualify for FARMS; mid-poverty is defined as between 30 and 50% of students qualify for FARMS; high-poverty is defined as more than 50% of students qualify for FARMS.

(d) Low-achieving is defined as less than 50% of 10^{th}–12^{th} grade students have passed the state tests in English and math; low- to mid-achieving is defined as between 50 and 60% of students have passed these tests; mid- to high-achieving is defined as between 60 and 70% of students have passed state tests; and high-achieving is defined as 70% or more of students have passed state tests.

Financial considerations. The author reviewed the district's Board of Education's annual report to determine the percentage of all district expenditures that are accounted for in this study. Expenditures dedicated to the instruction of students include expenditures for teacher salaries, special education, "other instructional costs," and textbooks and supplies. Instructional expenditures constitute 54.5% of the district budget (see Table 8). This study accounts for the majority of teacher salary expenditures (34.4% of the district budget) but does not account for expenditures allocated to substitute teachers, interns, paraprofessionals, librarians, or other instructional aides who are not included in course enrollment files. This study also includes a portion of special education expenditures (15% of the district budget) because it accounts for expenditures allocated to special education "classroom teachers," whether or not these teachers are included in the course enrollment files. As a result, this study accounts for roughly one-third of all district expenditures and around 60% of instructional expenditures.[9]

[9] This calculation is based on descriptive analyses and the reported district-wide average expenditure. The district-wide average PPE for the 2009-10 academic year was $12,000. The average per-pupil TRE calculated by this study is approximately $4,000. Hence, this study accounts for roughly one-third of all district expenditures.

Table 8: Percent of Expenditures by Category

Expenditure Category	**Percent of Total Budget %**
Instructional salaries	34.4
Fixed costs	18.0
Special education	15.0
Maintenance and operations	9.5
Mid-level administration	7.0
Transportation	5.7
Other instructional costs	3.4
Central Administration	3.0
Textbooks and supplies	1.7
Health services	0.9
Student personnel services	0.8
Food services	0.4
Community services	0.2
Capital outlay	0.1
Total instructional	**54.5**
Total	**100.1**

Table note: Percentages are off by one-tenth due to rounding.

The funding structure of the state in which the district resides is also of importance in this study. In this particular state, the state allocates funding for public education according to its foundation plan, which supplements district funding and sets funding weights for students in certain categories. The state then allocates funding to districts according to student need and in conjunction with other legislation that governs school finance. Specifically, the state allocates additional money for special education, ELL, and low-income students. The state's foundation plan includes a funding weight of 1.74 for special education students, 1.99 for ELL students, and 1.97 for low-income students (Verstegen, 2011). The district receives substantial funding from the state. In 2009-10, the state funded 51% of all district expenditures; local funding from the district funded 35% of expenditures, and the federal government funded 12% of expenditures. Although none of the high schools in the district received federal Title 1 funds in the 2009-10 academic year, the district received Title 1 funds, which were allocated to elementary and middle schools with larger proportions of low-income students.

District values and goals. Finally, district values and goals are potentially relevant in understanding how the district invests its resources. First, the district is committed to equity. Board policy emphasizes that education is a fundamental right and that equitable access to a high quality education should be provided to all students. The Board also states that resources should be targeted to students with the greatest academic needs. Second, the district believes that raising achievement is the result of what happens in the classroom, and they are committed to targeting resources to the classroom. This value is particularly relevant to this study because this study focuses on specific instructional resources that can be traced to individual classrooms.

Finally, this district strives to ensure that all graduating students are college and/or career ready. In the 2009-10 academic year, the graduation rate was just over 80%. Only one-fourth of graduating students met course requirements to enroll in the premier state university, and 50% of students planned to enroll in four-year colleges. Concerning job preparation, only 4.5% of graduating students went directly into the workforce, and of these students, only 18.5% obtained employment in a field related to their high school training program. The following table below displays data from student decision surveys concerning post-graduation plans. In response to these student outcomes, the district stated that it is currently working to both increase academic course requirements and re-design vocational programs to provide students with more opportunities to enroll in courses that are relevant, rigorous, and appropriate for college and career readiness.[10]

[10] All facts in this paragraph are outlined in the Board annual report.

Table 9: Post-Graduation Student Decisions

	Percent of graduating students
Planned to attend a four-year college	50%
Planned to go directly into workforce	4.5%
Unknown	45.5%

Variables

This section defines the variables used in this study. Independent variables include student demographic and achievement characteristics. Dependent variables include teacher resource expenditures (TREs) per pupil, class size teacher experience, peer achievement, and number of advanced placement (AP) courses.

Independent variables. This study assesses if certain student characteristics are related to equity of allocated resources. Student demographic characteristics include special education, English language learner (ELL), and low-income status; grade level; race/ethnicity; and gender. The following table outlines and defines student demographic variables.

Table 10: Student Demographic Variables

STUDENT-LEVEL VARIABLES		
Variable Name	**Description**	**Type of Variable**
	Demographic	
SPED	Special education status defined by having an individual education plan (IEP) (0=no, 1=yes)	Dichotomous
Gender	Gender (0=male, 1=female)	Dichotomous
POV	Free and reduced priced meals (FARMS) status (0=no, 1=yes)	Dichotomous
ELL	ELL status (0=no, 1=yes)	Dichotomous
Grade9	Grade 9 (0=no, 1=yes)	Dichotomous
Grade10	Grade 10 (0=no, 1=yes)	Dichotomous
Grade11	Grade 11 (0=no, 1=yes)	Dichotomous
Grade12	Grade 12 (0=no, 1=yes)	Dichotomous
Latino	Latino (0=no, 1=yes)	Dichotomous
African	African American (0=no, 1=yes)	Dichotomous
WhiteAsian[11]	White or Asian (0=no, 1=yes)	Dichotomous

[11] White and Asian student subgroups each account for a small percentage of the larger student population and both groups are predominantly middle class and both have similar achievement levels.

This study also employs student achievement variables. The testing structure of the state in which the district is located influences how student achievement variables are derived in this study. In this particular state, students must take and pass four state exams–in algebra, English, government, and biology–in order to graduate from high school, and students pass these tests if they score at a level deemed to be "proficient" or "advanced." Students may take these tests multiple times, and they do not have to take these tests annually. As a result, raw test scores may have different meanings depending on the year in which the students took the test. For example, one would expect student performance on tests to increase with age and/or additional years of education; thus, one would expect 12^{th} grade students to score higher than 9^{th} grade students. Therefore, a 9^{th} grade student who scores 500 on the English test during his/her 9^{th} grade year is theoretically higher achieving than a 12^{th} grade student who scores a 500 on the English test during his/her 12^{th} grade year.

Due to these complications in determining accurate current student achievement, this study employs a more basic measure of student achievement. First, this study creates a binary indicator of whether the student has passed the state test in an academic subject. Then, interaction variables between student binary achievement and grade level are derived. In doing so, this study analyzes resource allocation for students with different achievement status only for students within the same grade level. For example, this study compares per-pupil TREs for 12^{th} grade students who have passed state tests to per-pupil TREs for 12^{th} grade students who have not passed state tests. Though coding choice allows for a clear comparison of resources for students who have passed state tests with those who have not. Passing state tests is particularly important in this district because students must pass state tests to graduate from high school. Student achievement is not examined for 9th grade students, as few students take state tests their freshman year, and student achievement data are generally not available for these students.   The following table provides a summary of the student achievement variables derived and employed in this study.

Table 11: Student Achievement Variables

STUDENT-LEVEL VARIABLES		
Variable Name	**Description**	**Type of Variable**
	Achievement	
Gr10PELA	Interaction variable indicating whether a 10th grade student has passed the state English test (0=no, 1=yes)	Dichotomous
Gr10PMath	Interaction variable indicating whether a 10th grade student has passed the state math test (0=no, 1=yes)	Dichotomous
Gr11PELA	Interaction variable indicating whether a 11th grade student has passed the state English test (0=no, 1=yes)	Dichotomous
Gr11PMath	Interaction variable indicating whether a 11th grade student has passed the state math test (0=no, 1=yes)	Dichotomous
Gr12PELA	Interaction variable indicating whether a 12th grade student has passed the state English test (0=no, 1=yes)	Dichotomous
Gr12PMath	Interaction variable indicating whether a 12th grade student has passed the state math test (0=no, 1=yes)	Dichotomous

Available achievement data by grade are summarized in the table below. Note that the percentage of students who have passed the test and the mean test scores increase with student grade level. Most students have taken both the English and math tests at least once by the end of their 10th grade year.

Table 12: Available Student Achievement Data by Grade Level

Grade	English Score Available	Passed English Test	Mean English Score	Math Score Available	Passed Math Test	Mean Math Score
9th	5.5%	2%	375	74.9%	37%	375
10th	75.7%	47%	399	85.7%	52%	414
11th	86.6%	60%	405	88.5%	64%	423
12th	93.5%	68%	407	94.3%	69%	423

School-level variables are also created based on aggregates of student demographic and achievement variables for each school. School-level demographic and achievement variables are outlined and defined in the following table.

Table 13: School-Level Demographic and Achievement Variables

Variable Name	Description	Variable Type
SCHOOL-LEVEL VARIABLES		
	Demographic	
SCHSPED	% of special education students in the school	Continuous
SCHPOV	% of students in the school who qualify for FARMS	Continuous
SCHELL	% of ELLs in the school	Continuous
SCHLatin	% of Latino students in the school	Continuous
SCHAfrican	% of African American students in the school	Continuous
SCHWhAs	% of White and Asian students in the school	Continuous
SCHSize	Total enrollment	Continuous
	Achievement	
SCHELA	Average raw score on state English test for all students in a school	Continuous
SCHMath	Average raw score on state math test for all students in a school	Continuous
SCHPELA	Percent of 10^{th}–12^{th} grade students who have passed the state English test in the school	Continuous
SCHPMath	Percent of 10^{th}–12^{th} grade students who have passed the state math test in the school	Continuous
SCHAchieve	Principal component score for school that is a weighted linear combination of the previous four school-level achievement variables	Continuous

Dependent variables. This study merges numerous district raw data files to create one flat file with a student identification number linked to a number of resources, including teacher resource expenditures per pupil, resources in students' English and math classes, and number of AP courses taken. The following subsections define resource variables and discuss key assumptions in determining these variables.

Teacher resource expenditures per pupil. This study defines teacher resource expenditures (TREs) as the amount spent per pupil on teacher salaries. In this district, TREs account for roughly one-third of all district expenditures and 60% of instructional expenditures. The National Center for Education Statistics (NCES) (2013a) defines instructional expenditures as follows:

> Instruction expenditures are for services and materials directly related to classroom instruction and the interaction between teachers and students. Teacher salaries and benefits, textbooks, classroom supplies and extra curricular activities are included in Instruction. (p. 1)

According to NCES's definition, there are other instructional expenditures that this study does not account for, such as textbooks, classroom supplies, teacher benefits,[12] and extracurricular activities relating to instruction. This study also does not account for money spent on instructional or teacher aides who instruct students but who do not appear in course enrollment files. In this study, per-pupil TREs reflect how teacher salaries are ultimately allocated to students.

How teacher salaries are allocated to students was determined by a number of factors, including class sizes, teacher course loads, student course-taking behaviors, and length and duration of courses. Per-pupil TREs were calculated by the following method: First, each teacher's salary was evenly divided among the teacher's courses, accounting for the duration and term length of the course. For example, full-year courses were allocated a larger proportion of a teacher's salary than courses that met for only one quarter or semester. In addition, teachers who taught a few number of courses were identified and course expenditures were adjusted.[13] This analysis resulted in course expenditures. Then, course expenditures were divided by class size, yielding course expenditures per student. Finally, for each student, the course expenditures per students were aggregated for each student to reflect the per-pupil TRE for each student in the

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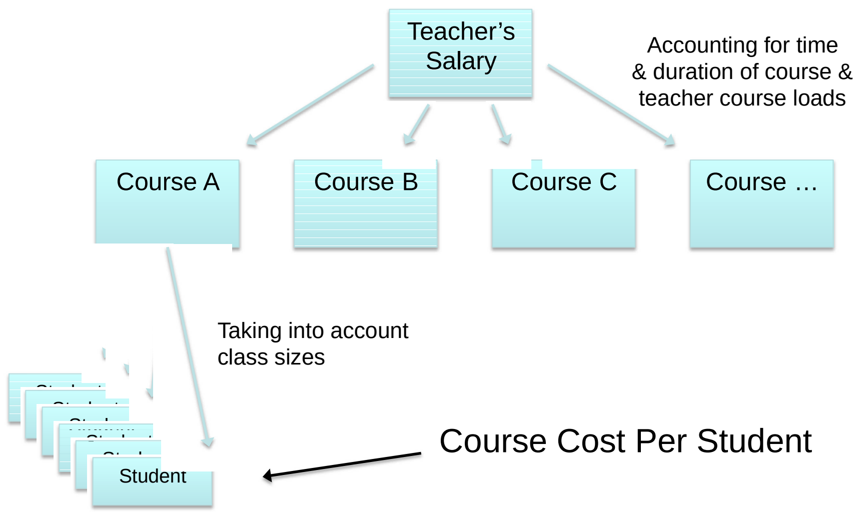
[12] In this district, teacher salary expenditures excluding benefits are strongly correlated with teacher salary expenditures including benefits (r = .975). For this reason, this study examines teacher salary expenditures only.

[13] See Appendix I for more detail.

district. The following figure depicts the allocation of teacher salaries to individual students.

Figure 2: Calculation of Per-Pupil TREs



Per-pupil TREs partially depend on the number of courses that each student takes. However, when examining descriptive statistics, it does not appear that number of courses taken dramatically varies across students with different characteristics. Twelfth grade students take fewer courses than younger students, on average, and there is more variation in number of courses taken for 12th grade students. When examining differences in number of courses taken for 12th grade students who have passed the state standardized tests, there is no difference in number of courses taken for 12th grade students who have different achievement status in math. Twelfth grade students who have passed the state English test take 0.2 courses more than 12th grade students who have not passed the state English test on average. Thus, although student course loads are one component of per-pupil TREs, large discrepancies in per-pupil TREs for students of different characteristics are not likely to the result of different numbers of courses taken.

Table 14: Number of Courses Taken By Students According to Student Characteristics

		Mean Number of Courses Taken	Standard Deviation
Special Education	Yes	7.4	1.4
	No	7.5	1.0
FARMS	Yes	7.5	1.1
	No	7.5	1.0
ELL	Yes	7.5	0.9
	No	7.6	1.1
Race	African-American	7.5	1.1
	Latino	7.5	1.0
	White or Asian	7.3	1.2
Gender	Male	7.5	1.0
	Female	7.6	1.1
Grade	9th	7.5	0.7
	10th	7.5	0.8
	11th	7.8	0.9
	12th	7.1	1.7
Math Achievement	Passed Test	7.5	1.1
	Not Passed Test	7.5	1.0
English Achievement	Passed Test	7.5	1.2
	Not Passed Test	7.5	0.9

Per-pupil TREs are calculated for instruction in all courses and for instruction in core-academic courses only. Total per-pupil TREs include teacher salary expenditures associated with all instruction–academic, elective, or vocational–but do not include expenditures relating to physical education, team sports, and personal fitness courses or courses in which a student is placed in an internship outside of the school. Core-academic TREs per pupil include traditional college-preparatory courses and academic courses in the English, math, science, history, reading, and foreign language departments. The following table outlines per-pupil TRE variables and relevant variables in calculating TREs per pupil.

Table 15: Per-pupil TRE Variables and Related Course and Teacher Variables

Variable Name	Description	Variable Type
STUDENT-LEVEL VARIABLES		
TRE	Teacher resource expenditure per pupil, outliers removed[14]	Continuous
TRE_CA	Teacher resource expenditure per pupil, core-academic subjects only and outliers removed	Continuous
COURSE-LEVEL VARIABLES		
Class_Size	Class size of course	Continuous
Course_Exp	Course expenditure	Continuous
Course_Exp_PP	Course expenditure per pupil	Continuous
TEACHER-LEVEL VARIABLES		
Teacher_Salary	Teacher salary	Continuous

In addition, regardless of whether special education, ELL, and reading classroom teachers were included in course enrollment files, these teacher salaries were allocated to students who benefit from their instruction. More detailed information about how these TREs per pupil were estimated as well as a discussion on how irregularities in the data were handled is provided in Appendix I. Appendix I also summarizes decision rules regarding missing data imputation and procedures for handling outliers.

Teacher salary data were not straightforward, and the financial file contained line item expenditures allocated to individual teachers for various purposes. In determining teacher salary, this study included all expenditures that are directly related to instruction and aggregated regular, leave, and performance pay and other stipends granted for teaching purposes. This study did not include teacher expenditures that are indirectly related to instruction, occur outside of the regular school year, or involve activities not related to instruction, such as professional development, summer school, and athletic coaching. Using these decision rules, the average high school teacher salary was $66,944. In this district, teacher salaries are determined by a collective bargaining agreement (CBA), which ties base salary to teacher years of experience, certification level, and

[14] See Appendix I for a discussion of treatment of outliers.

education. The Pearson correlation coefficient between teachers' salaries and years in the district is $r = .476$ ($p < .001$). Hence, teachers' years of teaching in the district explained 22.6% of variation in teacher salaries. During the 2009–10 academic year, teachers' salaries were not tied to measures of effectiveness. The following table provides descriptive information for teacher salaries.

Table 16: Teacher Salaries for High School Teachers

	Mean	Median	Standard Deviation	25th Percentile	75th Percentile
Teacher Salary	$66,944	$66,485	$17,692	$53,581	$82,873

Class sizes, teacher experience, peer achievement, and number of AP courses. Based on course enrollment data, this study also derives specific resource variables that reflect observable differences in classroom resources. The following table provides an overview of all additional resource variables used in this study.

Table 17: Additional Resource Variables

Variable Name	Description	Variable Type
	STUDENT-LEVEL VARIABLES	
NETF	New English teacher flag indicating whether the student's English teacher is new to the school, or has taught for less than three years in the school; if the student is enrolled in more than one English class, the average years of experience of the English teachers is first calculated and then the student is tagged as having a new English teacher if the average is less than three years in the school (0=no, 1=yes)[15]	Dichotomous
NMTF	New math teacher flag indicating whether the student's math teacher is new to the school, or has taught for less than three years in the school; the student is enrolled in more than one math class, the average years of experience of the math teachers is first calculated and then the student is tagged as having a new math teacher if the average is less than three years in the school (0=no, 1=yes)[16]	Dichotomous
ELACS	The class size of the student's English class; if the student is enrolled in more than one English class, the class sizes are averaged	Continuous
MathCS	The class size of the student's math class; if the student is enrolled in more than one math class, the class sizes are averaged	Continuous
PeerEPer	Peer achievement in English class defined by the percent of peers in English class who have passed the state English test; if the student is enrolled in more than one English class, peer achievement of the classes are averaged	Continuous
PeerMPer	Peer achievement in math class defined by the percent of peers in math class who have passed the state math test; if the student is enrolled in more than one math class, peer achievement of the classes are averaged	Continuous
AP	Number of AP courses a student is enrolled in for the academic year	Count

This study focuses on resources in students' English and math classes because these classes are essential for student success on state high school graduation exams as well as on national standardized tests often used for college admissions for students who wish to pursue post-secondary education. Second, research on the efficacy of resources such as class size and teacher experience has typically analyzed student outcomes in English and math, and therefore, it is unknown if class sizes and teacher experience are related to student outcomes in all academic subjects. Third, averages of class sizes and teacher experience may not be as informative as actual class sizes; for example, if a student is enrolled in a math class with a large number of students and an English course

[15] Forty-two percent of students are enrolled in more than one course in the English department.
[16] Thirty-five percent of students are enrolled in more than one course in the math department.

with a small number of students, the student's average class size does not reflect this variability. Thus, by focusing on available resources in students' English and math classes, this study provides a more nuanced analysis of resource allocation. These resource variables are derived as follows:

Class size. This study defines class size as the actual class size of a student's English or math class. In some cases, students are enrolled in more than one English or math class. In these cases, class sizes are averaged across all English or math courses per student.[17]

Teacher experience.[18] In this study, experienced teachers–in either English or math class–are defined to be teachers who have been teaching *in the school* for at least three years; total years of teaching experience are not available. It appears that, in this district, teachers who are new to their schools are also new to the district: Years in the district are highly correlated with years in the school ($r = .969$, $p < .001$, and see Table 18). It also appears that teachers who are new to the schools generally have lower salaries and hence likely have fewer total years of teaching experience than other teachers. However, some teachers with less than three years experience in the school have high teacher salaries, indicating these teachers are not new teachers. In summary, in most cases, teachers who are new to the school are also new to the profession, but there are some exceptions.

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[17] One result of this decision is that class sizes vary at the student level and are not constant at the classroom level. In addition, even though class sizes are averaged, TREs per course category per student are not. In other words, if a student is enrolled in two English courses, expenditures per student for both courses are allocated to the student and are reflected in the TRE for that student.

[18] This study recognizes that teacher certification and advanced degrees for high school math teachers has also been shown to impact student outcomes. Teacher experience has a similar impact on student outcomes as teacher certification and advanced degrees, and teacher experience, like teacher certification and advanced degrees, partially drives teacher salaries.

Table 18: Teacher Years of Experience

	Mean	**Median**	**Standard Deviation**	**25^{th} Percentile**	**75^{th} Percentile**
Teacher Years in District	8.5	5.9	8.5	2.9	10.9
Teacher Years in School	8.4	5.8	8.2	2.9	10.7

Based on the number of years the teacher has been teaching *in the school,* the author creates a dummy variable that flags teachers with less than three years of experience in the school. Research indicates that teachers are much more effective after their first few years of teaching (Rice, 2010), and to be consistent with the literature, this study employs this dummy variable as opposed to total years of experience teaching in the school.

In some cases, students are enrolled in more than one English or math class. For a student who is enrolled in more than one English class, the average years of teaching experience in the school of the student's English teachers is first calculated and then the student is tagged as having a new English teacher if this average is less than three years of teaching experience in the school. The same approach applies to identifying teacher experience for students who are enrolled in more than one math class. For example, if a student benefits from the instruction of an experienced math teacher and also has a novice math teacher, the student is still taught by at least one experienced math teacher. Therefore, if a student is enrolled in more than one math course, the student is considered to be taught by a novice math teacher if the student does not have at least one experienced teacher.

Peer achievement. This study defines peer achievement in English as the percentage of a student's peers in English class who have passed the state standardized test in English. Similarly, peer achievement in math is the percentage of a student's peers in math class who have passed the state standardized test in math. These percentages exclude the particular student's achievement, and if the student is enrolled in more than one English or math course, peer achievement is averaged across courses for each academic subject.[19]

Number of AP courses. Finally, to gauge access to academically rigorous courses, this study also examines the number of AP courses taken by 11th and 12th grade students. This study calculates the number of AP courses taken by each 11th and 12th grade student during the 2009-10 academic year. The number of AP courses is only calculated for 11th and 12th grade students because few younger students are enrolled in AP courses.

This district has an "open door" policy for AP courses meaning that any student may enroll in any AP course, though students with prior high achievement are especially encouraged to participate in AP courses.[20] All schools offer AP courses in the following subjects: biology, calculus, English language, English literature, human geography, U.S. government, psychology, statistics, and world history, and individual schools may choose to offer additional AP courses. The most frequently offered AP courses are in English and psychology, and the AP courses offered the least frequently are in sciences and math. Student enrollment in AP courses reflects both school informal practices that influence teacher and student sorting into courses as well as student choices.

School-level resource variables. School-level aggregates of resource variables are also derived from student-level variables (See Table 19). In some cases, school-level aggregates only include students in certain grades. For example, the school-level aggregate of number of AP courses taken by students is calculated only for 11th and 12th

[19] Averaging peer achievement when there is more than one class is a method employed by a recent study analyzing the distribution of peer achievement (Kalogrides & Loeb, 2013).
[20] Information provided in the Board's annual report.

grade students as few 9th and 10th grade students enroll in AP courses. In addition, due to the large amount of missing achievement data for 9th grade students, school-level aggregates of peer achievement are calculated for 10th through 12th grade students only. School-level aggregates of resource variables by school are provided in Appendix II.

Table 19: School-Level Resource Variables

Variable Name	**Description**	**Variable Type**
	SCHOOL-LEVEL VARIABLES	
SCHTRE	Average per-pupil TRE	Continuous
SCHTRE_CA	Average core-academic TRE per pupil	Continuous
SCHELACS	Average English class size in school	Continuous
SCHMathCS	Average math class size in school	Continuous
SCHNETF	Proportion of students in school with inexperienced English teacher	Continuous
SCHNMTF	Proportion of students in school with inexperienced math teacher	Continuous
SCHAP	Average number of AP courses taken by 11th and 12th grade students in school	Continuous
SCHPeerEPer	Average percent of peers in English class who have passed state English test for 10th–12th graders in school	Continuous
SCHPeerMPer	Average percent of peers in math class who have passed state math test for 10th–12th graders in school	Continuous

Chapter 4: Methods

This chapter discusses the methods employed in this study. Most notably, it outlines the analytic approach used to conduct a within-school equity analysis of resource allocation; the following sections also discuss the methods employed to address the other research questions. Table 20, below, provides an overview of the models utilized in this study. The chapter concludes by providing information on the software used in this study.

Table 20: Methods Utilized To Address Research Questions

Research Questions	**Method Type**	**Dependent Variable Name**	**Dependent Variable**
How does the within-school variation in teacher resource expenditures per pupil compare to the variation between schools?	Multi-level modeling (MLM)	TRE	Teacher resource expenditure per pupil
		TRE_CA	Core-academic teacher resource expenditure per pupil
Are teacher resource expenditures per pupil equitably distributed within schools?	MLM & Simple linear regression (SLR)	TRE	Teacher resource expenditure per pupil
		TRE_CA	Core-academic teacher resource expenditure per pupil
Do within-school allocation patterns of teacher resource expenditures per pupil vary across schools?	MLM	TRE	Teacher resource expenditure per pupil
		TRE_CA	Core-academic teacher resource expenditure per pupil
Are specific resources equitably allocated within schools, and do multiple resource advantages or disadvantages exist for some students?	Multiple linear regression (MLR)	TRE	Teacher resource expenditure per pupil
		TRE_CA	Core-academic teacher resource expenditure per pupil
	MLR	ELACS	Class size in English
		MathCS	Class size in math
	Logistic regression	NETF	New English teacher flag
		NMTF	New math teacher flag
	Poisson regression	AP	Number of AP courses
	MLR	PeerPELA	Percent of peers in English class who have passed state English test
		PeerPMath	Percent of peers in math class who have passed state math test

The first three research questions concern the equity of the allocation of teacher resource expenditures (TREs) per pupil. This study employs multilevel modeling (MLM) and simple linear regression (SLR) to evaluate the equity of the allocation of TREs per pupil. The last research question concerns the equity of the allocation of resources in students' English and math classes and the number of AP courses taken by students. To address the last research question, this study employs regression analysis for each school to gain a more nuanced understanding of the equity of the allocation of a number of resources within schools.

Within-School Variation in Per-Pupil TREs

Before any equity analysis of per-pupil TREs is conducted, this study tests if there is indeed considerable within-school variation in per-pupil TREs compared to the variation between schools. To address the first research question, *"How does the within-school variation in teacher resource expenditures per pupil compare to the variation between schools?"* this study employs multilevel modeling (MLM) because it determines if differences in per-pupil TREs are primarily the result of differences in spending between or within schools. To do so, MLMs compare the proportion of the variation in per-pupil TREs that occurs within schools to the proportion that occurs between schools. This analysis is necessary for this study because if within-school differences in per-pupil TREs exist and yet are small compared to between-school variation in per-pupil TREs, then policies should instead focus on equalizing resources between schools instead of addressing resource equity within schools.

MLM is the most appropriate method to analyze data with multiple levels (Bickel, 2007; Raudenbush & Bryk, 2002; Snijders & Bosker, 2012).[21] In this study, students are

[21] Ignoring the multilevel structure of the data also potentially results in biased results (Cohen, Cohen, West, & Aiken, 2003). In particular, the multiple linear regression (MLR) assumption that the residuals of individual students are independent from each other is violated in data with multiple levels (Cohen, Cohen, West, & Aiken, 2003). Because all students within the same school experience the same environment, observations of students in a particular school may share values on unobserved variables (Raudenbush & Bryk, 2002). The result is that residuals of students within one particular school may be correlated,

"nested" within schools and two levels are present: students at level 1 and schools at level 2. Student characteristics are referred to as level-1 variables and school characteristics as level-2 variables.

To parse the variation to the student and school levels, this study estimates the following multilevel model (MLM): the one-way analysis of variance (ANOVA) with random effects, also known as the fully unconditional model (Raudenbush & Bryk, 2002). This model is represented by the following:

Equation 1: Null MLM of Per-Pupil TREs

$$Y_{ij} = \beta_{0j} + r_{ij}$$
$$\beta_{0j} = \gamma_{00} + u_{0j}$$

Where:

Y_{ij}: per-pupil TRE for the ith student in school j

β_{0j}: school-level mean TRE per pupil for school j

r_{ij}: residual for the ith student in school j

γ_{00}: grand mean, average of all school means

u_{0j}: random school effect, or residual for school j.[22]

This model also provides an estimate for the grand mean, which is the average of all school-level mean TREs. More importantly, this model provides information on what proportion of the variance in per-pupil TREs occurs within schools compared to between schools (Raudenbush & Bryk, 2002). The intraclass correlation coefficient (ICC), or the proportion of variance in per-pupil TREs that occurs between schools, can be calculated from the estimates of this model. The ICC is calculated as follows:

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violating the MLR assumption of independence (Raudenbush & Bryk, 2002). This violation causes standard errors of the regression coefficients that are too small and increased Type I error rates (Cohen et al., 2003). In other words, independent variables may be found to be statistically significant predictors of the dependent variable when in fact, they are not. MLM accounts for nested data structures and provides better estimates of standard errors (Raudenbush & Bryk, 2002).

[22] Model assumptions are further discussed in Appendix IV.

Equation 2: Formula for ICC

$$\mathrm{ICC} = \frac{\tau_{00}}{\tau_{00} + \sigma^2}$$

Where:

τ_{00}: the variance in Y_{ij} attributable to between-school differences, $\mathrm{Var}(u_{0j}) = \tau_{00}$

σ^2: the variance in Y_{ij} attributable to within-school differences, $\mathrm{Var}(r_{ij}) = \sigma^2$.

If the within-school variation in per-pupil TREs is statistically and practically significant compared to the between-school variation, indicated by a small ICC, an investigation of within-school fiscal resource equity is warranted.

Equity Analysis of Per-Pupil TREs

To address the second research question, *"Are teacher resource expenditures per pupil equitably distributed within schools?"* this study develops an analytic approach for evaluating the equity of per-pupil TREs. This analysis has multiple parts corresponding to Berne and Stiefel's (1984) framework for evaluating equity in education: horizontal equity, vertical equity, and equal opportunity.

Horizontal equity. Horizontal equity is the equal treatment of equals, which implies that all students with equal needs receive the same amount of resources (Baker & Green, 2008). However, Odden and Picus (2008) point out that not "all children are alike" (p. 66). Children differ in grade level, prior performance, disability, low-income background, and limited English ability, and identifying subgroups of "like" students is difficult. For this reason, Toutkoushian and Michael (2007) argue that it would be very difficult to conduct a horizontal equity analysis for each subgroup of "like" students because there would be a large number of student subgroups. They remark that an important limitation of traditional horizontal equity analyses is that they "do not generally account for the effects of multiple dimensions of student and district need" (p. 398).

To resolve this issue, Toutkoushian and Michael (2007) provide one approach for analyzing horizontal equity that utilizes MLR to control for multiple factors of student need. Their idea is that once certain student needs are controlled for, then students are alike, and horizontal equity may be evaluated. The first step of their approach is to regress PPEs on legitimate categories of student need to obtain the residuals, or the differences between actual PPEs and expected PPEs given student needs. They argue that the residuals represent the differences in dollars for "like" students. Then, horizontal equity is determined based on the variation of the residuals instead of the actual PPEs. Conceptually, analyzing the variation of the residuals is similar to analyzing the variation of PPEs, but using the residuals instead of the actual PPEs controls for some reasons why per-pupil TREs differ across students.

The second step of their approach is to calculate the standard error of the estimate, which "represent[s] the average amount of variability" in PPEs across "like" students (p. 407). Toutkoushian and Michael (2007) posit that horizontal equity is achieved when the standard error of the estimate is 0; in other words, horizontal equity is violated if there is any variability in PPEs after controlling for student needs. One flaw to their approach, however, is that it does not allow for *any* variability in spending on "like" students before horizontal equity is violated, yet traditional horizontal equity analyses typically allow for *some* variation before horizontal equity is violated (Odden & Picus, 2008). To be consistent with traditional horizontal equity analyses, this study diverges from Toutkoushian and Michael's (2007) approach at this step and instead allows for some variation in PPEs before horizontal equity is violated. The following paragraphs outline this study's analytic approach for evaluating horizontal equity.

According to the literature, students who differ on the following variables are not alike: special education, ELL, and low-income status and grade level (Odden & Picus, 2008). Further, the state in which this district is located allocates additional funding for special education, ELL, and low-income students (Verstegen, 2011); hence, these students are unlike other students who do not need additional resources. In addition, grade level is also a common variable for defining "like" student subgroups because districts may target resources to students in certain grades (Odden & Picus, 2008). Thus, this study identifies "like" students as students who are in the same grade and who are similar in terms of special education, ELL, and low-income status.

This study first obtains the residuals of PPEs using Toutkoushian and Michael's (2007) MLR approach, controlling for special education, ELL, and low-income status and grade level, and then calculates the coefficient of variation (CV) using the residuals from the MLR analysis. The CV is a common statistic used to evaluate horizontal equity of PPEs (Odden & Picus, 2008), and it is typically calculated by dividing the standard deviation of PPEs by the mean PPE. The study employs the CV to evaluate the degree of variation because the CV is a good overall measure of variation because it takes into account all values in the data, and it is easily understood and interpretable. The study calculates the CV by dividing the standard deviation of the *residuals* by the average per-pupil amount. Therefore, in this study, the CV represents the degree of variation in PPEs after controlling for special education, ELL, and low-income status and grade level. Then, to determine if horizontal equity is achieved, this study compares the CV with a pre-determined criterion. Therefore, unlike Toutkoushian and Michael's (2007) approach, this analysis allows for some variation in PPEs before horizontal equity is violated.

To determine if horizontal equity is achieved, typically, the CV of PPEs is compared to a pre-determined criterion. A common criterion for achieving horizontal equity of PPEs in studies of interdistrict equity is a CV of less than 0.10, though several scholars argue that this criterion is too large for studies of intradistrict spending (Goertz & Stiefel, 1998; Odden & Picus, 2008). However, due to limited research on within-school horizontal equity of PPEs, there is no commonly accepted criterion for determining within-school horizontal equity. This study proposes the following approach: As per-pupil TREs are largely determined by teacher salaries, and there is variation of teacher salaries within schools, this study first calculates the CV of teacher salaries, and this value serves as the criterion for determining horizontal equity of PPEs within schools. The logic is that if per-pupil TREs do not vary more than teacher salaries within schools, horizontal equity is achieved. Alternatively, if the CV of the residuals is greater than the CV of teacher salaries, horizontal equity is violated.

MLM is appropriate for this analysis because it may be used to determine the average degree of within-school variation in PPEs after controlling for special education, ELL, and low-income status and grade level. The following MLM model controls for these variables, and residuals from this model are employed to determine horizontal equity. Conceptually, the level-1 residuals of this model represent the differences in spending for students within the same school, controlling for student needs.

The following equation outlines the MLM for this analysis. Variables are uncentered, and a fixed slope model is employed.[23] Random effects are added to the MLM in subsequent analyses.

<u>Equation 3: MLM for Horizontal Equity of Per-Pupil TREs</u>

Level-1

$$\mathrm{Y_{ij}} = \beta_{0j} + \beta_{1j}\mathrm{SPED_{ij}} + \beta_{2j}\mathrm{ELL_{ij}} + \beta_{3j}\mathrm{POV_{ij}} + \beta_{4j}\mathrm{GRADE10_{ij}} + \beta_{5j}\mathrm{GRADE11_{ij}} + \beta_{6j}\mathrm{GRADE12_{ij}} + \mathrm{r_{ij}}$$

Level-2

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

$$\beta_{kj} = \gamma_{k0} \qquad k \in \{1, 2, \dots, 6\}$$

Where:

$\mathrm{Y_{ij}}$: per-pupil TRE for the ith student in school j

β_{0j}: school-level average TRE for school j

$\mathrm{SPED_{ij}}$: student receives special education services (0=no, 1=yes)

$\mathrm{ELL_{ij}}$: student is English language learner (0=no, 1=yes)

$\mathrm{POV_{ij}}$: student qualifies for FARMS (0=no, 1=yes)

$\mathrm{GRADEK_{ij}}$: set of dummy codes for students in grade k, (0=no, 1=yes)

γ_{00}: "average" per-pupil cost for 9th grade students who are not special education, ELL, or low-income

γ_{10}: "average" slope for SPED students

γ_{20}: "average" slope for ELL students

γ_{30}: "average" slope for low-income students

γ_{40}: "average" slope for Grade10 students

γ_{50}: "average" slope for Grade11 students

γ_{60}: "average" slope for Grade12 students

$\mathrm{r_{ij}}$: residual for the ith student in school j

$\mathrm{u_{0j}}$: random school effect, or residual for school j.[24]

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[23] Grand-mean centering the level-1 variables to control for differences across schools in student populations does not change the residualized ICC. I do not center the variables in this model for ease of interpretation.

[24] I use "average" because these estimates are not true averages but rather weighted averages. Model assumptions are discussed in Appendix IV.

From this model, this study can also calculate a conditional ICC, which now represents the proportion of variation in per-pupil TREs that occurs between schools, controlling for differences in spending on special education, ELL, and low-income students and students in different grade levels. This study calculates the CV of per-pupil TREs by dividing the standard deviation of the level-1 residuals (r_{ij}) by the average per-pupil TRE (γ_{00} in the null model). This CV indicates the degree of within-school variation in per-pupil TREs, relative to the average per-pupil TRE and controlling for differences in student needs. The CV is calculated by:

Equation 4: Formula for Coefficient of Variation of Per-Pupil TREs

$$\mathrm{CV} = \frac{\sqrt{\sigma^2}}{\gamma_{00}}$$

Where:

σ^2: variation of the conditional level-1 residuals

γ_{00}: grand mean, average of all school means, *obtained from the null model in equation 1*.

To determine the criterion for achieving horizontal equity, this study employs a MLM to calculate the CV of teacher salaries, or the degree of within-school variation in teacher salaries. Clearly, per-pupil TREs depend on teacher salaries, and teacher salaries vary within schools. Put simply, if per-pupil TREs vary only to the same degree as teacher salaries within schools, then horizontal equity is achieved. The MLM and equation for determining the CV of teacher salaries within schools are expressed by the following:

Equation 5: MLM for Determining Criterion for Horizontal Equity of Per-Pupil TREs

$$\mathrm{Y_{ij}} = \beta_{0j} + \mathrm{r_{ij}}$$
$$\beta_{0j} = \gamma_{00} + \mathrm{u_{0j}}$$

Where:

$\mathrm{Y_{ij}}$: teacher salary for ith student in school j

β_{0j}: school-level average teacher salary school j

$\mathrm{r_{ij}}$: residual for the ith teacher in school j

γ_{00}: grand mean, average of all school means of teacher salaries

$\mathrm{u_{0j}}$: random school effect, or residual for school j.

Equation 6: Formula for Coefficient of Variation of Teacher Salaries

$$\mathrm{CV} = \frac{\sqrt{\sigma_T^2}}{\gamma_{00_T}}$$

Where:

σ_T^2: within-school variation of teacher salaries

γ_{00_T}: grand mean of teacher salaries

The results from the previous MLM and equation produce a CV of .26 for within-school variation in teacher salaries. Thus, horizontal equity of per-pupil TREs is achieved if the CV of per-pupil TREs is less than .26.

Vertical equity. Vertical equity is the unequal treatment of unequals, and vertical equity is achieved when students with greater educational needs receive sufficiently more resources. As discussed in Chapter 2, state funding weights for categorical student needs serve as one benchmark for achieving vertical equity for students with greater needs. The district in this study resides in a state that employs a foundation plan to provide state aid to districts based on proportions of special education, ELL, and low-income students. Specifically, the state employs a weight of 1.74 for special education students, 1.97 for low-income students, and 1.99 for ELL students (Verstegen, 2011). To determine if vertical equity is achieved, this study compares the actual funding weights for special education, ELL, and low-income students to the funding weights outlined in the state foundation plan for each student subgroup. Vertical equity is analyzed for one student characteristic at a time because states generally assign weights without consideration of student membership in more than one category. By defining vertical equity in terms of the weights used in the state foundation plan, this study ascertains if the district meets state goals in terms of categorical funding for students. In summary, in this study, vertical equity is achieved for a student subgroup if the actual funding weight is not less than the funding weight specified in the state foundation plan.

To assess vertical equity for special education, ELL, and low-income students, this study employs simple linear regression (SLR) models to determine the additional amount of money spent on special education, ELL, and low-income students relative to non-special education, non-ELL, and non-low-income students in the district. This study does not use MLMs for the vertical equity analysis because MLMs parse spending differences to within- and between-school components, and both within- and between-school components contribute to how much money is spent to educate these students. This study's analytic approach is most consistent with the intention of the state foundation plan, which implies that the district should spend a certain percentage more on categorical subgroups of students. Therefore, this approach does not produce within-school spending differences for students with categorical needs; however, it does provide an estimate of how much the district spends on these students using student-level teacher expenditure data. The SLR model for determining the vertical equity of special education students is written as follows:

Equation 7: SLR Model for Vertical Equity of Per-Pupil TREs for Special Education Students

$$Y_i = \beta_0 + \beta_1 SPED_i + r_i$$

Where:

Y_i: per-pupil TRE for the ith student in the district

β_0: average per-pupil TRE for all non-special education students in the district

$SPED_i$: student receives special education services (0=no, 1=yes)

β_1: additional expenditure amount for SPED students

r_i: residual for the ith student in the district.[25]

The slope coefficient, β_1, represents the incremental difference in dollars for special education students relative to non-special education students in the district. Similar SLR models are analyzed for low-income and ELL students.

This study determines vertical equity in terms of funding weights, as opposed to regression coefficients, because the state foundation plan also determines categorical funding in terms of weights. Actual funding weights for each student category–special education, ELL, and low-income–are derived from the SLR models. Then, the magnitude and direction of the weights are compared to the mandated state weights for each student category. The actual funding weight for special education students is calculated by:

Equation 8: Formula for Actual Funding Weight of Special Education Students

$$\text{Weight}_{\text{SPED}} = \frac{\beta_1 + \beta_0}{\beta_0}$$

Where:

β_0: average per-pupil TRE for non-special education students

β_1: additional dollar amount for SPED students

[25] Model assumptions are discussed in Appendix IV.

The same method applies to analyzing vertical equity for ELL and low-income students. Vertical equity for special education students is achieved if $\text{Weight}_{\text{SPED}} \geq 1.74$, vertical equity for ELL students is achieved if $\text{Weight}_{\text{ELL}} \geq 1.99$, and vertical equity for low-income students is achieved if $\text{Weight}_{\text{POV}} \geq 1.97$.

It must be noted that the state mandated weights for these student categories apply to all expenditures, not just TREs, and this study does not account for other instructional non-instructional expenses for special education, ELL, and low-income students. Thus, one could argue that the criteria for achieving vertical equity should be adjusted downwards since the district may spend additional dollars to educate various students. However, the per-pupil TREs derived by this study also do not include school-level expenditures that affect all students equally, and inclusion of these school-level expenditures would decrease actual funding weights.[26] Therefore, by including all expenditures in calculations of per-pupil TRE, the vertical equity weights may be greater than or less than the vertical equity weights derived by this study. However, as instruction is the most important function of schools, differential spending on instruction for special education, ELL, and low-income students should be reflected in actual funding weights of per-pupil TREs.

Equal opportunity. Equal opportunity is achieved if student characteristics that are illegitimate in predicting per-pupil TREs are not associated with TREs. One would not expect, for example, students with similar educational needs but of different races to receive different resources. Equal opportunity is traditionally analyzed using Pearson

[26] Assuming the weight of special education students is 1.74, adding school-level expenditures x to both special education and non-special education students may be modeled by the equation: $y = (1.74 + x)/(1 + x)$. As x increases, the y, or the vertical equity weight for special education students, decreases.

correlation coefficients. This study instead employs MLM to ascertain if there are linear relationships between student characteristics and per-pupil TREs while controlling for categorical student needs and grade level. Conceptually, both analytic approaches are similar.

Student race, gender, and achievement should not be related to per-pupil TREs, controlling for student needs (Odden & Picus, 2008). To address equal opportunity for students of different races, genders, and achievement levels, this study employs MLM to test whether student race, gender, and achievement predict allocations of per-pupil TREs, controlling for reasons why per-pupil TREs may legitimately vary within schools. The MLM to assess equal opportunity is defined by the following equation. Variables are uncentered, and this model includes fixed slopes only.[27] Random effects are included in the next section.

[27] I later group-mean center the level-1 variables in the following MLM, but I do not center the variables for this model for ease of interpretation because I wish to know how much more is being spent on each student subgroup.

Equation 9: MLM for Equal Opportunity of Per-Pupil TREs

Level-1

$$Y_{ij} = \beta_{0j} + \beta_{1j}SPED_{ij} + \beta_{2j}ELL_{ij} + \beta_{3j}POV_{ij} + +\beta_{4j}GRADE10_{ij} + \beta_{5j}GRADE11_{ij} + \beta_{6j}GRADE12_{ij} + \beta_{7j}LATINO_{ij} + \beta_{8j}WHITEASIAN_{ij} + \beta_{9j}Gr10PELA_{ij} + \beta_{(10)j}Gr10PMath_{ij} + \beta(11)jGr11PELAij + \beta(12)jGr11PMathij + \beta(13)jGr12PELAij + \beta(14)jGr12PMathij + \beta(15)jGENDER + rij$$

Level-2

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

$$\beta_{kj} = \gamma_{k0} \qquad k \in \{1, 2, \dots, 15\}$$

Where:

Y_{ij}: per-pupil TRE for the ith student in school j

β_{0j}: school-level average TRE for school j

$SPED_{ij}$: student receives special education services (0=no, 1=yes)

ELL_{ij}: student is English language learner (0=no, 1=yes)

POV_{ij}: student qualifies for FARMS (0=no, 1=yes)

$GRADEK_{ij}$: set of dummy codes for students in grade k, (0=no, 1=yes)

$LATINO_{Ij}$: dummy code for Latino students (0=no, 1=yes)

$WHITEASIAN_{Ij}$: dummy code for White or Asian students (0=no, 1=yes)

$GR10PELA_{ij}$: dummy code for 10th grade student who passed state English test

$GR10PMath_{ij}$: dummy code for 10th grade student who passed state math test

$GR11PELA_{ij}$: dummy code for 11th grade student who passed state English test

$GR11PMath_{ij}$: dummy code for 11th grade student who passed state math test

$GR12PELA_{ij}$: dummy code for 12th grade student who passed state English test

$GR12PMath_{ij}$: dummy code for 12th grade student who passed state math test

$GENDER_{ij}$: gender (0=male, 1=female)

γ_{00}: “average” school-level TRE for 9th grade male African American students who are not special education, ELL, or low-income and older students who have not passed state tests in English or math

γ_{10}: "average" slope for SPED students

γ_{20}: "average" slope for ELL students

γ_{30}: "average" slope for low-income students

γ_{40}: "average" slope for 10th grade students relative to 9th grade students

γ_{50}: "average" slope for 11th grade students relative to 9^{th} grade students

γ_{60}: "average" slope for 12th grade students relative to 9^{th} grade students

γ_{70}: "average" slope for Latino students relative to African American students

γ_{80}: "average" slope for White/Asian students relative to African American students

γ_{90}: "average" slope for 10th grade students who passed English test

$\gamma_{(10)0}$: "average" slope for 10th grade students who passed math test

$\gamma_{(11)0}$: "average" slope for 11th grade students who passed English test

$\gamma_{(12)0}$: "average" slope for 11th grade students who passed math test

$\gamma_{(13)0}$: "average" slope for 12th grade students who passed English test

$\gamma_{(14)0}$: "average" slope for 12th grade students who passed math test

$\gamma_{(15)0}$: "average" slope for female students

r_{ij}: residual for the ith student in school j

u_{0j}: random school effect, or residual for school j.[28]

Equal opportunity is achieved if student race, achievement, or gender are not predictive of TREs, which occurs when β_7 through β_{15} are not statistically different than 0.

Variation in Within-School Allocation Patterns of Per-Pupil TREs

This section discusses the method for analyzing the third research question: *"Do within-school allocation patterns of teacher resource expenditures per pupil vary across schools?"* This research question goes one step further than the previous analysis and examines whether within-school monetary resource allocation patterns differ for schools with dissimilar student populations. This study employs MLM to identify the best-fitting model to explain within- and between-school differences in monetary resource allocation. This multilevel analysis is beneficial because it provides statistically rigorous findings of school-level characteristics that are associated with within-school resource allocation patterns. However, this analysis is also somewhat limited due to the small number of level-2 units, or schools; the model potentially suffers from a lack of power. Power is the

[28] I use "average" because these estimates are not true averages; they are rather weighted averages of regression slopes in each school. Model assumptions are discussed in Appendix IV.

ability to identify an effect if the effect exists, and it is dependent on the number of level-2 units, among other things. In other words, while a MLM provides a sophisticated statistical analysis of within- and between-school patterns in the allocation of monetary resources, it may not identify all variables that are related to differences in within-school resource allocation patterns.

This study employs Snijders and Bosker's (2012) model building approach, which suggests that researchers build up from the level-1 model with fixed effects and simultaneously pursue the best-fitting and most parsimonious model. Random effects are added to the model if there is descriptive evidence that regression slopes vary across schools, but only random effects–or slope variances or covariances–that are statistically significant and that statistically significantly improve model fit should remain in the model. A Chi-Square test of the difference of model deviances is conducted to ensure that the addition of each random effect statistically significantly improves model fit with $p < .01$. Next, cross-level effects are added to the model to explain the random effects. A cross-level effect is an interaction variable between a level-2 and a level-1 variable. Cross-level effects can inform why regression slopes of level-1 independent variables vary across schools (Raudenbush & Bryk, 2002). Only cross-level effects that are useful in accounting for variation in regression slopes of level-1 independent variables across schools should remain in the model. Further, to avoid misleading findings, it is necessary to include level-2 variables that are used in cross-level effects as fixed effects in the model, even if the level-2 variables themselves are not statistically significant in predicting the outcome variable (Snijders & Bosker, 2012).

This model building approach results in inclusion of several random effects and one cross-level effect in modeling between-school differences in within-school monetary resource allocation patterns. For both models for expenditures per student and core expenditures per student, seven regression slopes for level-1 independent variables are allowed to randomly vary across schools, and the random effects are allowed to covary. For the most part, cross-level effects are not useful in reducing regression slope variance with one exception: a cross-level effect between the proportion of ELL students in the school and a student's ELL status statistically significantly reduces the random slope variance of ELL status on expenditures per student and core expenditures per student. Implications are discussed in Chapter 5, which addresses this study's findings.

The final MLM for understanding between-school differences in within-school resource allocation of per-pupil TREs is outlined on the following page. The final MLM for core-academic TREs per pupil is identical and therefore, it is not provided.

Equation 10: MLM for Understanding Between-School Differences in Within-School Allocation Patterns of Per-Pupil TREs

Level-1

$$Y_{ij} = \beta_{0j} + \beta_{1j}SPED_{ij} + \beta_{2j}ELL_{ij} + \beta_{3j}POV_{ij} + +\beta_{4j}GRADE10_{ij} + \beta_{5j}GRADE11_{ij} + \beta_{6j}GRADE12_{ij} + \beta_{7j}LATINO_{ij} + \beta_{8j}WHITEASIAN_{ij} + \beta_{9j}Gr10PELA_{ij} + \beta_{10j}Gr10PMath_{ij} + \beta 11jGr11PELAij + \beta 12jGr11PMathij + \beta 13jGr12PELAij + \beta 14jGr12PMathij + \beta 15jGENDER + rij$$

Level-2

$$\beta_{0j} = \gamma_{00} + \gamma_{01}SCHELL_j + u_{0j}$$

$$\beta_{1j} = \gamma_{10} + u_{1j}$$

$$\beta_{2j} = \gamma_{20} + \gamma_{21}SCHELL_j + u_{2j}$$

$$\beta_{3j} = \gamma_{30}$$

$$\beta_{4j} = \gamma_{40}$$

$$\beta_{5j} = \gamma_{50} + u_{5j}$$

$$\beta_{6j} = \gamma_{60} + u_{6j}$$

$$\beta_{7j} = \gamma_{70}$$

$$\beta_{8j} = \gamma_{80}$$

$$\beta_{9j} = \gamma_{90}$$

$$\beta_{(10)j} = \gamma_{(10)0}$$

$$\beta_{(11)j} = \gamma_{(11)0} + u_{(11)j}$$

$$\beta_{(12)j} = \gamma_{(12)0}$$

$$\beta_{(13)j} = \gamma_{(13)0} + u_{(13)j}$$

$$\beta_{(14)j} = \gamma_{(14)0} + u_{(14)j}$$

$$\beta_{(15)j} = \gamma_{(15)0}$$

Where:

Y_{ij}: per-pupil TRE for the ith student in school j

$SPED_{ij}$: student receives special education services (0=no, 1=yes) GMC

ELL_{ij}: student is English language learner (0=no, 1=yes) GMC

POV_{ij}: student qualifies for FARMS (0=no, 1=yes) GMC

GRADEK_{ij}: set of dummy codes for students in grade k, (0=no, 1=yes) GMC

LATINO_{Ij}: dummy code for Latino students (0=no, 1=yes) GMC

$\mathrm{WHITEASIAN}_{Ij}$: dummy code for White or Asian students (0=no, 1=yes) GMC

$\mathrm{GR10PELA}_{ij}$: dummy code for 10th grade student who passed state English test GMC

$\mathrm{GR10PMath}_{ij}$: dummy code for 10th grade student who passed state math test GMC

$\mathrm{GR11PELA}_{ij}$: dummy code for 11th grade student who passed state English test GMC

$\mathrm{GR11PMath}_{ij}$: dummy code for 11th grade student who passed state math test GMC

$\mathrm{GR12PELA}_{ij}$: dummy code for 12th grade student who passed state English test GMC

$\mathrm{GR12PMath}_{ij}$: dummy code for 12th grade student who passed state math test GMC

GENDER_{ij}: gender (0=male, 1=female) GMC

SCHELL_{j}: proportion of students who are ELLs in school j GRMC

γ_{00}: grand mean, average of all school means

γ_{10}: "average" school slope for SPED students

γ_{20}: "average" school slope for ELL students

γ_{30}: "average" school slope for low-income students

γ_{40}: "average" school slope for 10th grade students relative to 9th grade students

γ_{50}: "average" school slope for 11th grade students relative to 9th grade students

γ_{60}: "average" school slope for 12th grade students relative to 9th grade students

γ_{70}: "average" school slope for Latino students relative to African American students

γ_{80}: "average" school slope for White/Asian students relative to African American students

γ_{90}: "average" school slope for 10th grade students who passed English test

$\gamma_{(10)0}$: "average" school slope for 10th grade students who passed math test

$\gamma_{(11)0}$: "average" school slope for 11th grade students who passed English test

$\gamma_{(12)0}$: "average" school slope for 11th grade students who passed math test

$\gamma_{(13)0}$: "average" school slope for 12th grade students who passed English test

$\gamma_{(14)0}$: "average" school slope for 12th grade students who passed math test

$\gamma_{(15)0}$: “average” school slope for female students

γ_{01}: slope coefficient for SCHELL relative to proportion of ELL students in district

γ_{21}: increment to γ_{20} for schools with more ELL students than district average

r_{ij}: residual for the ith student in school j

u_{0j}: random school effect for the intercept, or residual for school j

u_{1j}: random school effect for the slope of SPED for school j

u_{2j}: random school effect for the slope of ELL for school j

u_{5j}: random school effect for the slope of Grade11 for school j

u_{6j}: random school effect for the slope of Grade12 for school j

$u_{(11)j}$: random school effect for the slope of Gr11PELA for school j

$u_{(13)j}$: random school effect for the slope of Gr12PELA for school j

$u_{(14)j}$: random school effect for the slope of Gr12PMath for school j.[29]

Centering refers to the process of subtracting a constant from all values of a predictor variable and is commonly used in MLM to facilitate interpretation (Enders & Tofighi, 2007; Snijders & Bosker, 2012). Two methods of centering are employed for this MLM: Level-1 predictor variables are group mean centered (GMC) and level-2 predictor variables are grand mean centered (GRMC). In this study, group mean centering refers to subtracting the school average on a particular variable from the student's value on the variable, and grand mean centering refers to subtracting the district average from the student's value on the variable. Group mean centering for level-1 variables is the most appropriate centering choice when examining the relationship between level-1 predictor variables and the dependent variable, and grand mean centering for level-2 variables is the best choice when examining the relationship between level-2 predictor variables and/or cross-level effects and the dependent variable (Enders & Tofighi, 2007). It should be noted that centering affects the interpretation of the regression slopes.

[29] I use "average" because these estimates are not true averages but rather weighted averages. Model assumptions are discussed in Appendix IV.

Equity of Within-School Allocation Patterns of Specific Resources

This section describes the method for analyzing the fourth and final research question, *"Are specific resources equitably allocated within schools, and do multiple resource advantages or disadvantages exist for some students?"* To better understand the combination of resources that individual students within a school receive, this study now conducts several MLR analyses for each school. Previous MLM analyses inform average within-school resource allocation patterns across schools in the district; however, they may not identify all resource allocation patterns within schools. For example, if a school spends more on teacher salaries but less due to larger class sizes, the MLM of per-pupil TREs does not reflect this resource substitution. Further, previous MLMs do not inform the equity of the allocation of multiple resources within a particular school. For example, previous analyses do not reveal if White students have larger per-pupil TREs *and* have higher peer achievement in a given school. To gain a more nuanced understanding of the equity of the allocation of resources within schools, this study simultaneously analyzes the equity of the allocation of a number of resources for each individual school. This analysis also yields an understanding of how the equity of the allocation of one resource relates to the allocation of another.

To determine if within-school resource allocation patterns of class sizes, teacher experience, peer achievement, and number of AP courses are equitable, this study combines Berne and Stiefel's (1984) concepts of vertical equity and equal opportunity. For equal opportunity to be achieved, student characteristics that are illegitimate in predicting TREs should also not be associated with other allocated resources. As previously discussed, student characteristics that should not be associated with TREs are student race, achievement, and gender. However, one would expect student achievement to be related to peer achievement and number of AP courses taken because high-achieving students may take more advanced courses and have more high-achieving peers than low-achieving students; thus, this study does not consider associations among student achievement, peer achievement, and number of AP courses taken to be violations of equal opportunity. In addition, students who have greater educational needs according to the state–special education, ELL, and low-income students–should also not receive inferior resources compared to other students; however, in the spirit of vertical equity, resource allocation patterns are still equitable if these students receive superior resources than other students.[30] Thus, the allocation of resources within schools is equitable if student race, gender, and achievement are not associated with allocated resources and if special education, ELL, and low-income students do not receive inferior resources than other students.

Overall resources include per-pupil TREs and number of AP courses taken by students in the 2009-10 academic year. Resources in students' English and math classes include class sizes, teacher experience, and peer achievement. By re-analyzing the allocation of per-pupil TREs within each school, this study attempts to understand how multiple resource advantages or disadvantages may exist for students within the same school. The following sections outline MLR models used to determine the equity of each allocated resource within each school.

[30] Berne and Stiefel's (1984) framework for analyzing equity is not typically used for analyzing the equity of non-expenditure resources. While it may be understood that certain students–such as special education and ELL students–cost more to educate, there is no consensus on how this money should be spent. Should these students have smaller class sizes or teachers with higher salaries or both? Therefore, I blend Berne and Stiefel's (1984) concepts of educational opportunity and vertical equity to address this research question.

Per-Pupil TREs. The MLR model employed to understand the equity of the allocation of per-pupil TREs in each school is written as follows:

Equation 11: MLR Model for Analyzing the Allocation of Per-Pupil TREs Within Each School

$$\mathrm{Y_i} = \beta_0 + \beta_{\mathrm{SPED}}\mathrm{SPED_i} + \beta_{\mathrm{POV}}\mathrm{POV_i} + \beta_{\mathrm{ELL}}\mathrm{ELL_i} + \beta_{\mathrm{GRADEK}}\mathrm{GRADEK_i} + \beta_{\mathrm{LATINO}}\mathrm{LATINO_i} + \beta_{\mathrm{WHITEASIAN}}\mathrm{WHITEASIAN_i} + \beta_1\mathrm{Gr10PELA_i} + \beta_2\mathrm{Gr10PMath_i} + \beta_3\mathrm{Gr11PELA_i} + \beta_4\mathrm{Gr11PMath_i} + \beta_5\mathrm{Gr12PELA_i} + \beta_6\mathrm{Gr12PMath_i} + \mathrm{r_i}$$

Where:

$\mathrm{Y_i}$: per-pupil TRE for ith student

$\mathrm{SPED_i}$: student receives special education services (0=no, 1=yes)

$\mathrm{POV_i}$: student qualifies for FARMS (0=no, 1=yes)

$\mathrm{ELL_i}$: student is English language learner (0=no, 1=yes)

$\mathrm{GRADEK_i}$: set of dummy codes for students in grade k, (0=no, 1=yes)

$\mathrm{LATINO_I}$: dummy code for Latino students (0=no, 1=yes)

$\mathrm{WHITEASIAN_I}$: dummy code for White or Asian students (0=no, 1=yes)

$\mathrm{GR10PELA_i}$: dummy code for 10th grade student who passed state English test

$\mathrm{GR10PMath_i}$: dummy code for 10th grade student who passed state math test

$\mathrm{GR11PELA_i}$: dummy code for 11th grade student who passed state English test

$\mathrm{GR11PMath_i}$: dummy code for 11th grade student who passed state math test

$\mathrm{GR12PELA_i}$: dummy code for 12th grade student who passed state English test

$\mathrm{GR12PMath_i}$: dummy code for 12th grade student who passed state math test

β_0: intercept, or average base spending per-pupil

β_{SPED}: average differential dollar amount allocated to special education students

β_{POV}: average differential dollar amount allocated to low-income students

β_{ELL}: average differential dollar amount allocated to English language learners

β_{GRADEK}: average differential dollar amount allocated to students in grade k

β_{LATINO}: average differential dollar amount for Latino students

$\beta_{\mathrm{WHITEASIAN}}$: average differential dollar amount for White or Asian students

β_m: ($m \neq 0$) average differential dollar amount for students in grade k ($k \neq 9$) who passed state test

$\mathrm{r_i}$: residual for the ith student.[31]

[31] Model assumptions are discussed in Appendix IV.

Class sizes. Next, this study analyzes student characteristics that are associated with differences in class sizes in students' English and math courses. The class size of a student's English or math class is regressed on student characteristics to assess if certain subgroups of students have smaller or larger class sizes than other students. If a student is enrolled in more than one course in the English or math department, the average class size per academic subject is used. The MLR model for understanding the equity of the distribution of English class sizes within schools is expressed as follows:

Equation 12: MLR Model for English Class Size

$$Y_i = \beta_0 + \beta_{SPED}SPED_i + \beta_{POV}POV_i + \beta_{ELL}ELL_i + \beta_{GRADEK}GRADEK_i + \beta_{LATINO}LATINO_i + \beta_{WHITEASIAN}WHITEASIAN_i + \beta_{FEMALE}FEMALE_i + \beta_1 Gr10PELA_i + \beta_2 Gr10PMath_i + \beta_3 Gr11PELA_i + \beta_4 Gr11PMath_i + \beta_5 Gr12PELA_i + \beta 6Gr12PMathi+ri$$

Where:

Y_i: class size in English for ith student

$SPED_i$: student receives special education services (0=no, 1=yes)

POV_i: student qualifies for FARMS (0=no, 1=yes)

ELL_i: student is English language learner (0=no, 1=yes)

$GRADEK_i$: set of dummy codes for students in grade k, (0=no, 1=yes)

$LATINO_I$: dummy code for Latino students (0=no, 1=yes)

$WHITEASIAN_I$: dummy code for White or Asian students (0=no, 1=yes)

$FEMALE_I$: dummy code for female students (0=no, 1=yes)

$GR10PELA_i$: dummy code for 10th grade student who passed state English test

$GR10PMath_i$: dummy code for 10th grade student who passed state math test

$GR11PELA_i$: dummy code for 11th grade student who passed state English test

$GR11PMath_i$: dummy code for 11th grade student who passed state math test

$GR12PELA_i$: dummy code for 12th grade student who passed state English test

$GR12PMath_i$: dummy code for 12th grade student who passed state math test

β_0: intercept of class size in English

β_{SPED}: average English class size difference for SPED students

β_{POV}: average English class size difference for low-income students

β_{ELL}: average English class size difference for ELLs

β_{GRADEK}: average English class size difference for kth grade students
β_{LATINO}: average English class size difference for Latino students
$\beta_{WHITEASIAN}$: average English class size difference for White or Asian students
β_{FEMALE}: average English class size difference for female students
β_m: (m≠0) average English class size difference for students in grade k (k≠9) who passed state test
r_i: residual for the ith student.[32]

The MLR model to estimate the within-school variation in math class sizes is the same as above except that Y_i represents the ith student's class size in math and the slope coefficients represent the incremental math class size differences.

Teacher experience. The study also determines whether student characteristics are associated with having a new English or math teacher. The dependent variable in these models is dichotomous, and a logistic link function is needed to estimate the models. The binary logistic model predicting having a new teacher in English (0=no, 1=yes) is written as follows:

Equation 13: Binary Logistic Regression Model for New English Teacher

$$\ln\left[\frac{\pi_i}{1-\pi_i}\right] = \beta_0 + \beta_{SPED}SPED_i + \beta_{POV}POV_i + \beta_{ELL}ELL_i + \beta_{GRADEK}GRADEK_i + \beta_{LATINO}LATINO_i + \beta_{WHITEASIAN}WHITEASIAN_i + \beta_{FEMALE}FEMALE_i + \beta_1 Gr10PELA_i + \beta_2 Gr10PMath_i + \beta_3 Gr11PELA_i + \beta_4 Gr11PMath_i + \beta_5 Gr12PELA_i + \beta_6 Gr12PMath_i$$

$Y_i \sim Bern(\pi_i)$

Where:

Y_i: NETF, student has new English teacher (0=no, 1=yes)
π_i: odds of having new teacher in English
$SPED_i$: student receives special education services (0=no, 1=yes)
POV_i: student qualifies for FARMS (0=no, 1=yes)
ELL_i: student is English language learner (0=no, 1=yes)
$GRADEK_i$: set of dummy codes for students in grade k, (0=no, 1=yes)

[32] Model assumptions are discussed in Appendix IV.

$LATINO_I$: dummy code for Latino students (0=no, 1=yes)
$WHITEASIAN_I$: dummy code for White or Asian students (0=no, 1=yes)
$FEMALE_I$: dummy code for female students (0=no, 1=yes)
$GR10PELA_i$: dummy code for 10th grade student who passed state English test
$GR10PMath_i$: dummy code for 10th grade student who passed state math test
$GR11PELA_i$: dummy code for 11th grade student who passed state English test
$GR11PMath_i$: dummy code for 11th grade student who passed state math test
$GR12PELA_i$: dummy code for 12th grade student who passed state English test
$GR12PMath_i$: dummy code for 12th grade student who passed state math test
β_0: intercept
β_{SPED}: average log odd difference for SPED students
β_{POV}: average log odd difference for low-income students
β_{ELL}: average log odd difference for ELLs
β_{GRADEK}: average log odd difference for kth grade students
β_{LATINO}: average log odd difference for Latino students
$\beta_{WHITEASIAN}$: average log odd difference for White or Asian students
β_{FEMALE}: average log odd difference for female students
β_m: ($m \neq 0$) average log odd difference for students in grades k ($k \neq 9$) who have passed the state test
$Y_i \sim Bern(\pi_i)$: Y_i follow Bernoulli distribution.[33]

The model for understanding the within-school distribution of new math teachers is similar to the above model, except Y_i represents NMTF, or whether the student has a new math teacher (0=no, 1=yes).

Peer achievement. This study also examines which student characteristics are associated with peer achievement in students' English and math classes. The peer effect in English class is defined as the percentage of a student's peers who have passed the state standardized test in English. This percentage excludes the student's achievement, and if the student is enrolled in more than one English course, peer achievement is averaged. The structure of the state testing program makes it difficult to compare student achievement across grades validly; hence, this analysis is conducted for students in each

[33] Model assumptions are discussed in Appendix IV.

grade separately. In addition, given that most 9th grade students and many 10th grade students have not yet taken the state tests, this analysis is conducted for students in the 11th and 12th grades and separately for students in each grade. To further control for prior student achievement because prior achievement is related to tracking and peer achievement, student grade point average (GPA) is added to the model (Kalogrides & Loeb, 2013). The MLR model for assessing the within-school distribution of peer achievement, or social capital, in English class for 11th grade students is written as:

<u>Equation 14: MLR Model for Peer Achievement in English Class for 11th Grade Students</u>

$$\mathrm{Y_i} = \beta_0 + \beta_{\mathrm{SPED}}\mathrm{SPED_i} + \beta_{\mathrm{POV}}\mathrm{POV_i} + \beta_{\mathrm{ELL}}\mathrm{ELL_i} + \beta_{\mathrm{LATINO}}\mathrm{LATINO_i} + \beta_{\mathrm{WHITEASIAN}}\mathrm{WHITEASIAN_i} + \beta_1\mathrm{PELA_i} + \beta_2\mathrm{PMath_i} + \beta_{\mathrm{GPA}}\mathrm{GPA_i} + \mathrm{r_i}$$

Where:

$\mathrm{Y_i}$: percentage of peers in English class who have passed state English test for ith student

$\mathrm{SPED_i}$: student receives special education services (0=no, 1=yes)

$\mathrm{POV_i}$: student qualifies for FARMS (0=no, 1=yes)

$\mathrm{ELL_i}$: student is English language learner (0=no, 1=yes)

$\mathrm{LATINO_i}$: dummy code for Latino students (0=no, 1=yes)

$\mathrm{WHITEASIAN_i}$: dummy code for White or Asian students (0=no, 1=yes)

$\mathrm{PELA_i}$: dummy code for passed state English test

$\mathrm{PMath_i}$: dummy code for passed state math test

$\mathrm{GPA_i}$: grade point average

β_0: intercept of peer effect

β_{SPED}: average difference for SPED students

β_{POV}: average difference for low-income students

β_{ELL}: average difference for ELLs

β_{LATINO}: average difference for Latino students

$\beta_{\mathrm{WHITEASIAN}}$: average difference for White or Asian students

β_1: average difference for students in who have passed the state test in English

β_2: average difference for students in who have passed the state test in math

β_{GPA}: average slope coefficient of GPA on peer effect

$\mathrm{r_i}$: residual for the ith student.[34]

[34] Model assumptions are discussed in Appendix IV.

Peer achievement in English class for 12th grade students is estimated in a similar manner. Peer achievement in math class is also estimated for 11th and 12th grade students separately. In the latter models, the Y_i represents the percentage of the student's peers who have passed the state math test.

Number of AP courses. Finally, the study examines the relationships between student characteristics and number of AP courses taken for students in each school. The number of AP courses taken by students in the 2009-10 academic year is regressed on student characteristics to identify student characteristics that are associated with AP course-taking behaviors. Given that most AP courses are taken by 11th or 12th grade students, this analysis is only conducted for 11th and 12th grade students. The dependent variable, number of AP courses, is a count variable. Thus, Poisson regression is the most appropriate method for this analysis. The regression model is expressed as follows:

Equation 15: Poisson Regression Model for Number of AP Courses

$$\ln[u_i] = \beta_0 + \beta_{SPED}SPED_i + \beta_{POV}POV_i + \beta_{ELL}ELL_i + \beta_{GRADE11}GRADE11_i + \beta_{LATINO}LATINO_i + \beta_{WHITEASIAN}WHITEASIAN_i + \beta_{FEMALE}FEMALE_i + \beta_1 Gr11PELA_i + \beta_2 Gr11PMath_i + \beta_3 Gr12PELA_i + \beta_4 Gr12PMath_i$$

$Y_i \sim$ Poisson(u_i)

Where:

Y_i: Number of AP courses enrolled in during the year

u_i: expected number of AP courses

$SPED_i$: student receives special education services (0=no, 1=yes)

POV_i: student qualifies for FARMS (0=no, 1=yes)

ELL_i: student is English language learner (0=no, 1=yes)

$GRADE11_i$: dummy code for students in grade 11, (0=no, 1=yes)

$LATINO_I$: dummy code for Latino students (0=no, 1=yes)

$WHITEASIAN_I$: dummy code for White or Asian students (0=no, 1=yes)

$FEMALE_I$: dummy code for White or Asian students (0=no, 1=yes)

$GR11PELA_i$: dummy code for 11th grade student who passed state English test

$GR11PMath_i$: dummy code for 11th grade student who passed state math test
$GR12PELA_i$: dummy code for 12th grade student who passed state English test
$GR12PMath_i$: dummy code for 12th grade student who passed state math test
β_0: intercept
β_{SPED}: average log difference for SPED students
β_{POV}: average log difference for low-income students
β_{ELL}: average log difference for ELLs
$\beta_{GRADE11}$: average log difference for 11th grade students
β_{LATINO}: average log difference for Latino students
$\beta_{WHITEASIAN}$: average log difference for White or Asian students
β_{FEMALE}: average log difference for female students
β_m: ($m \neq 0$) average incremental log difference for students in grades 11 and 12 who have passed the state test
$Y_i \sim$ Poisson(π_i): Y_i follow Poisson distribution.[35]

Software

This study employs two software programs, M*plus* 7 and HLM 6.06, to estimate the foregoing models. This study also employs SPSS Version 20 to clean and merge data, conduct descriptive analyses, check model assumptions, and calculate component scores of school-level achievement. This study employs HLM to estimate all MLMs because HLM offers restricted maximum likelihood estimation, which produces unbiased estimates of variance and covariance components when there are few level-2 units. Due to the small number of level-2 units, HLM may understate standard errors, particularly standard errors of level-2 variance components (McNeish & Stapleton, 2013). Hence, p-values of fixed effects close to .05 should be interpreted with caution and p-values of level-2 variance components with extreme caution.

This study employs M*plus* software to analyze all multiple linear, binary logistic, and Poisson regression models. M*plus* is useful because it estimates standard errors that are robust to violations of normality, meaning that it corrects the standard errors in the

[35] Model assumptions are discussed in Appendix IV.

scenario that the residuals deviate from perfect normality. M*plus* is also advantageous because it employs full information maximum likelihood (a method that uses all available data to estimate model parameters) and accounts for missing data in the independent variables (Enders, 2001). For cases where the value of the dependent variable is missing, however, M*plus* reverts to listwise deletion, and these cases are removed from the analysis. Finally, M*plus* is flexible when conducting regression analysis with non-continuous dependent variables; with relative ease, one can account for dichotomous and count dependent variables. Owing to these advantages, the regression models for each school are analyzed with M*plus.*

Chapter 5: Findings

This chapter discusses the findings for the study and after providing descriptive statistics, is organized according to the four research questions. First, this chapter compares the degree of variation in per-pupil TREs within schools to the variation between schools and finds that within-school variation in per-pupil TREs is substantially greater than between-school variation, even when controlling for certain reasons why per-pupil TREs might reasonably be expected to vary within schools. Second, this chapter provides the results of the equity analysis of the allocation of per-pupil TREs. This study finds that inequities in the allocation of per-pupil TREs exist within schools; in particular, horizontal equity is not achieved for all students, vertical equity is not achieved for low-income students, and it is debatable whether vertical equity is achieved for ELL students. Equal opportunity is also violated because schools spend more money on instruction for students who have passed state tests than on students who have not passed state tests. Third, this chapter explores the variation in within-school monetary resource allocation patterns across schools and finds that within-school monetary resource allocation patterns do in fact vary across schools, and few school-level characteristics are related to differences in within-school monetary resource allocation patterns. Finally, this chapter summarizes the within-school resource allocation patterns of a number of resources and determines the equity of the allocation of these resources. Results from the regression analyses conducted for each school indicate that schools may spend dramatically different amounts on students within the same school and that multiple resource advantages or disadvantages may exist for certain students. Before these findings are further discussed, this chapter outlines descriptive statistics.

Descriptive Findings

First, this section provides descriptive information concerning the resource variables derived and used in this study. Then, to better understand investment in various courses and curricular programs, this section examines course expenditures by course category. Finally, this section explores between-school differences in resources.

Descriptives of derived resource variables. The table below provides summary information of dependent variables.

Table 21: Means, Standard Deviations, and Percent Missing Values for Dependent Resource Variables

Dependent Resource Variable Description	Variable Name	Mean	Standard Deviation	% Missing
Per-pupil TRE	TRE	$3,904	$2,769	2.0
Core-academic TRE per pupil	TRE_CA	$2,876	$2,434	1.9
English class size	ELACS	32.7	8.48	0.7
Math class size	MathCS	33.7	8.56	6.6
New English teacher flag	NETF	0.31	0.46	11.8
New math teacher flag	NMTF	0.31	0.46	12.8
Percent of peers in English who have passed English test for 10^{th}–12^{th} graders only	PeerEPer	58%	49%	0.0
Percent of peers in math who have passed math test for 10^{th}–12^{th} graders only	PeerMPer	61%	48%	0.0
Number of AP courses for 11^{th} and 12^{th} graders only	AP	0.36	0.73	0.5

The district spends, on average, $3,904 per student on teacher salaries for all instruction and $2,876 per student on teachers salaries for core-academic instruction. Per-pupil TREs, as defined by this study, account for roughly one third of the total spending per pupil in this district.[36] Per-pupil TREs are very strongly correlated to core-academic TREs per pupil ($r=.925$, $p < .001$). The strong correlation is due to the fact that salary expenditures spent on core-academic instruction constitutes the majority (73%) of total salary expenditures.

[36] The Board's annual report indicates that total PPEs including all transportation, facility, and food service expenditures amount to approximately $12,000 per student.

Average class sizes in English and math are approximately 33 and 34, respectively. Approximately 31% of students have a new teacher in either English or math class.[37] On average, 58% of 10^{th} through 12^{th} grade students' peers in English class have passed the state English test, and 61% of their peers in math class have passed the state math test. Note that there is considerable variation in all of the dependent variables, implied by the magnitude of the standard deviations relative to the magnitude of the mean values of these variables.

Course expenditures by academic subject. The following table indicates how much money the district spends on various academic, elective, and vocational courses. The most expensive courses, in terms of course expenditures per student, are special education, remedial, and ESOL courses. The district spends more on advanced core-academic courses than on regular track core-academic courses. Finally, the district spends the least on fine arts, health, and other elective courses.

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[37] The cases where the dependent variable is missing are not included in the analysis as the software resorts to listwise deletion when the value of the dependent variable is missing. Missing data on the dependent variables are not of large concern, except for the substantial percentage of missing data on the new teacher flag variables. The missing data on these variables are primarily due to miscoding of staff identification numbers: approximately 5% of teachers cannot be linked to teacher characteristics, and years of teaching experience in the school are not known for these teachers. This miscoding appears to randomly occur across schools and across teachers who teach a variety of academic subjects and grade levels. The data suggest that the teachers with miscoded staff identification numbers do not systematically differ from other teachers. In addition, not all students are enrolled in a math course in a given year, and dependent variables relating to math class are unavailable for these students.

Table 22: Average Course Characteristics By Category Sorted by Average Course Expenditure Per Student

Subject Category	Average Expenditure Per Student $	Average Class Size	Average Teacher Salary $	Number of Students in Course in the District
Special Education	2,156	9	72,955	941
Core Academic Remedial All	1,419	13	67,164	3,547
Math Remedial	1,504	13	65,786	1,211
Social Studies Remedial	1,501	14	67,296	1,246
English Remedial	1,477	13	68,108	2,478
Science Remedial	1,141	16	65,636	2,005
Job Skills	1,219	21	76,589	2,385
Reading	849	19	69,757	1,976
ESOL All	727	23	72,703	1,841
English ESOL	858	19	72,910	1,413
Science ESOL	484	34	72,950	495
Social Studies ESOL	469	29	72,695	877
Math ESOL	369	34	71,707	1,140
AP Courses	652	25	69,710	5,311
Core Academic Advanced All	584	27	68,237	9,580
Math Advanced	1,088	22	74,521	1,223
Science Advanced	684	23	65,547	1,631
Social Studies Advanced	496	29	65,547	6,121
English Advanced	448	30	68,707	4,390
Life & Leadership Skills	577	34	57,585	593
AVERAGE OF ALL COURSES & TEACHERS	**511**	**29.6**	**66,944**	**NA**
Foreign Language All	488	33	66,255	23,753
Foreign Language Advanced	645	25	71,369	3,158
Foreign Language Regular	457	34	65,262	20,858
Other Elective (Journalism, Newspaper, Etc.)	470	29	58,388	1,804
Vocational All	407	28	66,188	32,021
Military Science	825	22	69,137	6,872
Technical / Certification	425	12	66,170	904
Media	388	34	66,200	1,552
Technology	366	35	60,896	8,053
Family & Consumer Sciences	309	36	62,500	14,313
Business	300	33	69,663	14,537

Subject Category	Average Expenditure Per Student $	Average Class Size	Average Teacher Salary $	Number of Students in Course in the District
Core Academic Regular All	404	33	66,511	40,082
Science	515	31	69,828	34,288
Math	478	31	71,483	35,964
English	345	32	60,373	34,831
Social Studies	334	37	63,843	31,249
College Skills	354	28	63,186	3,557
Fine Arts	353	32	62,060	26,096
Music	393	29	67,687	7,883
Drama	344	37	60,137	2,427
Art	342	35	60,140	18,449
Dance	301	30	56,669	2,127
SAT Prep	324	26	69,288	3,376
Health	201	31	65,546	14,234

Table Note: Values are organized by descending average course expenditure per student for each general course category.

As the table above indicates, the district spends the most in terms of course expenditures per student on special education and remedial courses, largely due to small class sizes, and special education students account for 61% of the students enrolled in remedial courses.[38] Courses for non-native English speakers (ESOL courses) have the second highest course expenditures per student; however, while the district spends much more on ESOL courses in English–due to small class sizes–the district actually spends less on ESOL math classes–due to large class sizes.

More money is directed to advanced core courses than regular track core courses in math, science, and English, but the differential in math is the most striking: The district spends more than double the amount per course per student on advanced math courses than on regular track math courses. The higher cost of advanced courses in math is due

[38] Reading is also considered to be a remedial course.

to smaller class sizes and, to a lesser extent, teachers with higher salaries. Finally, the district spends more on advanced foreign language courses per student and other elective courses than on regular track core academic or vocational courses.[39]

Between-school differences in resources. Though the primary purpose of this study is to investigate the equity of within-school resource allocation, it is important to know whether between-school inequities in resources exist. Across the district, inequities in resource allocation at the student level may be exacerbated if inequities exist in the allocation of resources both within and between schools. For example, if experienced teachers are inequitably distributed between and within schools, some students may have few chances to be taught by an experienced teacher.

The following table provides Pearson correlation coefficients of school-level characteristics and school-level average resources. The table shows that the schools serving the largest percentages of low-income students spend more on average per student than other schools, and that schools with higher achievement and larger proportions of White and Asian students spend less per student than other schools. However, when controlling for proportions of special education and ELL students, the correlations between TREs and school characteristics are not statistically significant ($p < .10$) in either case. In summary, schools with larger proportions of low-income, low-achieving, or African American students do not have larger TREs after controlling for differences in student need. This is a common finding in school finance literature (Berne & Stiefel, 1994; Owens & Maiden, 1999; Rubenstein, 1998; Stiefel et al., 2003).

[39] Military vocational courses are the exception.

The following table also indicates that there are school-level differences in other resources. To summarize, schools with substantial Latino populations have larger-than-average math class sizes. Schools with larger proportions of high-achieving and White and Asian students have the highest concentrations of experienced teachers and the highest AP enrollment. Finally, peer achievement is heavily determined by between-school differences in student achievement. This study later explores how these between-school differences in resources affect the distribution of resources at the student level.

Table 23: Pearson Correlation Coefficients of School-Level Characteristics and Resources

Resources Aggregated to the School Level	Variable Name	**School Characteristics**								
		% SPED	% ELL	% FARMS	% Latino	% African American	% White or Asian	% Pass English Test	% Pass Math Test	School Size
Average per-pupil TRE	SCHTRE	.32	.09	.33	.04	.09	-.32	-.52*	-.50*	-.35
Average core-academic TRE per pupil	SCHTRE_CA	.33	.28	.39’	.23	-.10	-.23	-.49*	-.45*	-.27
Average English class size	SCHELACS	-.35’	.04	-.13	.28	-.30	.14	.33	.35	.55**
Average math class size	SCHMathCS	-.11	.22	.22	.42*	-.35	-.05	.09	.11	.49*
% of students with new English teachers	SCHNETF	.30	.10	.24	-.07	.20	-.33	-.44*	-.39	-.23
% of students with new math teachers	SCHNMTF	-.06	-.22	-.05	-.25	.39’	-.43*	-.16	-.19	-.10
Average number of AP courses per 11th and 12th grade student	SCHAP	-.42*	.09	-.21	.12	-.33	.57**	.39	.34	.18
Average peer achievement in English for 10th–12th graders	SCHPeerEPer	-.73***	-.25	-.76***	-.21	-.09	.69***	.99***	.87***	.52*
Average peer achievement in math for 10th–12th graders	SCHPeerMPer	-.70***	-.03	-.56**	-.00	-.29	.74***	.93***	.99***	.57**

Table Notes:
(a) ‘ $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$;
(b) Given that there are only 20+ schools in this correlational analysis, statistical significance is difficult to achieve.
(c) School size is correlated to student achievement because the highest performing schools are also the largest ones.

Within-School Variation in Per-Pupil TREs

To address the first research question, "*How does the within-school variation in teacher resource expenditures per pupil compare to the variation between schools?*" this study employs multilevel modeling (MLM) to obtain the intraclass correlation coefficient (ICC), which determines how much variation in per-pupil TREs is the result of within- or between-school differences in spending.

Table 24: Null Model Results

	Null Model for TRE			Null Model for TRE_CA		
Fixed Effects	**Coefficient $**	**SE $**	**P-value**	**Coefficient $**	**SE $**	**P-value**
Intercept	$4,044	220	.000	$2,959	161	.000
Random Effects	**Variance**		**P-value**	**Variance**		**Variance**
$\mathrm{Var}(r_{ij}) = \sigma^2$	6769289		---	5410474		5410474
$\mathrm{Var}(u_{0j}) = \tau_{00}$	1060993		.000	573549		573549
ICC	.135			.095		

The table above shows that the ICC for per-pupil TREs is .135, meaning that only 13.5% of the variation in per-pupil TREs is due to between-school differences in spending and that the remaining 86.5% of the variation in per-pupil TREs occurs within schools. Hence, the vast majority of variation in per-pupil TREs occurs *within* schools. When examining the ICC for core-academic TREs per pupil, the ICC is .095, meaning that 90.5% of the variation in core-academic TREs per pupil occurs within schools.

The following figures provide graphical displays of the variation in per-pupil TREs within and between schools. Between-school variation in per-pupil TREs is evident; however, relative to the within-school variation, between-school variation in per-pupil TREs is small.

Figure 3: Between- and Within-School Variation in Per-Pupil TREs

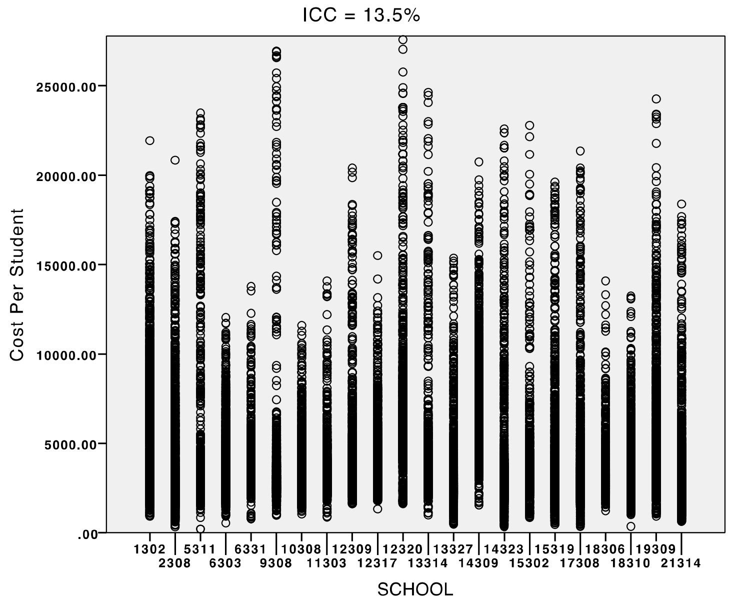
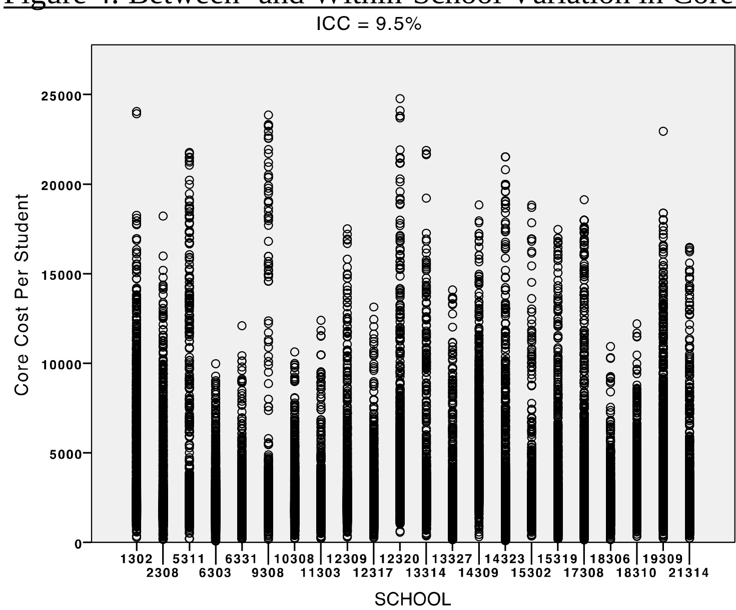
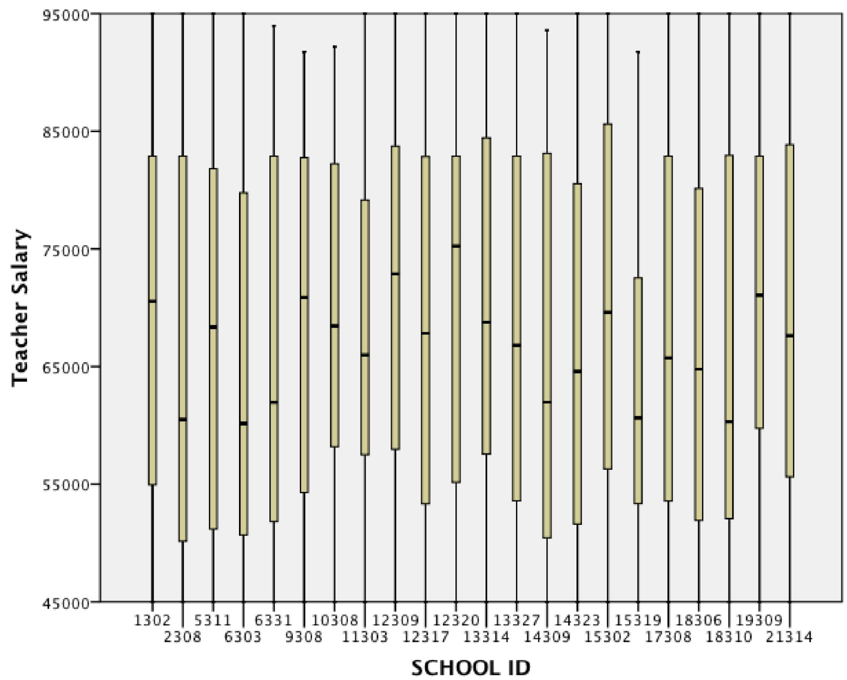


Figure 4: Between- and Within-School Variation in Core-Academic TREs Per Pupil



The large within-school variation in per-pupil TREs results from the fact that there is little variation in teacher salaries between schools. The following figure displays the variation in teacher salaries. From the figure, one may observe that although there are slight differences in the distributions of teacher salaries between schools, there is much more variation in teacher salaries within schools.[40] Thus, because the majority of variation in teacher salaries occurs within schools, the majority of per-pupil TREs occurs within schools.

Figure 5: Variation in Teacher Salaries



In addition, in this district, there is considerable variation in class sizes, which results in large differences in per-pupil TREs for students within the same school. For students within the same school, per-pupil TREs vary because course expenditures vary, and course expenditures vary primarily due to differences in class sizes; teacher salary and number of courses both have a smaller effect on course expenditures per student. The district's class size policy is liberal in that minimum class size is left to the discretion

[40] In fact, when calculating the coefficient of variation (CV) of teacher salaries between schools, the CV is 0.03, which falls below the commonly accepted criterion of 0.10 for between-school differences. Thus, according to a traditional horizontal analysis, between-school spending on teacher salaries is equitable in this district.

of the principal.[41] Some courses–such as advanced foreign language and music courses–are expensive to offer due to very small class sizes. Because there is so much variability in class sizes across courses, there is large variation in course expenditures per student and ultimately in per-pupil TREs for students within the same school. In summary, there is much more variation in per-pupil TREs within schools than between schools. The next section discusses whether the within-school variation in per-pupil TREs is equitable.

Equity Analysis of Per-Pupil TREs

To answer the second research question, "*Are teacher resource expenditures per pupil equitably distributed within schools?*" this study evaluates the horizontal equity, vertical equity, and equal opportunity of per-pupil TREs within schools (i.e., at the student level) and finds that the following equity standards are violated: horizontal equity for all students, vertical equity for low-income students, and equal opportunity for students with different achievement.

Horizontal equity. This study calculated the degree of within-school variation in per-pupil TREs for "like" students and determined that horizontal equity is achieved in this district if the degree to which per-pupil TREs vary within schools (controlling for special education, ELL, and low-income status and grade level) is less than the degree to which teacher salaries vary within schools. Horizontal equity is violated because the CV of per-pupil TREs is .46, which is substantially greater than the within-school variation in teacher salaries (indicated by a CV of .26). For core-academic TREs per pupil, the CV is .57, which is also substantially greater than the proposed horizontal equity benchmark. Thus, horizontal equity for both all and core-academic TREs per pupil is violated for

[41] This is outlined by Board policy.

“like” students, and there is considerable variation in spending on “like” students within schools.

Equation 16: Calculation of the CV of Per-Pupil TREs

$$\mathrm{CV} = \frac{\sigma}{\gamma_{00}} = \frac{1{,}883}{4{,}044} = .465$$

Table 25: Horizontal Equity MLM Results for Per-Pupil TREs and Core-Academic TREs Per Pupil

	Per-Pupil TREs			**Core-Academic TREs Per Pupil**		
Fixed Effects	**Coefficient $**	**SE $**	**P-value**	**Coefficient $**	**SE $**	**P-value**
Intercept	$3,304	222	.000	$2,657	159	.000
Special Education Status	$6,268	34	.000	$5,399	30	.000
ELL Status	$2,800	46	.000	$2,971	41	.000
Low-Income Status	-$20	19	.294	-$25	17	.147
Grade10	-$51	24	.038	-$261	22	.000
Grade11	$381	26	.000	-$176	23	.000
Grade12	$99	26	.000	-$791	23	.000
Random Effects	**Variance**		**P-value**	**Variance**		**P-value**
$\mathrm{Var}(r_{ij}) = \sigma^2$	3548218		---	2848966		---
$\mathrm{Var}(u_{0j}) = \tau_{00}$	1078277		.000	554993		.000
ICC	23%			16%		

A CV of .46 indicates that within schools and for two-thirds of students, TREs for “like” students may vary up to $1,500 ($3,304 x .465) per student. Per-pupil TREs may vary even more for the remaining one third of students. Given that the average salary expenditure per non-special education, non-ELL, and non-low-income pupil is $3,304, $1,500 is a large discrepancy in per-pupil TREs. For core-academic instruction, there are even larger disparities in per-pupil TREs for students within the same school.

These models–and the inclusion of special education, ELL, and low-income status and grade level dummy variables–reduce the amount of level-1 residual variance obtained from the previous null model by 47%. Thus, differences in special education, ELL, and low-income status and grade level account for a large proportion of the within-school variation in per-pupil TREs. However, the ICCs of these models indicate that even when controlling for differences in student need and grade level, the variation in per-pupil TREs within schools is still considerably larger than the variation between schools. The conditional ICCs obtained from these models indicate that 77% of the variation in per-pupil TREs and 84% of the variation in core-academic TREs per pupil result from within-school differences in spending, controlling for special education, ELL, and low-income status and grade level. In other words, the ICCs show that the large within-school variation in per-pupil TREs is not simply the result of differences in student need or grade level. In summary, horizontal equity is not achieved for "like" students in this district because there is statistically and practically significant variation in TREs for "like" students within the same school.

Vertical equity. Vertical equity is achieved for special education students, is not achieved for low-income students, and is arguably achieved for ELL students. The actual funding weight for special education students in this district is 2.81, which exceeds the state mandated weight of 1.74. In other words, the district spends, on average, 181% more on teacher salaries for special education students than for non-special education students, though according to the state foundation plan, the district only needs to spend 74% more on special education students. For core-academic TREs per pupil, the actual funding weight is 3.10, which also exceeds the categorical funding weight for special education students in the state foundation plan.

Table 26: Vertical Equity SLR Model Results for Special Education Students

	Per-Pupil TREs			Core-Academic TREs Per Pupil		
	Coefficient $	**SE $**	**P-value**	**Coefficient $**	**SE $**	**P-value**
Intercept	$3,393	11	.000	$2,438	10	.000
Special Education Status	$6,149	39	.000	$5,251	35	.000
R Squared	37.6%			35.6%		

Vertical equity is not met for all TREs for ELL students, but it is met for core-academic TREs for ELL students. The state mandated weight for ELL students is 1.99, and the actual funding weight for all TREs for ELL students is 1.61. In other words, the district spends, on average, 61% more on salaries for ELL students than for non-ELL students, and according to the state foundation plan, the district should spend 99% more on ELL students. Thus, the district spends 38 percentage points less on teacher salaries for ELL students than the amount mandated by the state foundation plan. However, the actual funding weight for teacher salaries in core-academic subjects for ELL students is 1.99. Thus, in terms of core-academic TREs per pupil, the district spends sufficiently more on instruction for ELL students relative to non-ELL students, according to the state foundation plan. Because the district spends at least 1.99 times more on core-academic TREs for ELL students than on non-ELL students, district funding is not in violation of state policy.

Table 27: Vertical Equity SLR Model Results for ELL Students

	Per-Pupil TREs			Core-Academic TREs Per Pupil		
	Coefficient $	**SE $**	**P-value**	**Coefficient $**	**SE $**	**P-value**
Intercept	$3,795	13	.000	$2,749	12	.000
ELL Status	$2,349	64	.000	$2,737	55	.000
R Squared	3.2%			5.6%		

Vertical equity is not met for low-income students in this district. The district spends only 13% more on teacher salaries for low-income students compared to other students, and there is a large gap between the actual funding weight and the state mandated weight for low-income students. The state funding weight for low-income students is 1.97, suggesting that 97% more should be spent on low-income students than on non-low-income students. Therefore, the district spends 84% less on teacher salaries for low-income students than the amount mandated by the state foundation plan. The district spends 17% more on teacher salaries in core-academic subjects for low-income students, relative to non-low-income students, but the actual funding weight of 1.17 for core-academic TREs per pupil is again substantially lower than the state funding weight of 1.97 for low-income students.

Table 28: Vertical Equity SLR Model Results for Low-Income Students

	Per-Pupil TREs			**Core-Academic TREs Per Pupil**		
	Coefficient $	**SE $**	**P-value**	**Coefficient $**	**SE $**	**P-value**
Intercept	$3,700	18	.000	$2,673	15	.000
ELL Status	$478	27	.000	$474	24	.000
R Squared	7%			9%		

The previous simple linear regression models for low-income students also do not account for the fact that low-income students are overrepresented in special education and ELL groups (see Table 29). When special education and ELL status are added to the model, the district spends only 2% more on teacher salaries and 4% more on teacher salaries in core-academic subjects for low-income students relative to non-low-income students. In summary, the district is far from providing low-income students with sufficiently more resources as suggested by the state foundation plan.

Table 29: Special Education and ELL Status by Low-Income Status

Socioeconomic Status	Percent Special Education	Percent ELL
Low-Income	12%	8%
Not Low-Income	8%	2%

Equal opportunity. Equal opportunity is not violated for students of different race/ethnicity and gender, holding student achievement constant, but equal opportunity is violated for students with different achievement levels. Equal opportunity is violated for students of different race/ethnicity when achievement is not held constant.

Table 30: Equal Opportunity MLM Results

	Expenditures Per Student			Core Expenditures Per Student		
Fixed Effects	**Coefficient $**	**SE $**	**P-value**	**Coefficient $**	**SE $**	**P-value**
Intercept	$3,298	223	.000	$2,650	160	.000
SPED	$6,327	35	.000	$5,423	31	.000
ELL	$2,858	48	.000	$2,991	43	.000
POV	-$14	29	.483	-$20	17	.246
Grade10	-$82	32	.012	-$196	29	.000
Grade11	$319	40	.000	-$168	36	.000
Grade12	-$213	44	.000	-$1,081	40	.000
Latino	-$26	31	.397	-$7	28	.785
White/Asian	$1	37	.972	$55	33	.097
Gr10PELA	$142	44	.002	$47	39	.236
Gr10PMath	-$71	44	.107	-$167	39	.000
Gr11PELA	$162	48	.000	$71	43	.100
Gr11PMath	-$60	49	.222	-$81	44	.066
Gr12PELA	$216	48	.000	$221	43	.000
Gr12PMath	$236	48	.000	$197	43	.000
Gender	$3	18	.840	$0	16	.975
Random Effects	**Variance**		**P-value**	**Variance**		**P-value**
$\mathrm{Var}(r_{ij}) = \sigma^2$	3540663		---	2841948		---
$\mathrm{Var}(u_{0j}) = \tau_{00}$	1088200		.000	558222		.000
ICC	23.5%			16%		
Model Fit: Deviance & Number of Estimated Parameters for Variance-Covariance Model	729370, 2			720947, 2		

For per-pupil TREs, schools spend more on 10th, 11th, and 12th grade students who have passed the state English test compared to students who have not passed the state English test. Schools also spend more on 12th grade students who have passed the state math test compared to students who have not passed the state math test.[42] Thus, equal opportunity is violated for student achievement, though the monetary differences are small. Schools spend roughly 4% more on 10th grade students, 5% more on 11th grade students, and 6.5% more on 12th grade students who have passed the state English test compared to students who have not. Schools also spend roughly 7% more on 12th grade students who have passed the state math test compared to those who have not. Taken together, schools spend 13.7% more on 12th grade students who have passed both English and math state tests compared to 12th grade students who have not passed either state test.

Recall that larger proportions of students in higher grades have passed the state tests than students in lower grades; specifically, around 50% of 10th grade, 60% of 11th grade, and 70% of 12th grade students have passed state tests. Therefore, for 10th grade students, this study tests if there are differences in spending on the lowest achieving 50% of students compared to higher achieving students. For 11th grade students, this study tests if there are differences in spending on the lowest achieving 40% of students compared to higher achieving students. Finally, for 12th grade students, this study tests if there are differences in spending on the lowest achieving 30% of students compared to higher achieving students. The effect sizes are the largest for 12th grade students, indicating that schools spend the least on the 30% lowest achieving group of students relative to higher achieving students, holding all else equal.

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[42] Other regression slopes are not statistically significant at $p < .05$ and therefore, are not considered to be statistically different than 0.

For core-academic TREs per pupil, equal opportunity is violated for 10th grade students who have passed the state math test and for 12th grade students who have passed either the English or math state test. For 12th grade students, schools spend 8% more on students who have passed the state English test, 7% more on students who have passed the state math test, and almost 16% more on students who have passed both the state English and math tests. Interestingly, schools spend less on 10th grade students who have passed the state math test than on 10th grade students who have not passed the state math test.

Although equal opportunity for student race is not violated (controlling for student achievement), student race is related to student achievement. Larger proportions of White and Asian students have passed both the English and math state tests compared to African American or Latino students. Higher proportions of African Americans have passed state tests compared to Latino students. Hence, equal opportunity is violated for student race/ethnicity when achievement is not held constant.

Table 31: Student Achievement by Race

Race	**Percent Passed English Test**	**Percent Passed Math Test**
White/Asian	55%	73%
African American	41%	53%
Latino	30%	49%

Finally, adding student race, gender, and achievement to these models does not reduce the level-1 residual variance substantially, relative to the previous horizontal equity model. The level-1 residual variance is reduced by only 0.2% with the addition of these variables. Thus, while student achievement is predictive of allocated per-pupil

TREs, student achievement, race, and gender are not as powerful in explaining resource differences as special education, ELL, and low-income status and grade level.

Variation in Within-School Allocation Patterns of Per-Pupil TREs

This section provides findings for the third research question, "*Do within-school allocation patterns of teacher resource expenditures per pupil vary across schools?*" This study finds substantial variation in within-school monetary resource allocation patterns between schools. For the models for both per-pupil TREs and core-academic TREs per pupil, seven regression slopes of level-1 independent variables are allowed to vary across schools because their inclusion statistically significantly improves model fit, but only one cross-level effect is statistically and practically significant in reducing the variation of regression slopes. It could be the case that the small sample size of high schools makes it difficult to identify patterns of within-school resource allocation between schools. Alternatively, schools in the same district may have very different within-school resource allocation patterns.

Table 32: Equal Opportunity MLM Results with Random and Cross-Level Effects for Per-Pupil TREs

	Model with Random Effects			**Model with Random & Cross-Level Effects**		
Fixed Effects	**Coefficient $**	**SE $**	**P-value**	**Coefficient $**	**SE $**	**P-value**
Intercept	$4,045	220	.000	$4,045	221	.000
SPED (GMC)	$6,841	875	.000	$6,841	875	.000
ELL (GMC)	$1,498	395	.001	$1,155	274	.001
POV (GMC)	$2	16	.881	$2	16	.907
Grade10 (GMC)	-$82	26	.003	-$82	26	.002
Grade11 (GMC)	$265	55	.000	$266	56	.000
Grade12 (GMC)	-$194	98	.062	-$196	98	.060
Latino (GMC)	$13	26	.605	$14	26	.592
White/Asian (GMC)	$86	31	.005	$86	30	.006
Gr10PELA (GMC)	$72	36	.045	$72	36	.046
Gr10PMath (GMC)	-$5	36	.887	-$4	36	.894
Gr11PELA (GMC)	$197	81	.025	$196	81	.026
Gr11Pmath (GMC)	$35	40	.389	$34	40	.396
Gr12PELA (GMC)	$254	75	.003	$259	76	.003
Gr12Pmath (GMC)	$247	67	.002	$342	68	.002
Gender (GMC)	-$1	15	.946	-$1	15	.932
SCHELL (GRMC)				$1,077	2553	.677
SCHELL (GRMC) x ELL (GMC)				$25,990	4362	.000
Random Effects	**Variance**		**P-value**	**Variance**		**P-value**
$\mathrm{Var}(r_{ij}) = \sigma^2$	2381293		---	2380944		---
$\mathrm{Var}(u_{0j}) = \tau_{00}$	1064255		.000	1076880		.000
Var (γ_{10}) = Variance of the slopes of SPED	16847878		.000	16849692		.000
Var (γ_{20}) = Variance of the slopes of ELL	2764338		.000	1047770		.000
Var (γ_{50}) = Variance of the slopes of Grade11	43305		.000	43680		.000
Var (γ_{60}) = Variance of the slopes of Grade12	182495		.000	181867		.000
Var ($\gamma_{(11)0}$) = Variance of the slopes of Gr11PELA	108549		.000	109883		.000
Var ($\gamma_{(13)0}$) = Variance of the slopes of Gr12PELA	89871		.000	91399		.000
Var ($\gamma_{(14)0}$) = Variance of the slopes of Gr12Pmath	63314		.000	65366		.000
ICC	30%			31%		
Model Fit: Deviance & Number of Estimated Parameters for Variance-Covariance Model	713577, 37			713524, 37		

Table Note: The random effects are allowed to covary in this model, and covariances are not included in this table for simplicity.

Table 33: Equal Opportunity MLM Results with Random and Cross-Level Effects for Core-Academic TREs Per Pupil

	Model with Random Effects			Model with Random & Cross-Level Effects		
Fixed Effects	**Coefficient $**	**SE $**	**P-value**	**Coefficient $**	**SE $**	**P-value**
Intercept	2,960	161	.000	2,960	157	.000
SPED (GMC)	5,902	797	.000	5,902	797	.000
ELL (GMC)	1,358	398	.003	1,126	262	.000
POV (GMC)	-1	14	.914	-2	14	.876
Grade10 (GMC)	-212	23	.000	-212	23	.000
Grade11 (GMC)	-227	60	.001	-226	60	.001
Grade12 (GMC)	-1,043	67	.000	-1,044	67	.000
Latino (GMC)	37	23	.106	37	23	.105
White/Asian (GMC)	121	27	.000	122	27	.000
Gr10PELA (GMC)	15	32	.632	15	32	.625
Gr10PMath (GMC)	-103	32	.002	-104	32	.002
Gr11PELA (GMC)	94	68	.180	94	36	.184
Gr11PMath (GMC)	-4	36	.898	-5	68	.888
Gr12PELA (GMC)	227	50	.000	230	53	.000
Gr12PMath (GMC)	184	50	.002	183	51	.002
Gender (GMC)	2	13	.885	1	13	.895
SCHELL (GRMC)				4,855	2,284	.046
SCHELL (GRMC) x ELL (GMC)				30,609	3,993	.000
Random Effects	**Variance**		**P-value**	**Variance**		**P-value**
$\mathrm{Var}(r_{ij}) = \sigma^2$	1902512		---	1902162		---
$\mathrm{Var}(u_{0j}) = \tau_{00}$	576164		.000	547297		.000
Var (γ_{10}) = Variance of the slopes of SPED	13962666		.000	13960190		.000
Var (γ_{20}) = Variance of the slopes of ELL	2919252		.000	1033486		.000
Var (γ_{50}) = Variance of the slopes of Grade11	59292		.000	60314		.000
Var (γ_{60}) = Variance of the slopes of Grade12	74818		.000	75843		.000
Var ($\gamma_{(11)0}$) = Variance of the slopes of Gr11PELA	72599		.000	73308		.000
Var ($\gamma_{(13)0}$) = Variance of the slopes of Gr12PELA	25921		.000	33032		.004
Var ($\gamma_{(14)0}$) = Variance of the slopes of Gr12PMath	27011		.000	28109		.004
ICC	23%			22%		
Model Fit: Deviance & Number of Estimated Parameters for Variance-Covariance Model	704948, 37			704891, 37		

Table Note: The random effects are allowed to covary in this model, and covariances are not included in this table for simplicity.

Differential amounts spent on teacher salaries for special education students vary substantially across schools indicated by the large variability in the regression slopes for special education status between schools, and no available school-level (level-2) variables account for why schools spend such different amounts on special education students. Differential amounts spent on teacher salaries for special education students (relative to non-special education students) range from $1,233 more per student to $15,957 more per student across schools. However, descriptive analyses indicate that regression slopes for special education students may vary across schools because 13 schools employ additional special education “classroom teachers” who do not teach specific courses. Thus, these teachers’ salaries are allocated to special education students on top of the money spent in providing courses to special education students, and as a result, these schools spend more on special education students relative to non-special education students compared to other schools.

Second, differential amounts spent on teacher salaries for ELL students also vary across schools, and differential amounts spent on teacher salaries for ELL students (relative to non-ELL students) range from $474 more per student to $5,148 more per student. However, the variability in the regression slopes for ELL students for per-pupil TREs is reduced by 62% (64% for core-academic TREs per pupil) by the addition of the cross-level effect, the proportion of ELL students in the school multiplied by individual student ELL status. This finding indicates that schools with more ELL students spend more on ELL students than other schools. This finding is consistent with descriptive analyses that indicate that schools with larger proportions of ELL students have additional ELL “classroom teachers” who do not teach specific courses. Hence, the

TREs per ELL student relative to non-ELL students are higher in schools that employ additional staff for ELL students.

Third, schools vary in how much more they spend on students who have passed state tests relative to students who have not passed state tests. Finally, schools vary in how much they spend on students in different grades. Available cross-level effects do not explain variability in these regression slopes.

Another noteworthy finding of these models is that when regression slopes are allowed to vary across schools, student race predicts both per-pupil TREs and core-academic TREs per pupil, albeit the estimated regression slopes are small. The district spends more on teacher salaries for White and Asian students than for African American students. The district spends approximately 1% more on teacher salaries for White and Asian students and 4% more on teacher salaries in core-academic subjects for White and Asian students compared to African American students.[43] Therefore, when regression slopes are allowed to vary between schools, equal opportunity for students of different race is violated.

Compared to the previous MLM with fixed effects only, this more flexible model reduces the level-1 residual variance for per-pupil TREs by almost 33%. Because the level-1 residual variance decreases, the ICC increases, and the resulting ICC for the final model for per-pupil TREs is 31%. Thus, despite the inclusion of a number of student and school variables in the MLM, the within-school variation in per-pupil TREs is still far greater than the between-school variation. In addition, the latter more flexible model with random effects has statistically significantly improved model fit compared to the

[43] Technically, the differential dollar amount may be more or less, depending on the proportion of White or Asian students in the school. Because the variables are group-mean centered, the interpretation is not straightforward.

equal opportunity model with fixed effects only. Conducting a likelihood ratio test of model deviances produces $\varkappa^2$=15793, with 35 degrees of freedom and a p-value of less than 0.001. As the final models have the best model fit, the estimates for the final models are the most precise. In summary, schools within the same district vary in how they allocate their resources, yet there is still much variation in the within-school allocation of per-pupil TREs that is not explained by available student or school characteristics.

Equity of Within-School Allocation Patterns of Specific Resources

Finally, to address the fourth and final research question, "*Are other resources equitably allocated within schools, and do multiple resource advantages or disadvantages exist for some students?*" this study examines the equity of a number of resources resulting from within-school allocation processes. Relationships between resources and student characteristics are analyzed in each high school, and common findings for each student subgroup are provided. Identifying common findings of within-school resource allocation is a subjective process; therefore, this study outlines decision rules for identifying common findings. A finding is considered to be common in the district if both of the following criteria are met: (a) There is a statistically significant difference in the distribution of the resource in approximately 20% schools; and (b) The direction (positive or negative) of the slope coefficients for a student characteristic is the same in greater than 70% of the schools with statistically significant differences. In other words, this study identifies a within-school resource allocation pattern when a finding is reoccurring in a number of schools.

Taken together, student characteristics explain about 54% of the variation in per-pupil TREs, core-academic TREs per pupil, and peer achievement, and student characteristics are more strongly correlated with resources in students' English classes than in students' math classes; student characteristics explain 31% of the variation in English class size–on average–compared to 21% of the variation in math class size, and they explain 37% of the variation in having a new English teacher compared to 22% of the variation in having a new math teacher. While some student characteristics–such as special education status–should theoretically be associated with allocated resources, other student characteristics–such as race and achievement–should not be associated with allocated resources. This study finds that inequities in student-level resources exist.

This chapter now provides common within-school resource allocation patterns for each student subgroup including special education, ELL, low-income, Latino, White or Asian, and high-achieving students.[44] This chapter also discusses how inequities in allocated resources may be exacerbated for some students who are members of more than one student subgroup.

Special education students. This section summarizes findings regarding common within-school resource allocation patterns for special education students. The first table below provides common within-school resource allocation patterns, and the second table displays effect sizes for resource variables regressed on special education status. Results by school are provided in Appendix III.

[44] This study does not find any meaningful within-school resource allocation patterns for students of different genders.

Table 34: Common Within-School Resource Allocation Patterns for Special Education Students

Common Within-School Resource Allocation Pattern	Percent of Schools with This Pattern
Higher per-pupil TREs	100%
Smaller English class sizes	95%
Smaller math class sizes	100%
Greater odds of having new math teacher	59%
Fewer AP courses	59%
Lower peer achievement in both English and math classes	100%

Table 35: Range and Median of Slope Coefficients for Individual Resources Regressed on Special Education Status

Dependent Variables	Range of Slope Coefficients	Median Slope Coefficient
Teacher resource expenditures per pupil	\$1,233 to \$15,957	\$6,737
Core-academic teacher resource expenditures per pupil	\$849 to \$14,780	\$5,199
English class size	-16 to +1.5	-11
Math class size	-16 to -3	-10
Odds of having new English teacher	< .1 to 12	1.0
Odds of having new math teacher	0.3 to 917	1.9
Log odds of number of AP courses	-2.7 to -0.4	-1.8
Peer effect in English class for 11th graders	-37% to -13%	-23.5%
Peer effect in English class for 12th graders	-37% to -7%	-25.5%
Peer effect in math class for 11th graders	-42% to -9%	-24.5%
Peer effect in math class for 12th graders	-43% to -7%	-28%

Table Note: Only results resulting from statistically significant slope coefficients at $p < .10$ are summarized in this table. In other words, slope coefficients that are not statistically different than 0 are not included in this table.

Special education status is the most informative variable in the MLR models predicting per-pupil TREs. In every school, special education students have higher per-pupil TREs–for all instruction and for core-academic instruction–than non-special education students. Per-pupil TREs are related to class size, and in almost every school, special education students have smaller class sizes in English and math compared to other students.

This study finds one surprising inequity in the allocation of resources for special education students: Special education students are more likely to have a new math teacher than other students in 59% of schools, sometimes considerably so. In addition, special education students take fewer AP courses than other students, and special education students' peers are lower achieving than those of other students; both of the latter findings result from special education student placement in remedial courses.

ELL students. This section summarizes findings regarding common within-school resource allocation patterns for ELL students. The first table below provides common within-school resource allocation patterns, and the second table displays effect sizes for resource variables regressed on ELL status. Results by school are provided in Appendix III.

Table 36: Common Within-School Resource Allocation Patterns for ELL Students

Common Within-School Resource Allocation Pattern	Percent of Schools with This Pattern
Higher per-pupil TREs	100%
Smaller English class sizes	100%
Larger math class sizes	50%
Lower odds of having new English teacher	50%
Lower peer achievement in both English and math classes	100%

Table 37: Range and Median of Slope Coefficients for Individual Resources Regressed on ELL Status

Dependent Variables	Range of Slope Coefficients	Median Slope Coefficient
Teacher resource expenditures per pupil	\$474 to \$5,148	\$1,650
Core-academic teacher resource expenditures per pupil	\$635 to \$5,310	\$1,750
English class size	-10 to -1	-5.5
Math class size	-12 to +3	1.4
Odds of having new English teacher	< .1 to 1.6	0.2
Odds of having new math teacher	0.3 to 6.2	2.3
Log odds of number of AP courses	-1.0 to +0.4	-0.3
Peer effect in English class for 11th graders	-32% to -13%	-27%
Peer effect in English class for 12th graders	-31% to -15%	-22.5%
Peer effect in math class for 11th graders	-24% to -4%	-18.5%
Peer effect in math class for 12th graders	-24% to -10%	-15.5%

Table Notes:
(a) Only results resulting from statistically significant slope coefficients at $p < .10$ are summarized in this table. In other words, slope coefficients that are not statistically different than 0 are not included in this table.
(b) 12 schools are eliminated from this analysis due to lack of ELL student populations.

After special education status, ELL status is the second most significant variable in predicting per-pupil TREs. Schools spend more on teacher salaries for ELL students partially because they offer smaller class sizes in English to ELL students, and this pattern is true in all schools. In English class, ELL students are also less likely to have a new English teacher in approximately 50% of schools. However, in another 50% of schools, ELL students have larger math class sizes, but only slightly so, with one to two more students in the class on average. Despite having larger math class sizes, schools spend more on TREs for ELL students than non-ELL students due to substantially smaller English class sizes, which drive up per-pupil TREs for ELL students. As with special education students, ELL students' peers have lower achievement than those of non-ELL students; this finding can be explained by grouping of ELL students in ESOL courses.

Low-income students. This section summarizes findings regarding common within-school resource allocation patterns for low-income students. The first table below provides common within-school resource allocation patterns, and the second table displays effect sizes for resource variables regressed on low-income status. Results by school are provided in Appendix III.

Table 38: Common Within-School Resource Allocation Patterns for Low-Income Students

Common Within-School Resource Allocation Pattern	Percent of Schools with This Pattern
Larger English class sizes	23%
Greater odds of having new English teacher	23%
Fewer AP courses	18%
Lower peer achievement in both English and math classes	27%

Table 39: Range and Median of Slope Coefficients for Individual Resources Regressed on Low-Income Status

Dependent Variables	Range of Slope Coefficients	Median Slope Coefficient
Teacher resource expenditures per pupil	-\$199 to +\$215	\$119
Core-academic teacher resource expenditures per pupil	-\$169 to +\$178	\$90
English class size	-1 to +1	0.5
Math class size	-1 to -0.4	-0.8
Odds of having new English teacher	1.4 to 10.8	1.25
Odds of having new math teacher	0.8	0.8
Log odds of number of AP courses	-0.5 to -0.4	-0.45
Peer effect in English class for 11th graders	-3.4% to -2.3%	-3.1%
Peer effect in English class for 12th graders	-4.0% to -2.0%	-3.5%
Peer effect in math class for 11th graders	-3.2% to -2.6%	-2.9%
Peer effect in math class for 12th graders	-4.6% to -2.3%	-3.5%

Table Note: Only results resulting from statistically significant slope coefficients at $p < .10$ are summarized in this table. In other words, slope coefficients that are not statistically different than 0 are not included in this table.

Low-income students are exposed to lower amounts of quality resources than non-low-income students, particularly in low- and mid-poverty schools. In a minority of schools (18%), low-income students take about half an AP class less than middle-class students, controlling for student achievement. In high-poverty schools, however, there is no difference in number of AP courses taken for low-income students relative to non-low-income students. A similar finding is that in 27% of schools, low-income students have lower achieving peers in their English and math classes than other students, but there are no peer achievement differences for low-income students in high-poverty schools. In other words, peer sorting according to student socioeconomic status occurs in low- and mid-poverty schools and does not occur in high-poverty schools. Differences in peer achievement for low-income students are small; nonetheless, they are statistically significant and indicate that in some low- and mid-poverty schools, low-income students are tracked with lower achieving peers, given students' abilities. Low-income students are also more likely to have new English teachers in 23% of schools, and in another 23% of schools, low-income students have larger English class sizes than middle-class students.

In some schools, multiple inequities in resources for low-income students exist. In three schools, for example, low-income students are more likely than other students to have new English teachers and have peers with lower achievement. In two schools, low-income students take fewer AP courses and also have lower achieving peers than middle-class students. Finally, in another two schools, low-income students are disproportionately taught by new teachers and have larger class sizes than middle-class students in the same school. These findings indicate that within schools, multiple resource inequities may exist for low-income students. These findings also provide evidence that resource allocation is related to teacher and student tracking where low-income students may be disproportionately represented in the lowest academic tracks, and the least experienced teachers may disproportionately teach the lowest track courses.

Latino students. This section summarizes findings regarding common within-school resource allocation patterns for Latino students. The first table below provides common within-school resource allocation patterns, and the second table displays effect sizes for resource variables regressed on Latino status. Results by school are provided in Appendix III.

Table 40: Common Within-School Resource Allocation Patterns for Latino Students Compared to African American Students

Common Within-School Resource Allocation Pattern	Percent of Schools with This Pattern
Smaller English class sizes	18%
Larger math class sizes	32%
Lower odds of having new English teacher	18%

Table 41: Range and Median of Slope Coefficients for Individual Resources Regressed on Latino Status

Dependent Variables	Range of Slope Coefficients	Median Slope Coefficient
Teacher resource expenditures per pupil	-$302 to +$1,296	$240
Core-academic teacher resource expenditures per pupil	-$381 to +$530	$261
English class size	-3 to -0.2	-2
Math class size	-0.8 to +2.7	1
Odds of having new English teacher	0.3 to 0.8	0.5
Odds of having new math teacher	0.5 to 2.0	1.3
Log odds of number of AP courses	-0.8 to +1.2	0.65
Peer effect in English class for 11th graders	-5% to +7.6%	6%
Peer effect in English class for 12th graders	-11% to +21%	0%
Peer effect in math class for 11th graders	-5.4% to +9%	0.5%
Peer effect in math class for 12th graders	-10% to +24%	-2.8%

Table Notes:
(a) Only results resulting from statistically significant slope coefficients at $p < .10$ are summarized in this table. In other words, slope coefficients that are not statistically different than 0 are not included in this table.
(b) The slope coefficient of $1,296 is likely confounded with money spent on ELL students in the school. This slope coefficient should be interpreted with caution.

Resource allocation patterns are mostly mixed for Latino students. Statistically significant differences in resources do exist for Latino students compared to African American students, but the direction of the findings are mixed. However, there are a few common findings. In 18% of schools, Latino students have slightly smaller English class sizes and are less likely to have new English teachers compared to African American students. In 32% of schools, Latino students have slightly larger math class sizes than African American students. These findings are consistent with the findings for ELL students, which is not surprising given that 70% of ELL students in this district are of Latino descent.

White and Asian students. This section summarizes findings regarding common within-school resource allocation patterns for White and Asian students. The first table below provides common within-school resource allocation patterns, and the second table displays effect sizes for resource variables regressed on White or Asian status. Results by school are provided in Appendix III.

Table 42: Common Within-School Resource Allocation Patterns for White and Asian Students Compared to African American Students

Common Within-School Resource Allocation Pattern	Percent of Schools with This Pattern
Higher per-pupil TREs	24%
Higher core-academic TREs per pupil	19%
Smaller math class sizes	28%
More AP courses	57%
Higher peer achievement in English class	24%
Higher peer achievement in math class	19%

Table 43: Range and Median of Slope Coefficients for Individual Resources Regressed on White and Asian Status

Dependent Variables	Range of Slope Coefficients	Median Slope Coefficient
Teacher resource expenditures per pupil	$176 to $591	$458
Core-academic teacher resource expenditures per pupil	-$384 to +$933	$218
English class size	-1.3 to +2.6	-0.3
Math class size	-4 to -1.3	-2.1
Odds of having new English teacher	0.5 to 0.7	0.6
Odds of having new math teacher	0.5 to 1.6	1.6
Log odds of number of AP courses	0.3 to 1.0	0.8
Peer effect in English class for 11th graders	4.5% to 7.1%	6.4%
Peer effect in English class for 12th graders	3.4%	6%
Peer effect in math class for 11th graders	-8.4% to +6.9%	6%
Peer effect in math class for 12th graders	1.8%	11%

Table Notes:
(a) Only results resulting from statistically significant slope coefficients at p < .10 are summarized in this table. In other words, slope coefficients that are not statistically different than 0 are not included in this table.
(b) One school is eliminated from this analysis due to a lack of a White and Asian student population.

There is some evidence that resource advantages exist for White and Asian students. The most notable finding is that in 57% of schools, White and Asian students take more AP courses than African American students, controlling for achievement on state tests. Peer sorting also appears to be at least somewhat related to student race: In roughly 20-25% of schools, White and Asian students' peers in English and math classes have higher student achievement than African American students' peers, controlling for student achievement. However, the effect sizes of differential peer achievement are small.

Twenty-four percent of schools spend more on teacher salaries for White and Asian students, relative to African American students, and 19% of schools spend more on teacher salaries in core-academic subjects for White and Asian students. The dollar differentials range from small to large, ranging from $176 to $591 more per student for all salaries and $140 to $933 more per student for salaries in core-academic subjects only. Only one school spends less on teacher salaries for White and Asian students, but this school has a very small (less than 1%) White and Asian student population; therefore, common patterns indicate that a portion of schools spend more on teacher salaries for White and Asian students than for African American students. It appears that the schools spend more on White and Asian students at least in part because White and Asian students have smaller classes than African American students. In 19% of schools, White and Asian students have smaller English class sizes than African American students, and in 28% of schools, White and Asian students have smaller math class sizes.

Multiple resource advantages for White and Asian students may exist in some schools, and teacher and student tracking likely explain these resource advantages. In seven schools (33%), White and Asian students have classes with peers of higher achievement *and* take more AP courses than African American students. Additional findings also suggest that teacher and student tracking are related to class sizes: In eight schools (38%), White and Asian students take more AP courses and have smaller class sizes than African American students, and in another three schools (14%), White and Asian students are less likely to have new teachers and have smaller class sizes compared to African American students. These findings indicate that White and Asian students may have several resource advantages compared to African American students within the same school.

Further, in the only two schools with substantial White and Asian student populations (24% and 27%), multiple resource advantages exist for White and Asian students. In one of the two schools, White and Asian students have smaller English class sizes, take more AP courses, have higher achieving peers, and larger per-pupil TREs than African American students. In the second school, White and Asian students have smaller English class sizes, are less likely to have new English teachers, and take more

AP courses than African American students. Thus, in schools with racial diversity and substantial White and Asian populations, White and Asian students have multiple resource advantages relative to minority students.

Students with different levels of achievement. This section summarizes findings regarding common within-school allocation patterns for students who have passed state standardized tests in English and/or math relative to students who have not passed state tests. The first table below provides common within-school resource allocation patterns, and the second table displays effect sizes for resource variables regressed on student achievement and grade level interaction dummy variables. Results by school are provided in Appendix III.

Table 44: Common Within-School Resource Allocation Patterns for Students Who Have Passed State Tests Relative to Students Who Have Not Passed State Tests

Common Within-School Resource Allocation Pattern	Percent of Schools with This Pattern for 10th Grade Students	Percent of Schools with This Pattern for 11th Grade Students	Percent of Schools with This Pattern for 12th Grade Students
Higher per-pupil TREs	---	36%	64%
Lower per-pupil TREs	32%	---	---
Larger English class sizes	36%	---	---
Larger math class sizes	27%	45%	---
Smaller math class sizes	---	---	23-32%
Lower odds of having new English teacher	45%	32%	27%
Lower odds of having new math teacher	32%	---	18-36%

Table Notes:
(a) Percentile ranges are provided when findings differ for students who have passed the state English test than for students who have passed the state math test.
(b) Cells are left blank when there is no reoccurring finding according to the inclusion criteria for common findings of within-school resource allocation.

Table 45: Range and Median of Slope Coefficients for Individual Resources Regressed on Passed State English Test Dummy Variable by Grade Level

Dependent Variables	**Range of Slope Coefficients for 10th Grade Students, Median**	**Range of Slope Coefficients for 11th Grade Students, Median**	**Range of Slope Coefficients for 12th Grade Students, Median**
Teacher resource expenditures per pupil	-$452 to +$730, $203	$288 to $1,239, $785	$385 to $1,106, $539
Core-academic teacher resource expenditures per pupil	-$310 to +$408, $70	-$413 to +$675, $320	$311 to $753, $422
English class size	-3.4 to +4, 1.75	-1.7 to +1.9, 0.2	-3 to +3.8, 0.8
Math class size	+1.4 to +3.3, 1.9	-2.8 to +3.2, 1.4	-4.9 to -1.6, -2.3
Odds of having new English teacher	0.1 to 3.6, 0.6	0.3 to 1.9, 0.4	0.1 to 8, 0.45
Odds of having new math teacher	0.1 to 2.3, 0.5	0.4 to 5.2, 0.6	0.3 to 2.1, 0.6
Log odds of number of AP courses	NA	0.5 to 2.1, 1.2	0.4 to 2.3, 1
Peer effect in English class	NA	3.5% to 12%, 6.9%	2.3% to 8.2%, 4%

Table Note: Only results resulting from statistically significant slope coefficients at $p < .10$ are summarized in this table. In other words, slope coefficients that are not statistically different than 0 are not included in this table.

Table 46: Range and Median of Slope Coefficients for Individual Resources Regressed on Passed State Math Test Dummy Variable by Grade Level

Dependent Variables	**Range of Slope Coefficients for 10th Grade Students, Median**	**Range of Slope Coefficients for 11th Grade Students, Median**	**Range of Slope Coefficients for 12th Grade Students, Median**
Teacher resource expenditures per pupil	-$323 to +$405, -$248	-$444 to +$800, $320	$272 to $635, $549
Core-academic teacher resource expenditures per pupil	-$411 to -$211, -$309	-$317 to +$859, $6	$272 to $686, $401
English class size	-2.9 to +3, 1.6	-2 to +2.2, -0.5	-1.8 to +4, 1.25
Math class size	+1.1 to +2.6, 1.4	-1.7 to +5, 2	-3.5 to +2.1, -2
Odds of having new English teacher	0.2 to 5, 1.9	0.1 to 0.6, 0.3	0.4 to 8, 0.5
Odds of having new math teacher	0.3 to 0.6, 0.5	0.4 to 2.3, 0.7	0.1 to 5.7, 0.3
Log odds of number of AP courses	NA	0.3 to 1.7, 1.1	0.5 to 2.1, 0.9
Peer effect in math class	NA	3% to 18%, 6.9%	2.7% to 7.5%, 4.25%

Table Note: Only results resulting from statistically significant slope coefficients at $p < .10$ are summarized in this table. In other words, slope coefficients that are not statistically different than 0 are not included in this table.

Similar to the findings from the estimated MLMs, schools spend more on teacher salaries for students who have passed the state tests than on those who have not. Sixty-four percent of schools spend more money on 12th grade students who have passed state tests–either in English or in math–than they do on low-achieving 12th grade students, or students who have not passed state tests. Schools spend more on 12th grade students who have passed state tests relative to low-achieving 12th grade students due to a combination of smaller class sizes and higher-paid teachers.

Of the 14 schools that spend more on 12th grade students who have passed state tests in either English or math, half of these schools spend more on students who have passed state tests in both English and math. Additional money spent on 12th grade students who have passed state tests in both English and math ranges from \$839 to \$1,741 per student for all teacher salaries and from \$640 to \$1,244 per student for teacher salaries in core-academic subjects. Given that the average regression intercept is around \$3,200 for all per-pupil TREs and \$2,600 for core-academic TREs per pupil, these additional amounts spent on 12th grade students who have passed the state tests are quite large.

Results are similar for 11th grade students who have passed the state English test, but the effect sizes are not as large for 12th grade students. Thirty-two percent of schools spend more on teacher salaries for 11th grade students who have passed the state English test, and only two schools spend less on 11th grade students who have passed the state English test. Greater spending on 11th grade students who have passed the state English test mostly coincides with these students being assigned to more experienced teachers.

However, there is no common pattern of schools spending more or less money on 11th grade students who have passed the state math test or on 10th grade students who have passed the state English test, controlling for achievement in the other subject. For these students, there are patterns of larger class sizes and fewer newer teachers. Thus, the lower expenditures per student due to larger class sizes is balanced with the higher expenditures per student due to higher teacher salaries, and the result is that schools do not spend substantially different amounts on these students relative to lower achieving students.

Finally, 32% of schools spend less money on 10th grade students who have passed the state math test compared to others. Tenth grade students who have passed the state math test are less likely to be taught by a new math teacher but also have larger class sizes in both math and English classes. Thus, the lower expenditures per student resulting from larger class sizes outweigh the greater expenditures per student resulting from more experienced and higher-paid teachers.

In summary, there are three common resource patterns in this district for spending on students of different achievement levels. The first pattern is increased spending for students who have passed state tests relative to lower achieving students due to a combination of smaller class sizes and more experienced teachers. Second, higher expenditures due to more experienced teachers may be balanced with lower expenditures due to larger class sizes, and when this occurs, schools do not spend appreciably different amounts of money on teacher salaries for students of different achievement levels. Third, students who have passed state tests may have more experienced teachers but also substantially larger class sizes or larger class sizes in multiple courses, resulting in schools spending less on these high-achieving students. In any case, students who have passed state tests are more likely to be taught by experienced teachers than lower achieving students, and this is true across all grades.

This study finds more occurrences and the largest effect sizes of resource inequities for 12th grade students compared to younger students. As previously discussed, 70% of 12th grade students have passed state tests. Thus, comparing allocated resources for 12th grade students who have passed state tests with resources allocated to 12th grade students who have not passed state tests informs disparities in resource allocation for the lowest achieving 30% of 12th grade students compared to higher achieving students. When comparing resource allocation for the lowest achieving 30% of students with higher achieving students, low-achieving students are allocated lower per-pupil TREs, larger class sizes in English and math, and more new English and math teachers. Thus, the lowest achieving students may have multiple resource disadvantages compared to higher achieving students.

Compounded effects for students. This section briefly explains how resource inequities may be even larger than previously described due to student membership in multiple categories and/or student attendance at different schools. Differences in per-pupil TREs caused by student membership in multiple student categories can be large. For example, one school spends 44% more on White and Asian 12th grade students who have passed the state math test than on African American 12th grade students who have not passed the state math test. In another school, 40% more is spent on middle-class 12th grade students who have passed the state English test than on low-income 12th grade students who have not passed the state English test. While these are some of the most extreme cases of inequitable spending within schools, it is worthwhile to note that within-school inequity in resources may be considerable in some cases, resulting in dramatic differences in how much schools spend on teacher salaries for various students.

In addition, both between- and within-school inequities in resources may produce even greater resource inequity at the student level. For example, between-school inequities in teacher experience may result in greater inequities in access to experienced teachers for low-achieving students than previously found. In one school, for example, 0% of 12th grade students who passed the state English test are taught by new English teachers, and 9% of low-achieving 12th grade students in the same school are taught by new English teachers. In another school, 26% of 12th grade students who passed the state English test are taught by new English teachers, and 55% of low-achieving 12th grade students in the same school are taught by new English teachers. Combining between- and within-school inequities in teacher experience yields extremely different levels of access to experienced teachers for two subgroups of students across two schools: 55% of 12th grade students who have not passed state tests in School A have new English teachers compared to none of 12th grade students in School B who have passed state tests. The difference in these percentages, which indicate access to experienced teachers resulting from both between- and within-school inequities in resources, is striking.

Chapter 6: Discussion

By calculating individualized per-pupil teacher resource expenditures (TREs) for each high school student in a large public school district, this study sought to create a sufficiently granular dataset with which to analyze both the variation in and the equity of the allocation of these TREs among individual students. This analysis reveals that there is, in fact, considerable variation in the allocation of per-pupil TREs within schools; moreover, these variations are not consistent with differences in student need. These results are particularly striking given the district's stated goals of ensuring equitable access to education and allocating additional resources to the students with the greatest needs. Given these findings, the further study of student-level TREs and the equity of their allocation seems ripe for future research and potentially useful for state, district, and school leaders as well. To this end, this chapter discusses the implications, directions for future research, and limitations of this dissertation.

Key Findings

Key findings of this dissertation include that the within-school variation in per-pupil TREs is much larger than the variation between schools. For students within the same school, inequities in per-pupil TREs and specific resources exist, and some students have multiple resource advantages compared to other students. Finally, the results of the study indicate that district and school leaders may be unaware of within-school resource allocation patterns.

There is greater variation in per-pupil TREs within schools than between schools. The within-school variation in per-pupil TREs dwarfs the variation between schools. This holds true for per-pupil TREs for all instruction and for core-academic instruction. While there is some variation (13.5%) in per-pupil TREs between schools, 86.5% of the variation in per-pupil TREs stems from within-school differences in spending. Per-pupil TREs are defined by allocating teacher salaries to individual students, and while there are slight differences in teacher salaries between schools, there is far more variation in teacher salaries within schools. Likewise, there is much more variation in per-pupil TREs within schools than between schools. Another factor that contributes to the large variation in per-pupil TREs within schools is the large variability in class sizes across courses. Class sizes are the most influential component of course expenditures per student, and class sizes vary dramatically across courses.

While it is not yet fully understood how much variation in per-pupil TREs should be tolerated and or expected given various constraints, this study extends school finance research by finding that there is more variation in per-pupil TREs within schools than between schools. School finance researchers traditionally studied interstate and interdistrict equity of fiscal resources until some researchers pointed out that there is considerable variation in teacher salaries between schools in the same district (Spatig-Amerikaner, 2012; Speakman et al., 1997), which led to studies of intradistrict differences in teacher salaries and/or per-pupil expenditures (Berne & Stiefel, 1994; Condron & Roscigno, 2003; Heuer & Stullich, 2011; Klein, 2008; Owens & Maiden, 1999; Rubenstein, 1998). Some districts conscientiously tried to reduce teacher salary differences across schools (Odden et al., 2003; see also *Hobson v. Hansen*), the result being that intradistrict equity was improved in some cases. In this subject district, teacher salaries are equitably allocated between schools, and because there are not dramatic differences in teacher salaries between schools, the majority of the variation in teacher salaries (and per-pupil TREs) occurs within schools. This study extends school finance research by contributing that there may be more differences in fiscal resources at the student level than at the school level, particularly when fiscal resources are equitably allocated between schools, and highlighting the need for a better understanding of the equity and allocation of fiscal resources at the student level.

Inequities in per-pupil TREs exist. As might be expected in a sample with considerable variation in per-pupil TREs for students within the same school, there are also inequities in the allocation of per-pupil TREs within schools and at the student level. To analyze the equity of per-pupil TREs within schools, this study started with Berne & Stiefel's framework for evaluating equity, which consists of three principles: horizontal equity, vertical equity, and equal opportunity. To determine horizontal equity and equal opportunity within schools, this study developed an analytic approach to account for multiple dimensions of student need by utilizing statistically rigorous analyses while hewing as close as possible to the spirit of Berne & Stiefel's framework. To assess vertical equity, this study calculated how much more money is spent on special education, English language learner (ELL), and low-income students relative to other students and compared actual funding weights to those outlined in the state foundation plan for each category of students.

Based on this analysis, inequities in per-pupil TREs within schools exist, and students in the same school do not necessarily receive equitable monetary resources. This study finds that horizontal equity is not achieved within schools, as there is considerable variation in per-pupil TREs for "like" students– "like" students are students who are similar in terms of special education, ELL, and low-income status and grade level. This finding is perhaps even more striking given the context of the analysis. This study generally bases its horizontal equity analysis on Toutkoushian and Michael's (2007) modification of Berne & Stiefel's (1984) framework for evaluating equity, which among other things holds that horizontal equity is violated if there is any variation in PPEs after controlling for certain variables. However, this study allows for some variation in per-pupil TREs to be more consistent with traditional horizontal equity analyses. Specifically, this study allows the variation in per-pupil TREs to be as large as the variation in teacher salaries within schools before horizontal equity is violated. Yet, nevertheless, horizontal equity was not achieved for students in the same school. Thus, despite controlling for differences in student need, variation in per-pupil TREs within schools is still quite large.

Equal opportunity for students with different achievement levels is violated because the majority of schools in this district spend more money on teacher salaries for students who have passed state tests compared to students who have not passed state tests. On average, schools spend 13.7% more on 12^{th} grade students who have passed state English and math tests compared to low-achieving 12^{th} grade students. Around 70% of 12^{th} grade students have passed state tests, so one implication of this finding is that schools spend the least on the lowest achieving 30% of students compared to higher achieving students, all else being equal. For core-academic TREs per pupil, schools spend 16% more on 12^{th} grade students who have passed both English and math state tests compared to low-achieving 12^{th} grade students. Schools do not spend more on high-achieving students than low-achieving students due to differences in student course loads because high- and low-achieving students are enrolled in the same number of course credits. In addition, equal opportunity is violated for student race because a few schools spend slightly more on White and Asian students than on African American students, holding all else equal, albeit the monetary differentials are small.

For horizontal equity and equal opportunity, this study finds that inequities in per-pupil TREs exist. However, student-level inequities in fiscal resources may not directly result from problematic district and school policies. Teacher and student sorting into courses ultimately affects how resources are allocated to individual students and results from a myriad of choices and constraints. Specifically, students (and parents) select which courses to take, teachers may have preferences in which courses that they teach, and school leaders may influence teacher assignment to various courses. Additionally, formal and informal school policies and constraints–such as scheduling constraints or prerequisite courses–may restrain students' decisions to enroll in various courses. Research is mixed in the role of student choice versus contextual constraints in students' decisions to participate in various courses (Brent et al., 1997; Oakes & Guiton, 1995; Tyson, 2013), and this study does not shed light on the role of student choice in the within-school allocation process. However, this study highlights that choices and constraints in the within-school resource allocation process result in inequities in per-pupil TREs.

Lastly, this study examines vertical equity for special education, ELL, and low-income students and determines whether state categorical funding for these student subgroups is ultimately allocated to these students. This study finds mixed results. Vertical equity is achieved for special education students; the district spends 181% more per pupil on teacher salaries and 310% more per pupil on teacher salaries in core-academic subjects for special education students relative to non-special education students. As for ELL students, the district spends 61% more on teacher salaries and 99% more on teacher salaries in core-academic subjects for ELL students than for non-ELL students. The state provides 99% more funding for ELL students in its contributions to districts. Thus, it is debatable whether vertical equity is achieved for ELL students because for all TREs, vertical equity is not achieved, but for core-academic TREs, vertical equity is achieved. Nevertheless, this study concludes that vertical equity is achieved for ELL students.

Vertical equity is not achieved for low-income students because the district spends only 13% more per low-income student relative to non-low-income students on all teacher salaries and only 17% more per pupil on teacher salaries in core-academic subjects. The funding weight in this state for low-income students is 1.97, implying that low-income students should receive 97% more resources than middle-class students. Thus, there is a substantial gap between the money spent on teacher salaries for low-income students and the categorical funding weights outlined in the state foundation plan. Further, the district spends only 2% more on teacher salaries and 4% more on teacher salaries in core-academic subjects for low-income students when controlling for special education and ELL status. Thus, the district does not achieve vertical equity for low-income students.

This vertical equity analysis highlights that state funding for low-income students does not ultimately reach individual low-income students, at least in terms of teacher salaries. To the contrary, state funding for special education and ELL students is ultimately allocated to special education and ELL students, and the district spends even more per special education student than required by the state. The district spends substantially more on teacher salaries for special education and ELL students because special education and ELL students are often grouped together for instruction, and they have small class sizes, particularly in English classes. These smaller class sizes drive up costs for special education and ELL students. It is less clear how state categorical funding for low-income student populations would be reflected in teacher salary differences for low-income students.

One might theoretically argue that state categorical funding benchmarks for low-income students should be compared against total PPEs, as opposed to per-pupil TREs, in a vertical equity analysis. Whether low-income students need more *instructional* resources to achieve the same educational outcomes as non-low-income students is perhaps debatable; however, there is some evidence that this is the case. For example, researchers find the low-income students may benefit from reduced class sizes (Krueger, 2002). One could argue that if the district receives categorical aid for 40% of its students who qualify for free and reduced-priced meals, the district should consider how to invest these resources in ways that improve student outcomes for low-income students, which would likely involve investing more per-pupil TREs for low-income students.

One might also argue that any failure to achieve vertical equity for low-income students is merely the result of all students, regardless of income level, being taught by the same teachers and attending the same classes as their non-low-income counterparts; however, this argument is not valid in this district. In this district, low-income (as well as minority) students are less likely to be enrolled in advanced courses and are more likely to have peers with lower achievement than their middle-class (and White) counterparts.

Though the district certainly does not spend *less* on teacher salaries for low-income students compared to other students, the district does not appear to be strategically directing additional dollars to the instruction of low-income students in terms of teacher salaries and class sizes. State funding for low-income populations could ultimately benefit low-income students if districts created monetary incentives to recruit and retain high-quality teachers in high-poverty schools.

Inequities in specific student-level resources exist. This study also analyzes the equity of the allocation of specific resources within each school to provide a more nuanced understanding of the equity of within-school resource allocation. Though the district spends much more on teacher salaries for special education and ELL students than general education students, special education students are more likely to be assigned to a new math teacher in 59% of schools. In addition, ELL students have larger-than-average math class sizes in 50% of schools; in fact, though the district spends much more on courses for non-native English speakers (ESOL courses) than regular track academic courses on average, the district spends $109 less per student on math courses for ELL students than regular track math courses due to larger-than-average class sizes. This finding highlights the fact that although an analysis of monetary resource allocation is informative, it may not capture all resource inequities in a given school.

This study also finds other resource inequities for low-achieving, low-income, and African American students beyond fiscal resources, and resource inequities may exist for these students across a number of resources simultaneously. This is particularly true for the lowest achieving students in the district. When comparing the lowest achieving 30% of 12th grade students with higher achieving 12th grade students, the lowest achieving students have almost every resource disadvantage compared to higher achieving students: larger math class sizes, more new teachers, less exposure to advanced curricula, and lower achieving peers. Even when schools do not spend more on high-achieving students than low-achieving students, schools consistently assign a disproportionate number of low-achieving students to the least experienced teachers.

When multiple resource inequities are present, the result is a potentially large difference in how much is spent on individual students within the same school. One of the most drastic examples of inequitable spending in per-pupil TREs occurs in a school that spends 44% more on 12th grade White and Asian high-achieving students than on 12th grade African American low-achieving students, controlling for special education, ELL, and low-income status. This differential is quite large, particularly for teacher resource expenditures.

School context relates to the equity of within-school resource allocation. For example, the relationship between advanced course-taking and student socioeconomic status and race appears to be more prevalent in schools with more racial and socioeconomic diversity: In low- and mid-poverty schools, low-income students take fewer advanced placement (AP) courses and have peers with lower achievement than non-low-income students. In the majority (57%) of schools, White and Asian students take more AP courses than African American students, controlling for student achievement. Thus, low-income and minority students may be “crowded out” of AP and other advanced courses in schools with larger proportions of middle class and White students (Tyson, 2013). In addition, interestingly, there are greater inequities in resource allocation for African American students in the two schools with the largest White and

Asian populations. Across these two schools, White and Asian students have higher per-pupil TREs, smaller class sizes, higher achieving peers, and fewer new teachers and take more AP courses compared to African American students. Again, it is unclear from this study the role that student choice plays in course-taking in this district. However, if students are voluntarily sorting themselves based on race, which causes inequitable allocated resources, district and school leaders should identify resource inequities and then find potential solutions for addressing them.

Within-school resource investment may not align with district goals. These findings indicate that district leaders may be unaware of within-school resource allocation patterns. Per its school board policy, the district is committed to providing equitable access to a high quality education for all students by allocating greater resources to students with the greatest needs, yet the district does not spend more on low-income students and spends less on low-achieving students than on middle-class or higher achieving students. Further, across the district, more money is directed to advanced core courses than regular track core courses in three out of the four core academic subjects, and the advanced math courses are twice as costly as the regular math courses. Another goal of the district is to prepare its students for college or careers, but the district spends more on foreign language courses and other elective courses than on regular track academic or vocational courses that prepare the majority of students for college or careers. Given its stated goals, the district may need to better align its monetary resources with its priorities. This may require re-examining the cost effectiveness of offering advanced foreign language or other non-core courses that are expensive due to very small class sizes, increasing student participation in courses that prepare them for college or the workforce, and financially investing in courses that are likely to affect student outcomes.

As previously discussed, it is unclear from this study to what extent choices and constraints affect how resources are allocated within schools. To be sure, districts have some responsibility to allocate their resources equitably and to provide equitable access to a high-quality education to all students. It may be the case, for example, that the district is providing equitable access to rigorous courses but that student course-taking choices result in stratified educational opportunities. It could also be the case that fewer students enroll in advanced courses, resulting in smaller class sizes (and higher costs) for advanced courses. Clearly, student and parent preferences play a role in how resources are allocated within a school. But the fact that student choice exists does not absolve districts and schools from the responsibility of ensuring that all students receive equitable resources. We know from other research that minority and low-income students may "opt out" of advanced courses if there are few minority and low-income students in those courses (Carter, 2013). However, district and school leaders can potentially address this issue by creating school cultures in which all students are encouraged to perform at their highest levels as well as academic supports for students who are not accustomed to participating in advanced courses (Hawley & Wolf, 2012).

It could also be the case that few teachers in the school are qualified to teach the advanced courses resulting in the most experienced teachers teaching the most advanced courses. To this point, districts and schools should be continually working to develop human capital so that all teachers are effective and there are an adequate number of effective teachers to distribute across a variety of courses. Further, as districts and schools move away from the static teacher salary and experiment with teacher performance pay, district and school leaders should create policies that incentivize experienced teachers to teach courses at all levels. School leaders may also exert influence on which courses students take and how teachers are assigned to courses (Koski & Horng, 2007; Leithwood et al., 2004).

In summary, the district may be meeting its goal to provide equitable access to a high-quality education for all students. This study points out, however, that providing equitable access may not be sufficient in providing a high-quality education for all students. Understanding the results of the within-school resource allocation process is potentially the first step for any district interested in addressing resource equity.

Implications and Suggestions for Future Research

This study has implications for both the educational research community as well as education leaders at the state, district, and school levels. Suggestions for future research are also described.

Research community. Given the paucity of research on student-level expenditure data, there are few examples of–and certainly no consensus regarding–a framework for how to calculate individualized TREs. Student-specific PPE figures ("per-pupil TREs") for this study were derived by taking individual teacher salaries and allocating them among students taught by that teacher, accounting for, among other things, the number of classes taught by the teacher, the length of each class, and the number of students in each class. This approach is reasonably comprehensive because it essentially accounts for the majority of instructional expenditures of every minute of a specific student's regular school day. Nevertheless, future studies may well adjust or refine it, and in any event, the calculation of student-level PPEs is itself a topic that merits further research and discussion.

As with the derivation of per-pupil TREs, more research and discussion on the logistics of conducting an equity analysis within schools is also warranted. This study is the first to outline an approach for analyzing the equity of per-pupil TREs for students within the same school. Specifically, in calculating the degree of variation in spending on “like” students, this study controls for reasons why per-pupil TREs should vary within schools. One would expect, for example, that schools spend more on teacher salaries for special education and ELL students. Further, this study compares the degree of variation in spending on “like” students within schools to the variation in teacher salaries within schools. Thus, this study shows that the degree of variation in per-pupil TREs within schools is much greater than the degree of variation in teacher salaries within schools. Future research may refine this approach for evaluating within-school horizontal equity.

This study is also the first to compare the variation in per-pupil TREs within schools to the variation between schools. The fact that there is much more variation in per-pupil TREs within schools than between schools, together with potential contrasts in resource investment and district values and goals, raises the possibility that other districts may face similar issues. Thus, research in other districts is warranted to determine if within-school variation in per-pupil TREs is practically significant in other contexts and results in resource inequities.

In addition, this study evaluates the equity of a number of resources within schools, but there are many more instructional resources that one could investigate. For example, future researchers could examine the equity of the distribution of effective teachers–identified by value-added measurements or teacher evaluation scores–in conjunction with other resources (Bastian, Henry, & Thompson, 2013). Future research could also examine the relationship between equitable resource allocation processes and student outcomes. Can schools, for example, improve student achievement by aligning resources with students who have the greatest academic needs? Research that examines how schools can improve student achievement by aligning resources with student needs is particularly relevant because if more equitable resource allocation patterns result in improved student achievement, then schools may potentially improve student achievement using the resources that they already possess.

Finally, this study explains about half of the variation in per-pupil TREs with student characteristic variables, but much variance is left unexplained, and there is room for further investigation of the reasons why per-pupil TREs vary within schools. Potential influences on per-pupil TREs, such as school leadership and student, parent, and teacher choices as well as scheduling and other course-related constraints, are not examined in this study and may better explain resource allocation patterns. Research on how choices and constraints influence the within-school resource allocation process in different school contexts would be particularly insightful because researchers could then inform how to create policy solutions that rectify stratification of educational opportunities for students within the same school.

State leaders. This study informs state leaders and policymakers whether state funding for categorical student subgroups is ultimately allocated to individual students. The study finds that for one large urban district, state funding for special education and ELL students does reach individual high school students, but this study also finds that state funding intended for low-income student populations is not being spent on low-income students in terms of TREs. Further, this study questions how state funding for low-income student populations should be allocated to low-income students. State leaders and policymakers should consider how to hold districts accountable for the allocation of state funding to categorical student subgroups.

District leaders. Until district leaders examine within-school resource allocation patterns, they may not be aware of how their policies and practices translate into actual resources for individual students or if resources are equitably distributed across students. Further, within-school resource allocation patterns may also be misaligned with district values and goals, and researching how resources are ultimately allocated to students is potentially the first step in re-aligning resources to meet district goals. For this reason, along with the recent push by the federal government's Race to the Top Fund to "improve the collection and use of data" (U.S. Department of Education, 2010, p. 3), district leaders should collect resource data and analyze within-school resource allocation patterns and should consider implementing student management data systems that make such data collection and within-school analyses of resources less burdensome.

To this end, within-school analyses of resources would be facilitated if data were collected in a more systematic manner. Specifically, districts could work to develop student-level data files that contain all student characteristics including demographic information, academic success in the district, disciplinary actions, and achievement on standardized tests. Course-level files that contain teacher demographic and quality information would also be incredibly useful. District should routinely produce financial summary information that provides teacher salary expenditure information as well as breakdowns of other financial expenditures allocated for various courses or programs. In summary, more integrated data systems are necessary to better understand the resources that individual students within a school receive and to ensure that the allocation of resources at the student level is consistent with district goals.

School leaders. School leaders are perhaps most able to address inequities in resource allocation within schools because they influence how resources are allocated through teacher assignments, class sizes, and student course-taking. Even if inequities in resources exist across districts and schools–and in many cases they do–school leaders can work to ensure that students with greater needs receive additional resources within their own schools. School leaders should be aware of how teacher and student sorting into classes creates resource advantages and disadvantages for various student subgroups.

School leaders–along with district leaders–may also need to examine policies relating to course taking to determine if all students have the opportunity to enroll in academically rigorous courses (Hawley & Wolf, 2012). Even if all students have equal access to academically rigorous courses, school leaders should consider how students select advanced courses and if all students with high test scores are equally encouraged to enroll in advanced and AP courses. Even though this district has an “open-door” AP course-taking policy, in which any student may take any AP course and access to AP courses is not restricted by prerequisite and teacher permission requirements, a disproportionate number of White and Asian and middle-class students are enrolled in these courses in some schools. School leaders can disaggregate student data by race and socioeconomic status to ensure that high-achieving minority and low-income students are equally likely to be enrolled in advanced courses as White, Asian, and middle-class students, and if they are not, identify other ways of encouraging high-achieving minority or low-income students to enroll in these courses. Addressing this issue is particularly important in schools with lower proportions of minority and low-income students, as such students are often “crowded out” of AP courses in schools with more middle class and White student populations (Tyson, 2013). It may be necessary to engage parents of low-income or minority families to ensure that they are knowledgeable about the academic offerings of the school or address low expectations of the academic capabilities of their children, which can contribute to differential academic track placements (Oakes & Guiton, 1995). Finally, school leaders can work to build academic support structures for students who are not accustomed to taking advanced courses (Hawley & Wolf, 2012).

School leaders may also wish to reconsider teacher assignment practices. In this district, high-achieving students are more likely to be taught by experienced teachers, and low-income students are more likely to be taught by inexperienced teachers; this is a common finding in the literature (Clotfelter, Ladd, & Vigdor, 2005; Player, 2010). In fact, research indicates that, given static teacher salary structures, school leaders may reward and help retain more effective teachers by assigning them to higher achieving students (Clotfelter et al., 2005; Player, 2010). But not only is this process inequitable, it may also be inefficient as student performance may be most enhanced when the most effective teachers teach the most academically struggling students (Clotfelter et al., 2005). School leaders can work to ensure the equitable distribution of experienced and effective teachers across advanced, regular track, and remedial courses and may have to create new staff policies or incentivize effective teachers to share in the teaching of low-achieving students (Bastian et al., 2013). Further, school leaders can identify teachers who are particularly effective in raising student achievement and assign these teachers to the students with the greatest academic needs. Finally, school and district leaders should consider how teacher and student sorting into classes creates small class sizes for some courses, resulting in high course expenditures per student. School and district leaders should flag courses with fewer students (and high course expenditures per student) and decide if investment in these courses contributes to school and district goals. More work needs to be done to support school and district leaders in addressing within-school inequities in resources and to identify the barriers that leaders continue to face.

Limitations

Technical limitations of this study are discussed in the Appendices; several non-technical limitations are discussed here as well. First, findings identified in this study may not be generalizable to all districts, particularly districts with very different demographic and socioeconomic attributes. However, given the degree of within-school variability in per-pupil TREs found in this study, it is possible–if not likely–that within-school variation in per-pupil TREs is considerable and that inequities in student-level resources occur in other districts.

Additionally, this study does not account for all instructional expenditures. By strategically choosing to investigate only instructional expenditures directly affecting classroom instruction, this study ignores much of spending within schools. For example, this study does not account for school-level resources, such as school administration, professional development, technology, textbooks and supplies, librarians, guidance counselors, and staff who primarily work with teachers, though these resources may be indirectly related to student achievement. Allocating school-level expenditures to individual students is likely to decrease the proportion of within-school variation in PPEs and increase the proportion of between-school variation in PPEs, compared to the proportions identified in this study. Further, this study does not account for school staff who are not classroom teachers but who may otherwise provide instruction to students or contribute to classroom management; examples of such school staff include instructional aides, student teachers, and instructional coaches.

The nature of the student achievement data is another limitation in this study. High school students must take and pass four standardized tests before graduating from high school, and while students may take these tests multiple times throughout their high school careers, many do not take each test annually. Thus, raw test scores are confounded with the grade level in which students take the tests. This study attempts to account for this dilemma by creating dummy achievement variables indicating whether or not a student has passed a state standardized test and by comparing student achievement only for students within the same grade. However, dummy variables of student achievement are not as informative as raw test scores. It is likely that student achievement is not fully controlled for in this study.

Finally, teacher quality data are not available for this study, and this study does not examine the distribution of effective teachers. This study infers teacher quality through teacher years of experience and salary, which may not accurately reflect teacher effectiveness. Relatedly, this study does not account for a number of observable and unobservable student, teacher, parent, and school leader characteristics and choices that affect and determine the equitable allocation of resources within schools.

Conclusion

Creating schools where all students–regardless of background, race, or socioeconomic status–have equitable educational resources is a daunting task without a simple solution. Narrowing the racial and socioeconomic achievement gap in student achievement will require more than merely providing students with equitable resources (Rothstein, 2013; Welner & Carter, 2013), but a more equitable allocation of resources can only help. This study is one of the first in the literature to attempt to link multiple resources to individual students for all high school students, and it does so for all high school students in a large urban public school district.

Analysis of the data reveals that per-pupil TREs vary considerably within schools and much more than across schools in the district. There is also variation in how individual schools allocate their resources, and within-school allocation patterns of per-pupil TREs vary across schools. The study finds that inequities in student-level resources do exist, even in a district that is committed to equity of resources for all students. Specifically, this study finds inequities in the allocation of per-pupil TREs, class sizes, teacher experience, peer achievement, and number of AP courses. These findings highlight the need for future research on within-school resource allocation because understanding and evaluating the equity of resource allocation within schools may be necessary to provide equitable access to a high quality education for all students.

Appendices

Four appendices are included in this study. The first appendix describes key decisions and assumptions in estimating teacher resource expenditures (TREs) per pupil. The second appendix provides demographic and resource information for each school. The third appendix contains the regression analysis results for each school. The final appendix discusses model fit and assumptions for all of the models estimated in the study.

Appendix I: Key Assumptions and Decisions in Estimating Per-Pupil TREs

This appendix describes the key decisions and assumptions made in estimating per-pupil TREs. This appendix describes how the sample was obtained, per-pupil TREs were calculated, outliers were identified, and missing data were handled.

Sample selection. This study employs a sample of high school students for several reasons. First, high school students take a number of courses and are taught by multiple teachers; thus, there is variation in allocated resources within schools. Second, tracking may be more common in high schools, and tracking relates to resource equity. Finally, the data are the most reliable for high school students in the district. Elementary school data are problematic because they do not indicate the amount of time each student spends with each teacher. In other words, I could not distinguish if students were with the teacher for most of the day or for only one hour. Assuming that elementary school teachers spend equal time with all students is likely incorrect and would potentially confound the findings. Middle school data are mostly reliable, but a few students are linked to multiple courses in all academic subjects. Hence, it is impossible to accurately estimate per-pupil TREs for roughly 5% of middle school students. Data for high school students posed the least complications, and I have confidence that the data adequately reflect the resources allocated to individual high school students.

The sample of students was created using the following rubric: All students from all traditional high schools were initially included in the analysis. Then, special education students who spent more than 60% of their day outside of regular instruction were removed from the sample because these students may have atypical educational experiences and expenditures; the students who were removed constitute 0.3% of all high school students. Approximately three and a half percent of high school students attended more than one school in the academic year. These students were included in the analysis more than once if reliable estimated per-pupil TREs existed for students at each school. The resulting sample contains 41,537 high school students.

Table 47: Number of Students in Sample by Grade Level

Grade	**Number of Students by Grade Level**	**Relative Percent (%) of Students by Grade Level**
Grade 9	12,583	30.3
Grade 10	10,963	26.4
Grade 11	8,997	21.7
Grade 12	8,982	21.6
Missing	12	0.0
Total	**41,537**	100.0

I reviewed the state Department of Education handbook for the 2009–2010 academic year to ensure that these data are reliable and contain all students and schools. The state Department of Education handbook indicates that, for the 2009-2010 academic year, there were around 20 high schools and 60,000 students in grades 7–12,[45] and the National Center for Education Statistics (NCES) reports that in the 2010–2011 academic

[45] Total number of students in grades 9–12 is not available.

year, there were around 40,000 high school students (Institute of Education Sciences, 2013). The sample includes a larger number of high school students than cited by either the state Department of Education or NCES. The discrepancy in the sample sizes is most likely due to student mobility and the fact that these data were collected at different times throughout the year.[46] Given that all traditional high schools are included in the data and that the sample size is similar to those provided by the state Department of Education and NCES, the study concludes that the sample is adequate in representing the district's student population of high school students.

Calculating per-pupil TREs. This section describes several challenges encountered while cleaning the data and calculating per-pupil TREs. Teacher salary data were not straightforward because the financial file contained line-item expenditures allocated to individual teachers for various purposes. In determining teacher salary, I included all salary expenditures that were directly related to instruction and that reflected how much districts pay teachers for instructional purposes. I included regular, leave, and performance pay, and other stipends granted for instructional purposes. I did not include salary expenditures that were indirectly related to instruction or that involved activities not related to instruction, such as professional development and athletic coaching. I also excluded salary expenditures that were allocated for summer school or other instructional purposes outside of the regular academic school year.

I also examined whether specialty "classroom teachers," such as ESOL, special education, and reading teachers were included in the course enrollment files. All

[46] Student mobility refers to students leaving the district as well as transferring to another school within the district. This study doubly counts students who appear in the course enrollment data more than once, as long as complete course enrollment information is available for the student at each school. This study roughly counts 3% of students twice.

“classroom teachers” were found in the course enrollment files except for five ELL, 32 special education, and two reading teachers. These teachers’ salaries were evenly allocated to ELL, special education, or all students within the school to produce accurate per-pupil TREs. It should also be noted that some non-“classroom teachers,” such as resource teachers and guidance counselors, were identified as teaching courses in course enrollment files. For these teachers, I allocated their salaries to the courses that they taught and then examined if the small teacher loads resulted in abnormally large course expenditures.

There were abnormalities in the high school data. I reviewed the total number of courses taught by individual teachers. The average teacher course load was around 5.5 course credits, with some elective teachers responsible for up to nine course credits. I reviewed teachers with course loads of less than four credits and tagged cases where the course expenditure was abnormally high for the school, or more than one and a half times the average expenditure for that course in a particular school. This analysis identified 3.6% of courses, and for these courses, I allocated the teacher salaries as if the teachers taught five course credits total. The rationale is that these teachers likely have other responsibilities other than teaching fewer courses and if their salaries are fully allocated to the few courses, the course expenditures would be inaccurately too large. For special education and ESOL teachers, I allocated their salaries as if these teachers taught four course credits total, as special education and ESOL teachers generally have lighter teaching loads and teach four courses each. I also reviewed courses with very small class sizes, and it did not appear that there were any mistakes after the initial cleaning of the data.[47]

The choice whether to code a course as a core-academic course was heavily dependent on the district's course guidebook. If a course such as creative writing was listed in the English department, it was coded as a core-academic course. In summary, I used the district course guidebook and coded all courses offered in the English department as English courses. The same approach applies to courses in other academic departments. There were a few exceptions, however; the district considered yearbook and school newspaper courses as English courses, and I coded these courses as elective courses instead of core-academic courses because they were often offered after school.[48]

Missing data. Nine high school teachers were missing staff identification numbers and 120 teachers (out of 2,277 total high school teachers) could not be linked to a valid teacher identification number and thus were missing salary information. The financial data containing salary information for teachers included staff identification numbers that are five digits in length. However, in course enrollment data, 120 teachers had staff identification numbers that were between 9 and 11 digits in length, and these teachers could not be identified in the financial data. Thus, it was impossible to link these 120 teachers to their salaries. These 120 teachers were scattered across schools, and every school had at least one teacher who could not be linked to his/her salary. Further, there was no pattern as to the types of courses that teachers with missing salary information taught. These 120 teachers likely had miscoded staff identification numbers, and the miscoding of staff identification numbers likely occurred in the district office.

[47] I originally cleaned the data by school to correct any obvious errors.
[48] The full data diary, which is available upon request, lists all courses coded as core-academic courses.

As a result of the total 129 high school teachers with missing salary information, 5.5% of all high school courses could not be linked to a teacher's salary, and 31% of high school students were taught by at least one teacher with a missing salary. For courses linked to teachers with missing salaries, I imputed the course expenditures based on school and district average course expenditures. If possible, the missing course expenditure was imputed from the school-level average expenditure for the specific course; in this case, if a student was taught by a teacher with a missing salary, the student received the school-level average expenditure for that particular course. 53.5% of the missing course expenditures were imputed in this manner. If school-level average course expenditures were not available for the particular course, then the course expenditure was imputed from the school-level average expenditure of all the courses in the course category (math, English, etc.). I imputed 38% of the courses with missing course expenditures in this manner. Finally, for the remaining 8.5% of courses with missing expenditures that could not be imputed with school-level averages, I imputed the district-level average expenditure for that particular course. Imputing course expenditures using school-level average expenditures is preferable to using district-level average expenditures because district-level expenditures are confounded by within- and between-school differences in course expenditures. The imputation of missing course expenditures may have either reduced or increased within-school variation in per-pupil TREs. However, given that only 5.6% of course expenditures were imputed, the estimated per-pupil TREs are likely reliable indicators of how much money is spent on teacher salaries for individual students.

Outliers. As a result of the imputed missing course expenditures, per-pupil TREs were able to be estimated for over 99% of high school students. However, outliers clearly existed; for example, one student was estimated to have a TRE of $148,010. Such large expenditures for a few students potentially distort true average per-pupil TREs for the large majority of students. Thus, this study excluded outlier cases, and outliers were identified by the residuals (e_i) of the following multiple linear regression model:

$$Y_i = \beta_0 + \beta_{SPED}SPED_i + \beta_{ELL}ELL_i + \beta_{GRADEK}GRADEK_i + e_i$$

Where:

Y_i: per-pupil TRE for ith student

β_0: intercept, or base spending per-pupil in 9th grade

$SPED_i$: student receives special education services (0=no, 1=yes)

ELL_i: student is English language learner (0=no, 1=yes)

$GRADEK_i$: set of dummy codes for students in grade k, (0=no, 1=yes)

β_{SPED}: differential dollar amount allocated to special education students, on average

β_{ELL}: differential dollar amount allocated to English language learners, on average

β_{GRADEK}: differential dollar amount allocated to students in grade k, on average

e_i: residual for the ith student.

Outliers were identified after controlling for grade level and special education and ELL status, hence taking into account that certain students typically cost more to educate than others. Outliers were identified if the residuals from the previous model were further than three standard deviations from the mean. Roughly one and a half percent of all students were identified as having outlier expenditures per student for both total per-pupil TREs and core-academic TREs per pupil. Thus, the final sample included approximately 98% of high school students. Outlier cases were spread across all schools, and the percentages of outlier cases in each school are provided in Table 48. Histograms of all TREs with and without outliers are also provided in the following figures.

Table 48: Percent Missing Per-Pupil TRE and Core-Academic TRE Per Pupil By School

School ID	Missing TRE %	Missing TRE_CA %
1302	1.4	1.5
2308	0.7	0.8
5311	3.2	3.2
6303	1.2	1.0
6331	1.2	1.2
9308	6.6	7.1
10308	0.2	0.3
11303	0.4	0.4
12309	1.2	1.2
12317	1.1	0.5
12320	4.9	5.1
13314	2.7	1.6
13327	0.8	0.8
14309	4.6	4.5
14323	2.8	2.7
15302	1.5	1.2
15319	1.4	1.5
17308	2.1	1.4
18306	1.2	1.3
18310	0.9	0.5
19309	4.5	5.2
21314	0.9	0.9

Figure 6: Histogram of Per-Pupil TREs, All Values

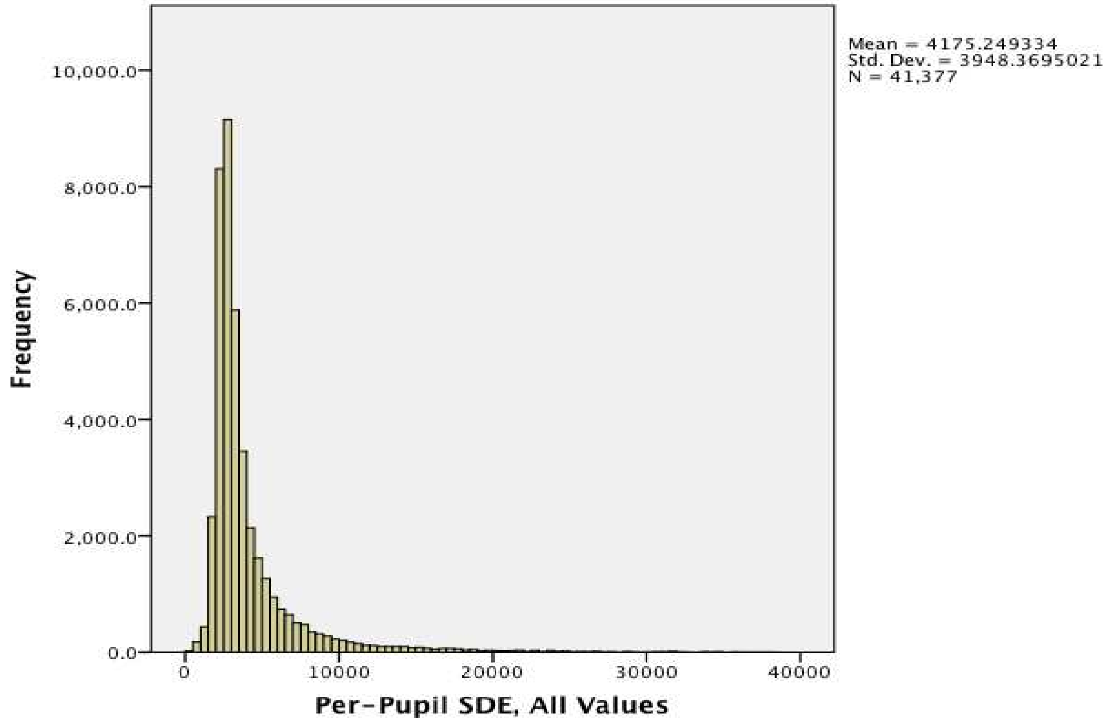
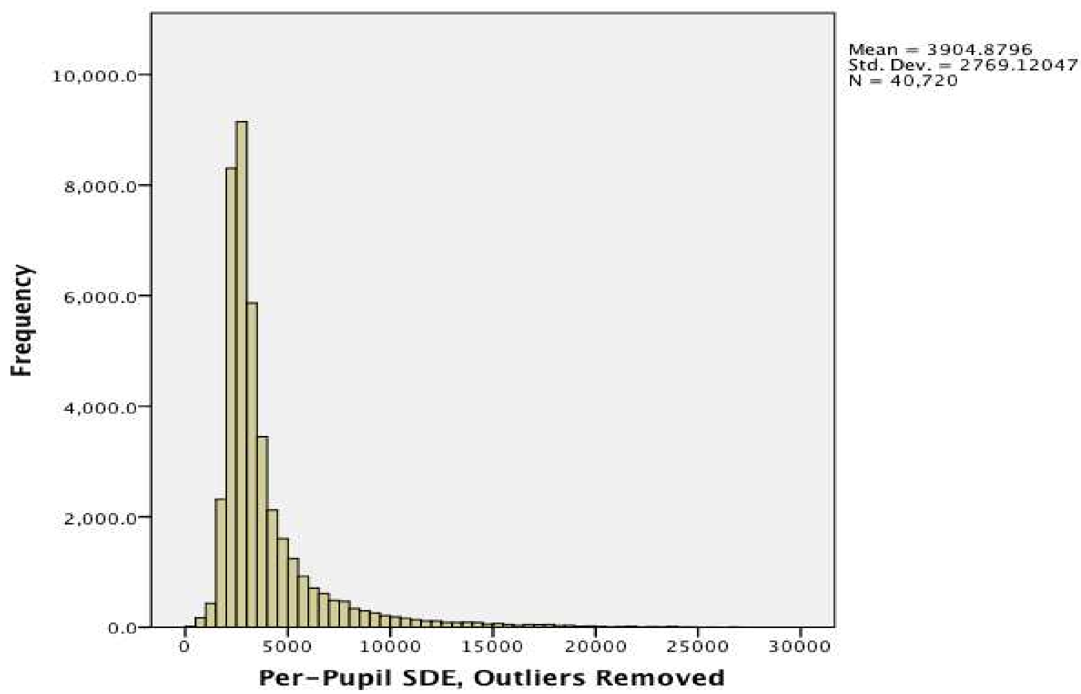


Figure 7: Histogram of Per-Pupil TREs, Outliers Removed



Appendix II: High School Profiles

This appendix provides demographic and resource for each school. Specifically, Table 49 outlines high school characteristics for each school, and Table 50 provides means and standard deviations of resource variables for each school.

Table 49: High School Characteristics

	FARMS %	ELL %	SPED %	Size	African-American %	Latino %	White & Asian %	Passed English Test 10-12th Graders %	Passed Math Test 10-12th Graders %	Mean Teacher Salary $	Mean Teacher Years in School	Mean Principal Years in School	Number of AP Courses Offered
1st Quartile Poverty High Schools													
School 14323	22	0	9	3,106	70	6	24	69	72	65,419	9	11	8
School 11303	24	0	9	1,207	87	3	9	63	68	66,179	7	12	9
2nd Quartile Poverty High Schools													
School 15302	29	0	9	1,149	93	2	4	61	61	70,884	11	15	8
School 9308	31	0	12	1,000	93	3	3	53	52	68,128	6	11	10
School 15319	31	0	10	2,900	93	3	3	61	59	62,588	6	15	6
School 21314	32	3	7	2,844	63	10	27	78	79	68,948	12.5	15	16
School 5311	32	0	13	1,663	90	5	4	52	54	66,268	6	16	8
School 12309	36	4	6	1,934	82	8	9	60	58	71,019	9	13	15
School 13327	37	0	8	2,721	96	2	2	70	72	67,652	7	9	6
School 13314	38	0	8	1,420	96	1	1	59	57	70,541	8	7	11

	FARMS %	ELL %	SPED %	Size	African-American %	Latino %	White & Asian %	Passed English Test 10-12th Graders %	Passed Math Test 10-12th Graders %	Mean Teacher Salary $	Mean Teacher Years in School	Mean Principal Years in School	Number of AP Courses Offered
School 10308	44	6	10	1,986	70	16	14	60	66	68,078	10.5	21	8
School 6303	45	0	10	2,720	96	2	1	53	57	62,434	9	18	6
School 12317	47	5	9	1,501	88	9	3	54	56	67,968	7	26	8
School 14309	50	7	11	1,748	80	16	3	52	61	64,912	8.5	3	10
3rd Quartile Poverty High Schools													
School 6331	52	0	12	918	96	2	1	48	56	64,596	7	14	7
School 18310	53	11	12	1,165	89	9	2	47	53	65,508	6	29	5
School 12320	54	0	11	1,348	98	1	1	40	42	69,706	8	25	6
School 18306	59	0	15	1,000	94	5	0	40	46	64,961	7	1	5
School 1302	59	18	11	2,321	42	49	8	52	58	69,073	10.5	1	9
School 19309	60	12	10	2,241	53	39	8	54	59	70,144	9	13	7
School 17308	60	14	9	2,710	47	47	5	54	57	67,026	8	21	7
School 2308	62	12	9	1,935	55	41	4	45	58	64,680	5.5	6	6

Table 50: Means and Standard Deviations of Resources By School

	Per-Pupil TRE $ Mean S.D.	Core-Academic TRE Per Pupil $ Mean S.D.	English Class Size Mean S.D.	Math Class Size Mean S.D.	New English Teacher Dummy Mean S.D.	New Math Teacher Dummy Mean S.D.	% of Peers Who Passed English Test 10-12th Graders Only Mean S.D.	% of Peers Who Passed Math Test 10-12th Graders Only Mean S.D.	Number of AP Courses Per Student 11th–12th Graders Only Mean S.D.
1st Quartile Poverty High Schools									
School 14323	3,297 2,588	2,534 2,542	34 7	33 7	.40 .49	.14 .35	68 20	71 19	.40 .80
School 11303	3,558 1,607	2,358 1,476	32 7	31 8	.12 .32	.55 .50	61 18	67 18	.32 .65
2nd Quartile Poverty High Schools									
School 15302	4,004 2,933	2,829 2,569	31 7	31 8	.15 .35	.40 .49	59 23	60 21	.14 1.0
School 9308	4,244 4,324	3,110 3,893	35 10	35 10	.36 .48	.21 .41	54 21	53 21	.59 .44
School 15319	3,212 2,437	2,244 1,970	36 8	35 6	.28 .45	.69 .46	57 22	57 23	.20 .53
School 21314	3,204 1,956	2,394 1,738	31 7	32 5	.07 .26	.01 .08	74 20	78 20	.80 .86
School 5311	4,043 3,892	3,168 3,573	31 8	30 8	.43 .49	.18 .39	50 24	55 24	.34 1.1
School 12309	3,876 2,403	2,890 2,097	33 8	31 7	.31 .46	.55 .50	57 29	60 26	.72 .64
School 13327	3,043 1,629	2,118 1,390	32 9	40 9	.24 .43	.35 .48	66 23	71 20	.27 .56

	Per-Pupil TRE $ Mean S.D.	Core-Academic TRE Per-Pupil $ Mean S.D.	English Class Size Mean S.D.	Math Class Size Mean S.D.	New English Teacher Dummy Mean S.D.	New Math Teacher Dummy Mean S.D.	% of Peers Who Passed English Test 10-12th Graders Only Mean S.D.	% of Peers Who Passed Math Test 10-12th Graders Only Mean S.D.	Number of AP Courses Per Student 11th–12th Graders Only Mean S.D.
School 13314	4,215 3,153	3,141 2,718	29 7	31 7	.40 .49	.05 .22	57 18	58 17	.22 .49
School 10308	3,158 1,447	2,374 1,302	35 9	34 7	.28 .45	.24 .43	55 23	64 20	.30 .76
School 6303	3,472 1,646	2,214 1,132	33 9	34 10	.31 .44	.41 .49	50 22	56 22	.15 .65
School 12317	3,958 1,810	2,574 1,538	34 11	32 10	.26 .46	.37 .48	52 22	54 16	.50 .43
School 14309	6,698 2,833	4,917 2,646	34 8	34 8	.51 .50	.43 .50	48 21	59 23	.35 .65
3rd Quartile Poverty High Schools									
School 6331	3,861 1,785	2,690 1,527	31 9	27 7	.57 .50	.46 .50	44 23	54 21	.25 .48
School 18310	4,065 1,766	3,196 1,622	25 5	27 6	.84 .37	.37 .48	45 20	53 21	.17 .49
School 12320	7,222 4,054	4,893 3,553	30 7	33 8	.53 .50	.42 .49	37 24	41 24	.22 .57
School 18306	3,582 1,601	2,482 1,299	28 8	35 10	.13 .33	.26 .44	38 26	44 22	.25 .66
School 1302	4,537 3,268	3,769 3,098	31 8	34 7	.16 .37	.03 .18	49 20	57 22	.35 .57
School 19309	4,314 3,081	3,470 2,854	33 9	35 8	.06 .23	.13 .33	50 24	58 22	.28 .70
School 17308	3,572 2,839	2,821 2576	36 9	39 10	.49 .50	.47 .50	52 23	57 21	.37 .52
School 2308	3,854 2,806	2,936 2,360	35 9	36 9	.44 .50	.29 .45	41 22	56 22	.44 .93

Appendix III: Regression Results By School

This appendix provides regression results for each school. Table 51 provides regression results for the models predicting per-pupil TREs and core-academic TREs per pupil. Table 52 provides regression results for specific instructional resources. Table 53 provides regression results for peer achievement.

Table 51: Regression Results for Per-Pupil TREs and Core-Academic TREs Per Pupil By School

	Depend. Variables	Intercept	SPED	ELL	FARMS	Latino	White/ Asian	10th Passed English	10th Passed Math	11th Passed English	11th Passed Math	12th Passed English	12th Passed Math	R Squared
1st Quartile Poverty Schools														
School 14323	TRE	2,606*** (41)	9,098*** (286)	—	139* (64)			-316* (128)						76.5%
	TRE_CA	2,212*** (41)	8,705*** (306)	—	115’ (64)									74.7%
School 11303	TRE	3,238*** (66)	3,407*** (317)	—										35.2%
	TRE_CA	2,734*** (64)	3,124*** (293)	—				-219’ (131)	-283’ (149)					45.0%
2nd Quartile Poverty Schools														
School 15302	TRE	2,920*** (63)	9,603*** (440)	—			458* (218)	-452* (180)	405* (176)					76.6%
	TRE_CA	2,345*** (58)	8,008*** (434)	—			592* (298)							72.7%
School 9308	TRE	3,273*** (105)	15,957*** (592)	—					-323’ (192)			539’ (288)	619* (183)	86.4%
	TRE_CA	2,506*** (96)	14,789*** (552)	—					-321’ (193)					88.0%

Table Notes:
(a) The slope coefficients are in terms of dollars.
(b) African American and 9th grade students are the reference groups for the race and grade level dummy variables.
(c) “10th Passed English” is the slope coefficient for the interaction variable, the 10th grade dummy variable multiplied by the PassELA dummy variable.
(d) The models also control for grade level.
(e) The p-values are as follows: ‘ p < .10, * p < .05, ** p < .01, *** p < .001, and standard errors are provided in parentheses. Slope coefficients that are not statistically significant are excluded for ease of interpretation.
(f) This analysis is conducted in Mplus7 with the maximum likelihood with robust standard errors estimator. This estimator is chosen due to slight deviations from normality of the residuals.

	Depend. Variables	Intercept	SPED	ELL	FARMS	Latino	White/ Asian	10th Passed English	10th Passed Math	11th Passed English	11th Passed Math	12th Passed English	12th Passed Math	R Squared
School 15319	TRE	2,591*** (53)	6,752*** (279)	—	121’ (67)		591* (261)				320’ (177)		572*** (158)	59.7%
	TRE_CA	2,139*** (47)	5,222*** (246)	—		-192’ (107)		-142’ (79)					272* (123)	56.0%
School 21314	TRE	2,548*** (44)	6,247*** (281)	474*** (112)		244* (96)			-298’ (152)					61.3%
	TRE_CA	1,956*** (40)	5,411*** (277)	636*** (99)		261** (91)	223*** (43)		-309* (138)	384** (138)	330* (144)			58.9%
School 5311	TRE	2,802*** (83)	11,690*** (351)	—	215* (93)	-302* (124)			-288’ (158)			708** (213)	561** (196)	82.6%
	TRE_CA	2,353*** (77)	10,611*** (326)	—	178* (84)	-381* (154)			-411* (161)		-317* (143)	606*** (173)	393* (163)	82.7%
School 12309	TRE	3,199*** (55)	8,891*** (357)	1,468*** (203)			220* (99)	-323** (115)	277* (122)				272’ (149)	72.3%
	TRE_CA	2,491*** (54)	7,269*** (333)	1,648*** (211)		320** (116)	218* (107)	-310** (99)		309’ (166)			686*** (165)	64.6%
School 13327	TRE	2,713*** (42)	3,481*** (268)	—	119* (55)	-288’ (169)							551** (166)	32.2%
	TRE_CA	2,175*** (36)	2,996*** (241)	—	90* (45)	-274’ (141)			-211’ (117)				410** (139)	39.8%
School 13314	TRE	3,303*** (61)	12,105*** (396)	—				501** (181)		288’ (160)		441’ (239)	398’ (221)	82.5%
	TRE_CA	2,653*** (62)	9,477*** (325)	—		403’ (255)	-384* (176)	402* (166)	-372* (161)	330* (160)			543** (181)	78.6%

	Depend. Variables	Intercept	SPED	ELL	FARMS	Latino	White/ Asian	10th Passed English	10th Passed Math	11th Passed English	11th Passed Math	12th Passed English	12th Passed Math	R Squared
School 10308	TRE	2,591*** (55)	1,859*** (169)	1,853*** (179)		240* (97)	176* (78)			484** (174)	-444* (199)	557*** (159)		27.2%
	TRE_CA	2,242*** (51)	1,548*** (155)	2,024*** (170)		157’ (84)	140’ (74)		-248* (114)	441** (135)	-418** (155)	335** (123)		28.4%
School 6303	TRE	3,191*** (51)	1,233*** (136)	—	-199** (59)			203* (100)	222* (99)	785*** (182)		1,106*** (167)	635*** (169)	15.2%
	TRE_CA	2,462*** (42)	849*** (116)	—				-164* (71)		197* (98)		413*** (105)		11.5%
School 12317	TRE	3,255*** (75)	2,655*** (250)	1,447*** (247)		303’ (169)				902*** (223)				27.3%
	TRE_CA	2,622*** (68)	2,528*** (244)	1,567*** (224)		530*** (147)				265* (134)				34.4%
School 14309	TRE	6,085*** (122)	4,810*** (318)	3,168*** (293)			933** (348)	730** (235)		1239*** (291)				32.0%
	TRE_CA	4,965*** (116)	4,358*** (308)	3,725*** (273)				408’ (212)		675** (239)				35.5%
3rd Quartile Poverty Schools														
School 6331	TRE	3,526*** (96)	2,480*** (276)	—										25.3%
	TRE_CA	2,753*** (86)	2,409*** (243)	—				345’ (180)						32.2%
School 18310	TRE	3,698*** (88)	2,247*** (240)	897*** (178)							800*** (195)			20.7%
	TRE_CA	3,178*** (86)	1,733*** (214)	939*** (159)		438* (183)					859*** (193)	753** (236)	491* (245)	18.8%

	Depend. Variables	Intercept	SPED	ELL	FARMS	Latino	White/ Asian	10^{th} Passed English	10^{th} Passed Math	11^{th} Passed English	11^{th} Passed Math	12^{th} Passed English	12^{th} Passed Math	R Squared
School 12320	TRE	6,307*** (132)	12,365*** (421)	—		1,296’ (670)							-685’ (377)	70.9%
	TRE_CA	4,384*** (118)	11,165*** (436)	—										72.5%
School 18306	TRE	2,962*** (77)	2,403*** (219)	—			—		320’ (167)				547’ (313)	30.4%
	TRE_CA	2,428*** (68)	1,747*** (182)	—			—							24.1%
School 1302	TRE	2,904*** (76)	7,884*** (260)	5,148*** (114)	-119’ (72)							385* (178)		76.0%
	TRE_CA	2,334*** (73)	6,763*** (247)	5,310*** (122)	-169* (68)					-413’ (211)		573** (171)		75.2%
School 19309	TRE	3,172*** (69)	9.926*** (328)	4,140*** (147)		-175* (70)		248’ (137)					426’ (242)	76.3%
	TRE_CA	2,653*** (67)	9,108*** (298)	4,114*** (146)				283* (138)				375’ (195)	356’ (206)	75.3%
School 17308	TRE	2,706*** (75)	8,368*** (334)	1,316*** (112)	-126’ (75)							624*** (156)		63.2%
	TRE_CA	2,219*** (74)	6,874*** (312)	1,615*** (109)	-132’ (74)							431* (169)		57.4%
School 2308	TRE	2,766*** (86)	6,722*** (274)	4,097*** (175)										64.4%
	TRE_CA	2,485*** (76)	5,176*** (240)	3,968*** (161)								311* (158)	329’ (181)	64.8%

Table 52: Regression Results for Specific Resources By School

1st Quartile Poverty High Schools										
	Dependent Variables	**SPED**	**ELL**	**FARMS**	**Latino**	**White/ Asian**	**Female**	**10th, 11th, or 12th Pass English**	**10th, 11th, or 12th Pass Math**	**R Squared**
School 14323	English class size	-13*** (.75)	—			-0.6* (.25)	-0.7*** (.19)			35.5%
	Math class size	-10*** (.81)	—		1* (.50)			*12th*: -2.4*** (.68)	*11th*: -1.1’ (.67) *12th*: -1.5* (.72)	15.8%
	Odds of new English teacher	1.4* (.16)	—			0.7** (.10)		*10th*: 0.6* (.22) *11th*: 1.9** (.23)		15.8%
	Odds of new math teacher		—					*10th*: 0.7’ (.23)	*10th*: 0.5’ (.46) *12th*: 0.1* (.86)	39.2%
	Log odds of number of AP courses	-1.5** (.48)	—	-0.4** (.16)		0.6*** (.10)	0.4*** (.11)	*11th*: 0.9*** (.26) *12th*: 1.0*** (.24)	*11th*: 1.3*** (.32) *12th*: 0.9*** (.24)	—

Table Notes:
(a) The models also control for grade level unless otherwise noted, and they also include an intercept.
(b) African American serves as the baseline student race.
(c) The p-values are as follows: ‘ p < .10, * p < .05, ** p < .01, *** p < .001, and standard errors are provided in parentheses. Slope coefficients that are not statistically significant are excluded for ease of interpretation.
(d) The slope coefficients of the interaction variables between achievement and grade level are combined into two columns.
(e) The models predicting teacher experience estimate the probability of having an inexperienced teacher. The slope coefficients represent the odd ratios of having an inexperienced teacher. The standard errors are in terms of log odds.
(f) For the models concerning the number of AP courses per student, these models account for the fact that the dependent variable is a count variable, and an R squared value is not available. The slope coefficients represent the average log odds of number of AP courses taken by students in the category. Only 11th and 12th grade students are included in this analysis, as the vast majority of 9th and 10th grade students are not enrolled in AP courses.
(g) This analysis is conducted in Mplus7 with the maximum likelihood with robust standard errors estimator.
(h) Finally, when estimating the models with categorical and count dependent variables (new teachers and number of AP courses), occasionally the model does not converge, typically because there are a few students in a category or inadequate variance on a variable for a particular student group. In this case, Mplus7 indicates the problematic variable(s), and one or more variables are removed to achieve model convergence. All removed variables are noted.

	Dependent Variables	SPED	ELL	FARMS	Latino	White/ Asian	Female	10th, 11th, or 12th Pass English	10th, 11th, or 12th Pass Math	R Squared
School 11303	English class size	-11*** (1.0)	—					*10th*: 2.5*** (.65)		30.3%
	Math class size	-11*** (1.3)	—			-1.3’ (.74)	-0.9* (.43)	*12th*: -3.4* (1.5)	*11th*: 2.3* (1.2) *12th*: -3.5* (1.5)	20.1%
	Odds of new English teacher[49]	7.7*** (.21)	—					—	—	33.7%
	Odds of new math teacher		—					*10th*: 2.3* (.33) *11th*: 0.4** (.32) *12th*: 0.3** (.44)	*11th*: 1.7’ (.32) *12th*: 0.3* (.48)	18.0%
	Log odds of number of AP courses		—			0.8*** (.18)	0.6** (.17)	*11th*: 1.6*** (.40)	*11th*: 1.0* (.40) *12th*: 0.9’ (.47)	—
2nd Quartile Poverty High Schools										
School 15302	English class size	-11*** (1.0)	—					*12th*: 1.6* (.78)	*12th*: 1.5* (.73)	36.7%
	Math class size	-11*** (1.2)	—			-2.1’ (1.1)	-0.8* (.42)		*10th*: 1.9* (.80) *11th*: 2.1* (.98) *12th*: -3.3** (1.1)	19.1%
	Odds of new English teacher[50]		—					—	—	60.2%
	Odds of new math teacher		—				0.6** (.13)	*11th*: 1.8’ (.322)	*11th*: 0.6’ (.32) *12th*: 0.3** (.38)	6.5%
	Log odds of number of AP courses		—				1.0** (.32)	*11th*: 2.1** (.72) *12th*: 1.3’ (.78)		—

[49] Due to convergence problems, the interaction variables between achievement and grade level are removed from the model.
[50] Due to convergence problems, the interaction variables between achievement and grade level are removed from the model.

	Dependent Variables	**SPED**	**ELL**	**FARMS**	**Latino**	**White/ Asian**	**Female**	**10^{th}, 11^{th}, or 12^{th} Pass English**	**10^{th}, 11^{th}, or 12^{th} Pass Math**	**R Squared**
School 9308	English class size	-14*** (1.3)	—				-1.4* (.75)		*10^{th}:* 2.4’ (1.4)	22.7%
	Math class size	-10*** (1.2)	—						*10^{th}:* 2.6** (.90) *11^{th}:* 2.4* (1.1)	31.7%
	Odds of new English teacher		—				0.6** (.16)	*10^{th}:* 0.5* (.39) *11^{th}:* 0.4* (.41)	*11^{th}:* 0.2*** (.39)	25.2%
	Odds of new math teacher	3.7*** (.28)	—						*12^{th}:* 5.7** (.65)	22.8%
	Log odds of number of AP courses	-2.5** (.95)	—					*11^{th}:* 0.7** (.23) *12^{th}:* 0.9** (.30)	*11^{th}:* 0.8*** (.21) *12^{th}:* 0.5’ (.29)	—
School 15319	English class size	-11*** (.61)	—				-1*** (.24)		*11^{th}:* -1* (.51)	35.5%
	Math class size	-9.5*** (.65)	—			-1.5* (.58)			*12^{th}:* -1.1’ (.58)	25.8%
	Odds of new English teacher	0.7* (.17)	—	1.2* (.10)				*10^{th}:* 0.7’ (.20)	*10^{th}:* 0.6** (.20)	2.5%
	Odds of new math teacher	1.7* (.23)	—					*11^{th}:* 0.6’ (.21) *12^{th}:* 0.6* (.23)	*10^{th}:* 0.6’ (.24) *11^{th}:* 0.7’ (.20) *12^{th}:* 0.3*** (.22)	16.9%
	Log odds of number of AP courses[51]	—	—				0.6*** (.16)	*11^{th}:* 0.6* (.28) *12^{th}:* 1.3* (.54)	*11^{th}:* 0.8** (.26) *12^{th}:* 1.0* (.41)	—

[51] SPED status is removed from this model due to convergence problems.

	Dependent Variables	SPED	ELL	FARMS	Latino	White/ Asian	Female	10^{th}, 11^{th}, or 12^{th} Pass English	10^{th}, 11^{th}, or 12^{th} Pass Math	R Squared
School 21314	English class size	-5*** (.82)	-2*** (.54)			-0.5’ (.27)		*10^{th}*: 1.6** (.55)	*10^{th}*: 0.9’ (.54)	17.6%
	Math class size	-3*** (.60)		-0.4’ (.22)				*10^{th}*: 1.8** (.65)	*10^{th}*: 1.3’ (.66) *11^{th}*: 1.2’ (.72)	7.2%
	Odds of new English teacher[52]	0.7* (.17)	—	1.2* (.10)				*10^{th}*: 0.7’ (.20)	*10^{th}*: 0.6** (.20)	2.5%
	Odds of new math teacher[53]	1.7* (.23)	—					*11^{th}*: 0.7’ (.21) *12^{th}*: 0.6* (.23)	*10^{th}*: 0.6’ (.24) *11^{th}*: 0.7’ (.20) *12^{th}*: 0.3*** (.22)	16.9%
	Log odds of number of AP courses	-0.4* (.18)		-0.5*** (.11)		0.7*** (.07)		*11^{th}*: 1.8*** (.45) *12^{th}*: 0.9** (.26)	*11^{th}*: 1.1** (.43) *12^{th}*: 1.1** (.32)	—
School 5311	English class size	-15*** (.71)	—			-1.3’ (.76)		*12^{th}*: -2.0** (.71)	*12^{th}*: -1.8** (.69)	48.9%
	Math class size	-12*** (.91)	—		1.3’ (.75)				*12^{th}*: 1.8** (.63)	26.8%
	Odds of new English teacher	0.3*** (.23)	—		0.4** (.26)	0.5’ (.32)	0.7* (.12)	*11^{th}*: 0.6* (.27)	*10^{th}*: 2.4** (.30) *12^{th}*: 0.5* (.30)	28.1%
	Odds of new math teacher	3.7*** (.23)	—						*10^{th}*: 0.3* (.43) *11^{th}*: 0.4* (.46) *12^{th}*: 0.2* (.84)	41.7%
	Log odds of number of AP courses[54]	—	—	-0.4* (.16)		0.6** (.19)	0.5*** (.13)	*11^{th}*: 1.6*** (.33) *12^{th}*: 0.8* (.33)	*11^{th}*: 1.3*** (.36) *12^{th}*: 2.0*** (.42)	—

[52] ELL status is removed from this model due to convergence problems
[53] ELL status is removed from this model due to convergence problems.
[54] SPED status is removed from this model due to convergence problems.

	Dependent Variables	SPED	ELL	FARMS	Latino	White/ Asian	Female	10th, 11th, or 12th Pass English	10th, 11th, or 12th Pass Math	R Squared
School 12309	English class size	1.5*** (.10)	-1.5*** (.14)	-0.1** (.04)	-0.2* (.10)		0.1** (.04)	*11th*: 0.2* (.09) *12th*: 0.2* (.09)	*11th*: 0.1’ (.08)	36.9%
	Math class size	-7*** (.88)	-4*** (.88)				0.6* (.28)	*10th*: 1.7** (.56) *11th*: 1’ (.58)	*11th*: 3*** (.55)	18.1%
	Odds of new English teacher							*10th*: 3.6*** (.29) *11th*: 0.5’ (.34)	*10th*: 2.4** (.29) *11th*: 0.6’ (.32)	60.6%
	Odds of new math teacher	0.5* (.31)	0.2*** (.36)					*11th*: 0.5* (.29) *12th*: 0.4* (.37)	*11th*: 0.5’ (.27) *12th*: 0.2*** (.33)	12.2%
	Log odds of number of AP courses			-0.4** (.14)		0.3* (.13)		*11th*: 1.4*** (.33) *12th*: 1.9*** (.40)	*11th*: 1.1** (.32) *12th*: 1.7*** (.35)	—
School 13327	English class size	-9*** (.73)	—	-1*** (.26)		2.6** (.93)	1.1*** (.25)	*10th*: 4*** (.63)	*10th*: 3*** (.63) *11th*: 1’ (.53) *12th*: 4*** (.99)	40.9%
	Math class size	-12*** (.88)	—	-1** (.31)	2.6* (1.2)		0.6’ (.30)	*10th*: 2** (.69) *11th*: 3.2*** (.83)	*10th*: 1.4’ (.72) *11th*: 1.6’ (.85)	28.5%
	Odds of new English teacher	1.6** (.19)	—	0.8* (.12)				*10th*: 0.1*** (.62) *11th*: 0.3*** (.31) *12th*: 0.5* (.27)	*11th*: 0.5* (.34) *12th*: 0.4*** (.26)	40.0%
	Odds of new math teacher	0.3*** (.23)	—			1.6’ (.28)		*10th*: 1.7* (.22)		6.8%
	Log odds of number of AP courses[55]	—	—			1.0*** (.20)	0.2’ (.12)	*11th*: 1.5** (.45) *12th*: 2.3*** (.56)	*11th*: 1.2** (.46) *12th*: 0.8** (.28)	—

[55] SPED status is removed from this model due to convergence problems.

	Dependent Variables	SPED	ELL	FARMS	Latino	White/ Asian	Female	10^{th}, 11^{th}, or 12^{th} Pass English	10^{th}, 11^{th}, or 12^{th} Pass Math	R Squared
School 13314	English class size	-11.5*** (.77)	—			2.4* (1.0)			*12^{th}:* 1.7** (.61)	31.9%
	Math class size	-11*** (.74)	—					*11^{th}:* 1.7* (.76)		22.2%
	Odds of new English teacher	6.5*** (.32)	—				0.7* (.13)	*10^{th}:* 0.4** (.30)	*12^{th}:* 0.5* (.36)	20.6%
	Odds of new math teacher[56]	917*** (1.2)	—		—	—				63.2%
	Log odds of number of AP courses	-1.9’ (1.0)	—				0.4’ (.18)	*11^{th}:* 0.8* (.38) *12^{th}:* 0.7* (.33)	*12^{th}:* 0.6* (.28)	—
School 10308	English class size	-1.2*** (.10)	-1.0*** (.10)	0.2’ (0.04)		-0.1’ (.06)	-0.2*** (.04)	*11^{th}:* -0.5*** (.10) *12^{th}:* -0.3* (.12)		21.9%
	Math class size	-10*** (.81)	-1.1’ (.63)		-0.8* (.40)	-1.3** (.45)		*11^{th}:* -2.8** (.88) *12^{th}:* -1.6’ (.89)	*12^{th}:* -2.8** (.83)	23.0%
	Odds of new English teacher[57]	1.7* (.22)	0.0*** (1.0)	1.4** (.12)			0.6*** (.12)	*11^{th}:* 0.3* (.46)		62.5%
	Odds of new math teacher	1.5* (.19)	2.8*** (.22)	0.8’ (.12)		0.5** (.19)		*10^{th}:* 0.3*** (.30)		18.0%
	Log odds of number of AP courses[58]	—				0.8*** (.17)		*11^{th}:* 1.8** (.63) *12^{th}:* 0.6* (.30)	*12^{th}:* 1.2** (.40)	—

[56] Student race is removed from this model due to convergence problems.
[57] Due to convergence problems, the interaction variables between achievement and grade level for 12^{th} grade students are removed from the model.
[58] SPED status is removed from this model due to convergence problems.

	Dependent Variables	SPED	ELL	FARMS	Latino	White/ Asian	Female	10th, 11th, or 12th Pass English	10th, 11th, or 12th Pass Math	R Squared
School 6303	English class size	-10*** (.60)	—	0.6' (.31)				*10th*: 1.3' (.65) *12th*: -2** (.75)	*11th*: -2* (.89)	15.5%
	Math class size	-12*** (.75)	—			-2.7' (1.6)		*11th*: 1.7' (.97)		22.8%
	Odds of new English teacher	2.8*** (.17)	—	1.3* (.10)			0.8** (.10)	*10th*: 1.5* (.19) *11th*: 0.4** (.31) *12th*: 0.5* (.30)	*12th*: 0.5* (.30)	28.3%
	Odds of new math teacher	2.1*** (.15)	—					*10th*: 1.7** (.19)		6.7%
	Log odds of number of AP courses	-2.0* (1.0)	—		1.1* (.51)	1.0* (.39)	0.3' (.19)	*11th*: 1.2** (.36) *12th*: 1.3** (.45)	*11th*: 1.1** (.35) *12th*: 0.9* (.42)	—
School 12317	English class size	-14*** (1.0)	-7*** (1.3)		-3** (1.1)					34.7%
	Math class size	-11*** (1.1)				-4* (1.6)		*12th*: -3.6** (1.3)		16.9%
	Odds of new English teacher	2.1** (.25)						*10th*: 0.4' (.46) *11th*: 0.3** (.49) *12th*: 0.4* (.36)	*12th*: 0.4** (.36)	23.5%
	Odds of new math teacher		0.3** (.42)					*10th*: 0.5* (.32)		11.2%
	Log odds of number of AP courses	-2.6*** (.72)	-1.0** (.31)		0.8** (.24)	0.8** (.26)	0.4** (.12)	*11th*: 0.5** (.17) *12th*: 0.80** (.27)	*11th*: 0.3' (.17) *12th*: 0.5' (.27)	—

	Dependent Variables	SPED	ELL	FARMS	Latino	White/ Asian	Female	10^{th}, 11^{th}, or 12^{th} Pass English	10^{th}, 11^{th}, or 12^{th} Pass Math	R Squared
School 14309	English class size	-8*** (.90)	-10*** (.76)					*10^{th}:* 1.4* (.67)	*10^{th}:* 2.4** (.76)	26.9%
	Math class size	-8*** (.75)	3*** (.83)			-2.3’ (1.3)		*11^{th}:* 1.4’ (.77)	*10^{th}:* 1.4* (.70) *11^{th}:* 2* (.82)	25.1%
	Odds of new English teacher	0.5*** (.21)	0.0*** (.43)		0.7’ (.22)			*10^{th}:* 3.1* (.46) *12^{th}:* 4*** (.38)	*10^{th}:* 5*** (.38)	56.2%
	Odds of new math teacher	0.7* (.18)	3.7*** (.24)		1.3’ (.15)				*12^{th}:* 0.3** (.38)	16.8%
	Log odds of number of AP courses[59]	—			-0.8** (.28)	0.8** (.24)	0.2’ (.13)	*11^{th}:* 1.2*** (.29) *12^{th}:* 1.3*** (.31)	*11^{th}:* 1.1** (.34) *12^{th}:* 0.8* (.31)	—
3^{rd} Quartile Poverty High Schools										
School 6331	English class size	-16*** (.91)	—		-2’ (1.2)		1.1* (.43)	*10^{th}:* -3.4** (1.2)		53.2%
	Math class size	-10*** (.90)	—		2.7* (1.4)		-0.8’ (.42)			24.7%
	Odds of new English teacher	0.0*** (.44)	—						*11^{th}:* 0.3’ (.66) *12^{th}:* 8*** (.48)	69.0%
	Odds of new math teacher	2.2** (.25)	—						*11^{th}:* 2.2’ (.45) *12^{th}:* 2.6’ (.50)	16.5%
	Log odds of number of AP courses[60]	—	—			1.4*** (.32)	0.6* (.22)	*11^{th}:* 1.3** (.42)	*11^{th}:* 1.1’ (.56) *12^{th}:* 0.9’ (.52)	—

[59] SPED status is removed from this model due to convergence problems.
[60] SPED status is removed from this model due to convergence problems.

	Dependent Variables	SPED	ELL	FARMS	Latino	White/ Asian	Female	10th, 11th, or 12th Pass English	10th, 11th, or 12th Pass Math	R Squared
School 18310	English class size	-6*** (.64)	-5*** (.55)		-2** (.63)			*10th*: 1.7* (.67) *11th*: 1.9** (.57) *12th*: 1.4* (.62)	*11th*: -1.3* (.59)	28.1%
	Math class size	-6*** (.74)	1.1* (.43)				0.5’ (.30)	*12th*: -2.3** (.84)		21.8%
	Odds of new English teacher	0.1*** (.29)		1.6* (.42)	0.3** (.44)			*10th*: 0.2*** (.35) *12th*: 0.3*** (.37)	*10th*: 0.2*** (.40)	36.8%
	Odds of new math teacher	7.5*** (.24)	6.2*** (.26)					*11th*: 0.6’ (.32)	*10th*: 0.5* (.33) *12th*: 2.2’ (.48)	22.5%
	Log odds of number of AP courses[61]	-1.2’ (1.0)				—		*12th*: 1.4* (.54)	*12th*: 0.97’ (.56)	—
School 12320	English class size	-12*** (.72)	—	0.5’ (.29)				*12th*: 1.4* (.54)	*12th*: 1.0’ (.56)	36.1%
	Math class size	-16*** (.80)	—					*12th*: -2.3** (.74)	*10th*: 1.1’ (.62) *11th*: -1.7’ (.95) *12th*: -2.3** (.72)	40.0%
	Odds of new English teacher	0.3*** (.28)	—		0.5* (.40)			*12th*: 8** (.65)		56.6%
	Odds of new math teacher	2.6*** (.24)	—					*12th*: 2.1’ *.38)	*11th*: 2.3* (.34) *12th*: 1.9’ (.25)	11.2%
	Log odds of number of AP courses	-0.9’ (.50)	—			1.1*** (.28)		*12th*: 0.7’ (.35)	*11th*: 1.0*** (.26)	—

[61] The White/Asian student dummy variable is removed from this model due to convergence problems.

	Dependent Variables	SPED	ELL	FARMS	Latino	White/ Asian	Female	10th, 11th, or 12th Pass English	10th, 11th, or 12th Pass Math	R Squared
School 18306	English class size	-4.5*** (.84)	—						*10th*: -2.9** (1.0)	27.1%
	Math class size	-6*** (1.3)	—					*10th*: 2.1' (1.2)		7.8%
	Odds of new English teacher[62]	12*** (.37)	—		—	—		—	—	47.8%
	Odds of new math teacher	1.7* (.23)	—		2.0' (.40)	4.3' (.80)				15.8%
	Log odds of number of AP courses	-1.6' (.87)	—		1.2*** (.25)	1.2*** (.23)	0.6** (.19)	*11th*: 1.0*** (.26)	*11th*: 1.4*** (.35) *12th*: 2.1* (1.1)	—
School 1302	English class size	-9*** (.56)	-3.5*** (.45)	0.8** (.27)				*10th*: 1.9** (.68) *11th*: -1.7* (.69)	*10th*: 1.7* (.69)	36.1%
	Math class size	-10*** (.60)	1.4*** (.32)		0.6* (.26)		-0.7** (.24)	*10th*: 1.4** (.52)	*11th*: 1.3* (.53) *12th*: -1.6* (.72)	28.9%
	Odds of new English teacher		0.4*** (.25)					*10th*: 0.2' (.85) *12th*: 0.1**(1.1)		61.5%
	Odds of new math teacher	248*** (.62)			0.5* (.32)			*10th*: 0.1' (.63)		55.3%
	Log odds of number of AP courses	-2.1*** (.59)				0.5** (.16)	0.3* (.12)	*11th*: 0.6* (.25) *12th*: 0.4* (.20)	*12th*: 0.9*** (.24)	—

[62] Due to convergence problems, race and the interaction variables between student achievement and grade level are removed from the model.

	Dependent Variables	SPED	ELL	FARMS	Latino	White/ Asian	Female	10th, 11th, or 12th Pass English	10th, 11th, or 12th Pass Math	R Squared
School 19309	English class size	-12*** (.87)	-6*** (.54)				-1** (.31)	*10th*: -1’ (.54)	*10th*: 1’ (.56) *12th*: -1.5’ (.84)	32.8%
	Math class size	-9*** (.77)	1.6** (.51)		0.9** (.33)			*12th*: -1.9* (.77)	*11th*: 2.1** (.71)	22.2%
	Odds of new English teacher[63]	0.2* (.74)							*11th*: 0.1* (1.0)	35.7%
	Odds of new math teacher[64]		3.1*** (.21)		1.3’ (.16)			*10th*: 0.1’ (.94) *11th*: 5.2** (.56)	*10th*: 0.3’ (.69)	51.6%
	Log odds of number of AP courses	-1.8* (.71)					0.3’ (.13)	*11th*: 1.0** (.31) *12th*: 0.8** (.28)	*11th*: 0.9** (.33) *12th*: 1.1*** (.31)	—
School 17308	English class size	-11*** (.83)	-10*** (.44)				0.7** (.28)	*10th*: 2.0** (.69)	*10th*: 1.5* (.70) *12th*: -1.5’ (.87)	37.0%
	Math class size	-10*** (1.0)	1.7** (.48)	-0.8* (.41)	0.9* (.42)			*11th*: -1.8* (.88) *12th*: -4.9*** (1.2)		9.7%
	Odds of new English teacher	0.5*** (.15)	0.2*** (.16)				0.8* (.09)	*10th*: 0.6* (.20)		16.2%
	Odds of new math teacher	1.4* (.15)	1.9*** (.13)						*10th*: 0.6* (.18)	13.8%
	Log odds of number of AP courses	-1.4** (.52)	0.4* (.17)		0.5*** (.13)	0.7*** (.18)	0.5*** (.12)	*11th*: 1.2*** (.27) *12th*: 0.9*** (.23)	*11th*: 0.7* (.28) *12th*: 0.6** (.21)	—

[63] Due to convergence problems, the interaction variables between achievement and grade level for 12th grade students are removed from the model.
[64] Due to convergence problems, the interaction variables between achievement and grade level for 12th grade students are removed from the model.

	Dependent Variables	SPED	ELL	FARMS	Latino	White/ Asian	Female	10^{th}, 11^{th}, or 12^{th} Pass English	10^{th}, 11^{th}, or 12^{th} Pass Math	R Squared
School 2308	English class size	-6*** (.96)	-6*** (.73)	1.0** (.40)				*11^{th}:* 1.7* (.79) *12^{th}:* 3.8*** (.77)	*11^{th}:* 2.2** (.86) *12^{th}:* 2.5** (.64)	22.7%
	Math class size	-3*** (.70)					-0.7' (.40)	*10^{th}:* 3.3*** (.92)	*10^{th}:* 2.0* (.81) *11^{th}:* 5***(.93)	11.2%
	Odds of new English teacher	1.6* (.22)	0.5*** (.19)		0.8' (.12)			*11^{th}:* 1.9* (.26) *12^{th}:* 0.2** (.54)	*10^{th}:* 1.9* (.26)	40.9%
	Odds of new math teacher		0.2*** (.28)		0.6**).1 4)			*11^{th}:* 0.4** (.36)		24.1%
	Log odds of number of AP courses	-2.7** (1.0)			-0.8*** (.21)		0.3* (.14)	*11^{th}:* 1.2*** (.31)	*11^{th}:* 1.7** (.52) *12^{th}:* 1.6*** (.39)	—

Table 53: Regression Results for Peer Achievement By School

	Dependent Variables	**Grade Level**	**Intercept**	**SPED**	**ELL**	**FARMS**	**Latino**	**White/ Asian**	**Pass Test**	**GPA**	**R Squared**
School 14323	% of peers passed English test	11^{th}	41*** (1.3)	-14*** (2.5)	—	-3.1** (1.0)			3.5** (1.1)	11*** (.56)	51.9%
		12^{th}	46*** (1.3)	-22*** (2.7)	—		2.7* (1.3)		2.9** (1.0)	10*** (.56)	52.9%
	% of peers passed math test	11^{th}	44*** (1.3)	-14*** (2.4)	—	-3.2** (1.0)			4.4*** (1.1)	11*** (.52)	53.3%
		12^{th}	53*** (1.4)	-21*** (3.1)	—				3.4** (1.2)	8.8*** (.56)	47.7%
School 11303	% of peers passed English test	11^{th}	36*** (1.9)	-15*** (3.4)	—			5.8** (2.2)		11*** (.74)	52.5%
		12^{th}	49*** (2.3)	-23*** (4.5)	—	-4.0* (1.8)				8.8*** (1.0)	47.6%
	% of peers passed math test	11^{th}	47*** (1.9)	-17*** (3.3)	—			6.9** (2.3)	5.0*** (1.3)	8.6*** (.75)	52.3%
		12^{th}	56*** (2.7)	-27*** (5.4)	—	-3.5’ (2.0)			6.9** (2.1)	6.1*** (1.0)	46.4%

Table Notes:
(a) African American serves as the baseline student race.
(b) The p-values are as follows: ‘ $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$, and standard errors are provided in parentheses. Slope coefficients that are not statistically significant are excluded for ease of interpretation.
(c) Each model is run for either all 11^{th} graders or all 12^{th} graders. Given the structure of the state assessment program, analyzing student achievement within each grade is the most compelling analytic method.
(c) This analysis is conducted in Mplus7 with the maximum likelihood with robust standard errors estimator.
(d) The results are similar if the average raw score in English or math is used instead of the percentage of peers who passed the English or math standardized tests. It is not surprising that similar results occur if raw scores are used instead of achievement dummy variables because the two measures of s are strongly correlated.

	Dependent Variables	Grade Level	Intercept	SPED	ELL	FARMS	Latino	White/ Asian	Pass Test	GPA	R Squared
School 15302	% of peers passed English test	11th	32*** (2.9)	-20*** (5.5)	—				5.2* (2.1)	12*** (1.3)	48.6%
		12th	40*** (3.0)	-25*** (5.4)	—		21* (8.9)		4.1’ (2.1)	12*** (1.2)	48.7%
	% of peers passed math	11th	34*** (2.8)	-22*** (5.2)	—				10*** (2.3)	10*** (1.3)	50.1%
		12th	41*** (2.9)	-26*** (4.8)	—	-4.5* (2.0)	24** (8.2)		7.5*** (2.0)	10*** (1.3)	52.0%
School 9308	% of peers passed English test	11th	21*** (3.1)	-17*** (4.6)	—		7.6* (3.1)		8.0*** (2.1)	13*** (1.3)	49.2%
		12th	35*** (3.1)	-14** (5.5)	—		11* (5.0)		4.4’ (2.4)	11*** (1.3)	44.1%
	% of peers passed math	11th	20*** (2.8)	-18** (5.5)	—				18*** (2.3)	10*** (1.3)	56.7%
		12th	41*** (2.8)	-25*** (7.0)	—					9.2*** (1.0)	46.2%
School 15319	% of peers passed English test	11th	38*** (1.8)	-24*** (2.8)	—	-2.3’ (1.2)			3.5** (1.2)	9.7*** (.73)	45.6%
		12th	49*** (1.4)	-31*** (2.1)	—				3.1** (1.0)	8.1*** (.60)	57.4%
	% of peers passed math test	11th	38*** (1.7)	-26*** (2.9)	—		-5.4’ (3.1)		3.1** (1.2)	9.7*** (.73)	48.5%
		12th	46*** (1.4)	-31*** (2.2)	—		3.4’ (2.0)		4.8*** (1.0)	7.8*** (.65)	56.0%

	Dependent Variables	Grade Level	Intercept	SPED	ELL	FARMS	Latino	White/ Asian	Pass Test	GPA	R Squared
School 21314	% of peers passed English test	11th	43*** (2.4)	-27*** (4.2)	-27*** (2.8)	-3.4* (1.3)		6.7*** (1.2)	10*** (2.0)	9.0*** (.75)	60.3%
		12th	47*** (2.0)	-20*** (3.6)	-17*** (2.9)	-3.6** (1.1)		3.4*** (.81)	5.4** (1.7)	11*** (.56)	64.6%
	% of peers passed math test	11th	49*** (2.2)	-24*** (2.7)	-21*** (3.2)	-2.6* (1.1)		5.6*** (1.1)	6.6*** (1.8)	9.0*** (.67)	59.1%
		12th	56*** (2.0)	-22*** (4.6)	-14*** (3.0)	-3.3** (1.1)		1.8* (.76)	6.3** (1.8)	8.5*** (.47)	59.4%
School 5311	% of peers passed English test	11th	28*** (2.2)	-37*** (2.9)	—			7.1* (2.8)	7.3*** (1.6)	11*** (1.0)	57.4%
		12th	35*** (2.1)	-31*** (3.4)	—				3.6* (1.4)	12*** (.90)	59.8%
	% of peers passed math test	11th	34*** (2.0)	-42*** (2.9)	—				8.5*** (1.5)	10*** (.90)	65%
		12th	40*** (2.1)	-29*** (3.3)	—				3.8* (1.4)	11*** (.95)	56%
School 12309	% of peers passed English test	11th	16*** (2.7)	-27*** (3.6)	-27*** (4.7)				10*** (2.3)	17*** (1.0)	66.2%
		12th	41*** (2.1)	-37*** (5.4)	-19*** (4.8)	-3.5* (1.3)	-10.6** (4.0)		3.5' (1.8)	13*** (.79)	68.7%
	% of peers passed math test	11th	25*** (2.2)	-26*** (3.2)	-19*** (4.1)				7.8*** (1.9)	14*** (.90)	66.0%
		12th	37*** (1.9)	-34*** (4.4)	-12** (4.6)	-4.6** (1.3)	-10.4** (3.5)		2.7' (1.4)	14*** (.79)	68.2%

	Dependent Variables	Grade Level	Intercept	SPED	ELL	FARMS	Latino	White/ Asian	Pass Test	GPA	R Squared
School 13327	% of peers passed English test	11th	38*** (2.0)	-26*** (3.6)	—		5.6* (2.8)		7.9*** (1.6)	11*** (.81)	51.4%
		12th	54*** (1.8)	-22*** (3.0)	—				2.3’ (1.3)	9.5*** (.65)	48.5%
	% of peers passed math	11th	45*** (1.6)	-22*** (3.1)	—		6.4** (2.3)	4.3* (2.1)	7.3*** (1.3)	10*** (.67)	52.3%
		12th	64*** (1.6)	-39*** (5.1)	—	-2.3* (1.1)				6.0*** (.65)	55.7%
School 13314	% of peers passed English test	11th	43*** (2.0)	-27*** (2.7)	—			7.4** (2.3)		8.6*** (.92)	51.4%
		12th	43*** (1.8)	-35*** (3.4)	—			9.8* (3.9)		11*** (.83)	62.5%
	% of peers passed math	11th	41*** (2.1)	-29*** (3.1)	—			8.5** (2.7)	6.7*** (1.7)	8.0*** (.99)	54.8%
		12th	38*** (1.7)	-33*** (3.1)	—			14** (5.2)		10*** (.82)	61.9%
School 10308	% of peers passed English test	11th	31*** (2.6)	-24*** (3.3)	-32*** (2.9)			4.5* (1.9)	6.0*** (1.6)	11*** (1.0)	60.0%
		12th	44*** (2.0)	-28*** (3.7)	-27*** (3.3)				2.6’ (1.5)	10*** (.71)	59.0%
	% of peers passed math test	11th	44*** (2.1)	-31*** (3.6)	-16*** (2.5)		3.4’ (1.9)		6.9*** (1.6)	9.2*** (.86)	63.0%
		12th	52*** (2.0)	-34*** (4.4)	-11*** (1.5)				3.4* (1.5)	8.5*** (.70)	58.7%

	Dependent Variables	Grade Level	Intercept	SPED	ELL	FARMS	Latino	White/ Asian	Pass Test	GPA	R Squared
School 6303	% of peers passed English test	11^{th}	31*** (1.8)	-27*** (2.6)	—				4.0** (1.5)	10*** (.83)	52.8%
		12^{th}	42*** (1.6)	-19*** (2.3)	—	-2.0* (1.0)			3.0** (1.1)	9,9*** (.68)	45.7%
	% of peers passed math	11^{th}	39*** (1.5)	-11*** (1.9)	—				3.8** (1.1)	9.0*** (.63)	43.4%
		12^{th}	47*** (1.4)	-17*** (1.8)	—					7.6*** (.61)	40.9%
School 12317	% of peers passed English test	11^{th}	27*** (2.5)	-13*** (3.0)	-13** (4.5)				8.4*** (1.9)	10*** (1.1)	37.2%
		12^{th}	36*** (2.7)	-7.2* (3.2)	-21*** (3.1)		-11** (3.4)		5.2** (1.8)	12*** (1.0)	43.7%
	% of peers passed math	11^{th}	30*** (2.4)	-9** (3.1)	-12* (4.9)			-8.4* (3.9)	9.1*** (1.7)	10*** (1.0)	38.8%
		12^{th}	39*** (2.4)	-10*** (2.9)	-20*** (3.4)		-8.7** (2.9)		3.1’ (1.8)	11*** (.95)	41.3%
School 14309	% of peers passed English test	11^{th}	34*** (2.3)	-20*** (3.1)	-23*** (4.0)		-5.1* (2.3)		8.5*** (1.7)	7.9*** (1.1)	47.0%
		12^{th}	38*** (2.0)	-26*** (2.9)	-23*** (3.1)				5.3** (1.6)	10*** (1.0)	55.6%
	% of peers passed math test	11^{th}	48*** (2.2)	-23*** (3.1)	-18*** (3.9)		-5.6* (2.3)		7.3*** (1.8)	5.9*** (1.0)	45.1%
		12^{th}	49*** (1.6)	-24*** (2.7)	-16*** (2.5)				2.9* (1.3)	8.4*** (.78)	55.3%

	Dependent Variables	Grade Level	Intercept	SPED	ELL	FARMS	Latino	White/ Asian	Pass Test	GPA	R Squared
School 6331[65]	% of peers passed English test	11th	21*** (4.5)	-31*** (3.2)	—		—	—	4.9’ (3.0)	11*** (1.9)	52.7%
		12th	38*** (4.0)	-26*** (3.3)	—			—		8.4*** (1.7)	48.3%
	% of peers passed math test	11th	31*** (4.6)	-30*** (3.4)	—		—	—	5.9* (2.6)	10*** (1.7)	52.2%
		12th	47*** (3.7)	-43*** (4.9)	—			—	5.5* (2.6)	8.4*** (1.7)	68.3%
School 18310	% of peers passed English test	11th	27*** (2.9)	-23*** (3.5)	-16*** (2.3)				5.5** (1.8)	9.1*** (1.2)	42.7%
		12th	34*** (2.6)	-33*** (4.5)	-15*** (3.6)				6.6** (2.2)	10*** (1.1)	63.0%
	% of peers passed math test	11th	34*** (2.8)	-24*** (3.5)	-4.4’ (2.6)					9.5*** (1.2)	38.9%
		12th	41*** (2.6)	-37*** (5.4)	-10*** (2.3)				4.4’ (2.4)	9.7*** (1.0)	64.3%
School 12320[66]	% of peers passed English test	11th	19*** (2.4)	-23*** (3.4)	—			—	5.7** (1.9)	10*** (1.1)	47.7%
		12th	19*** (2.5)	-36*** (3.1)	—			10*** (2.9)	6.0** (1.7)	14*** (1.2)	64.6%
	% of peers passed math test	11th	21*** (2.5)	-25*** (3.4)	—			—	9.4*** (2.0)	10*** (1.1)	53.5%
		12th	28*** (2.2)	-36*** (2.7)	—			11*** (1.3)	4.1** (1.5)	13*** (1.0)	66.1%

[65] Student race is removed from the model for this school because the model does not converge and the school is mostly comprised of African American students.
[66] Student race is removed from the model for this school because the model does not converge and the school is mostly comprised of African American students.

	Dependent Variables	Grade Level	Intercept	SPED	ELL	FARMS	Latino	White/ Asian	Pass Test	GPA	R Squared
School 18306[67]	% of peers passed English test	11th	19*** (2.3)	-23*** (3.5)	—		6.3* (3.1)			12*** (1.3)	56.5%
		12th	28*** (3.0)	-16*** (2.8)	—			-13*** (1.7)	5.2** (2.0)	10*** (1.4)	44.6%
	% of peers passed math test	11th	19*** (2.7)	-25*** (3.4)	—		9.0* (3.7)		7.7** (2.2)	15*** (1.2)	64.7%
		12th	28*** (2.9)	-20*** (3.1)	—			—	4.8* (2.1)	11*** (1.4)	51.3%
School 1302	% of peers passed English test	11th	36*** (2.3)	-26*** (2.9)	-31*** (2.0)			4.9* (2.3)	6.9*** (1.6)	7.8*** (.88)	60.5%
		12th	44*** (2.4)	-32*** (3.3)	-25*** (2.0)		-2.8* (1.4)		8.2*** (1.7)	9.2*** (.90)	64.8%
	% of peers passed math test	11th	47*** (2.1)	-26*** (3.0)	-20*** (1.8)				6.0*** (1.5)	6.3*** (.79)	54.6%
		12th	54*** (1.9)	-30*** (3.1)	-16*** (1.3)		-2.8* (1.1)		4.6** (1.5)	8.4*** (.86)	62.7%
School 19309	% of peers passed English test	11th	31*** (2.1)	-22*** (3.3)	-32*** (2.6)			6.4* (2.6)	9.0*** (1.7)	9.9*** (1.0)	57.0%
		12th	43*** (2.3)	-18*** (3.7)	-31*** (3.6)				3.3* (1.5)	9.8*** (.95)	51.6%
	% of peers passed math test	11th	40*** (1.8)	-28*** (3.1)	-24*** (2.1)			6.5** (2.0)	6.7*** (1.4)	9.0*** (.81)	58.7%
		12th	53*** (1.9)	-22*** (3.8)	-24*** (3.1)				3.2* (1.4)	7.7*** (.84)	51.0%

[67] Student race is removed from the model for this school because the model does not converge and the school is mostly comprised of African American students.

	Dependent Variables	**Grade Level**	**Intercept**	**SPED**	**ELL**	**FARMS**	**Latino**	**White/ Asian**	**Pass Test**	**GPA**	**R Squared**
School 17308	% of peers passed English test	11^{th}	39*** (2.0)	-18*** (3.0)	-27*** (1.8)				12*** (1.6)	5.9*** (1.0)	51.0%
		12^{th}	43*** (1.9)		-27*** (2.1)				4.8*** (1.3)	10*** (.82)	48.7%
	% of peers passed math test	11^{th}	43*** (2.0)	-23*** (3.0)	-19*** (1.6)				11*** (1.4)	5.7*** (.88)	48.1%
		12^{th}	49*** (1.6)	-7.3** (2.4)	-18*** (1.5)		-1.8’ (1.0)		3.7** (1.1)	9.1*** (.71)	43.8%
School 2308	% of peers passed English test	11^{th}	22*** (2.6)	-18*** (3.1)	-21*** (2.7)		-3.4’ (2.0)		9.1*** (2.0)	8.9*** (1.1)	51.9%
		12^{th}	26*** (2.5)	-23*** (3.1)	-23*** (2.6)		-4.1** (1.5)		6.2*** (1.5)	11*** (1.1)	53.9%
	% of peers passed math test	11^{th}	37*** (2.6)	-25*** (3.7)	-18*** (2.7)				11*** (2.0)	8.3*** (1.1)	51.8%
		12^{th}	45*** (2.3)	-23*** (3.7)	-14*** (2.0)		-4.0** (1.3)		4.8** (1.5)	9.2*** (.97)	50.0%

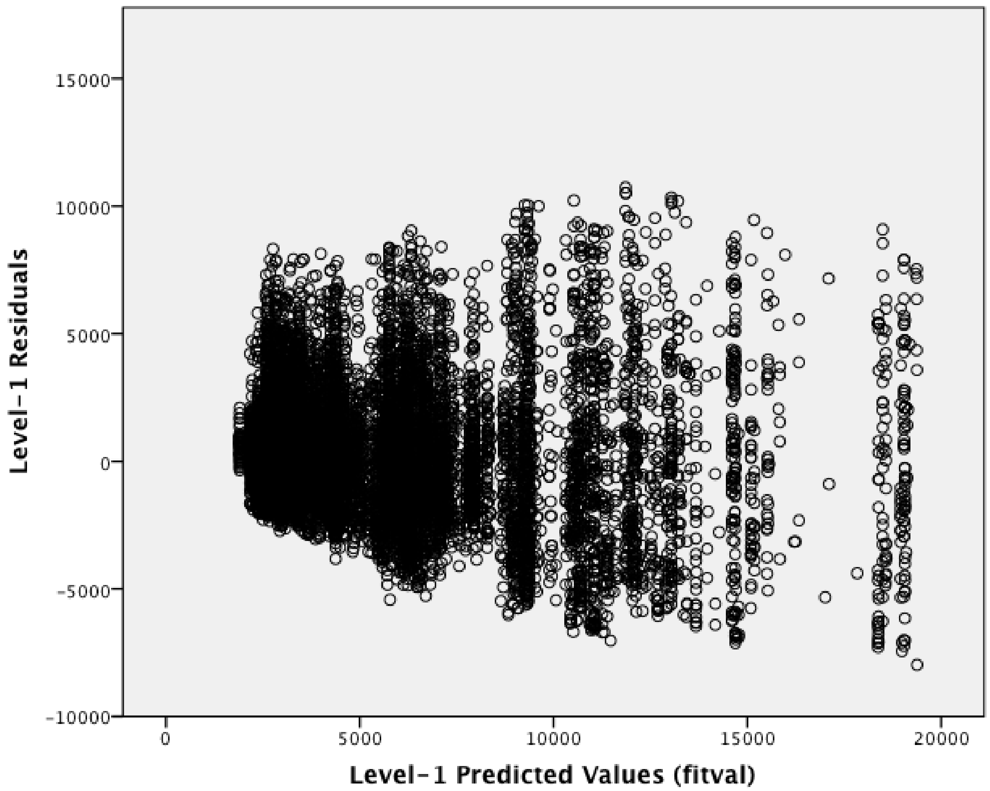
Appendix IV: Model Assumptions and Fit

This appendix provides evidence that model assumptions are mostly met and that model fit is adequate for all models employed in this study. This appendix first addresses the model assumptions for the multilevel models. Second, it addresses the model assumptions for the multiple linear regression models. Third, it addresses the model assumptions for the binary logistic regression models. Finally, it addresses the model assumptions for the Poisson regression model. In highlighting potential violations of model assumptions, this appendix also provides technical limitations to this study.

Multilevel Models (MLMs). MLMs require a number of assumptions to be met: (a) Level-1 residuals are independently and normally distributed with a mean of 0 and a constant variance within each school; (b) level-1 predictors are independent of the level-1 residuals; (c) level-2 random error vectors are independent among the level-2 units and are multivariately normally distributed with a mean of 0 and constant variances and covariances; (d) level-2 predictor variables and residuals are independent of one another; (e) level-1 and level-2 residuals are independent of one another; (f) level-1 predictor variables are not correlated with level-2 residuals, and level-2 predictor variables are not correlated with level-1 residuals (Raudenbush & Bryk, 2002; Snijders & Bosker, 2012).

Most of the MLM assumptions appear to have been met for both the models with TRE and TRE_CA as the outcome variables. However, two assumptions appear to have been violated. First, there appears to be slight deviations from homogeneity of variance within each school. In other words, the variation in the level-1 residuals appears to differ across schools, as seen in the following Figure 6.

Figure 8: Evidence of Non-Constant Variance of Level-1 Residuals Across Schools Part I



In addition, the non-constant variance of the level-1 residuals across schools appears to be at least partially due to the atypically large variation of level-1 residuals in two schools (see Figure 7). However, even with the exclusion of these two outlier schools, there is still some variation in level-1 residuals across schools. I attempted to model the heterogeneity of variance of level-1 residuals across schools, and no available variables statistically significantly improved the heterogeneity of variance. Finally, special education status appears to be related to level-1 residuals (see Figure 8), and there is more variation in level-1 residuals for special education students than for non-special education students.

Figure 9: Evidence of Non-Constant Variance of Level-1 Residuals Across Schools Part II

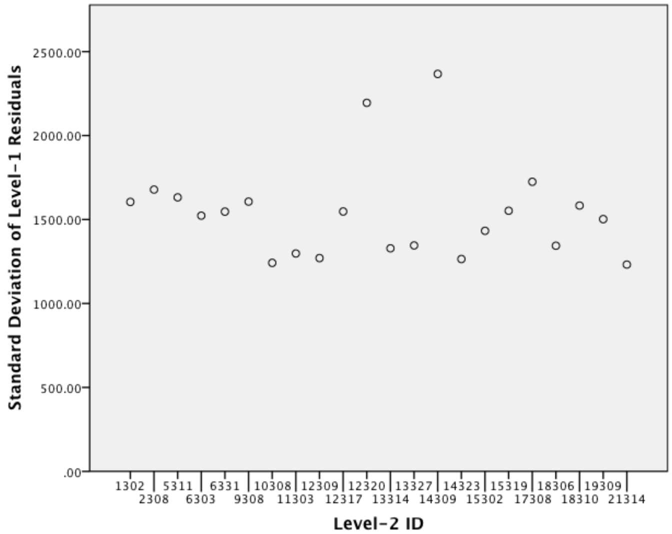
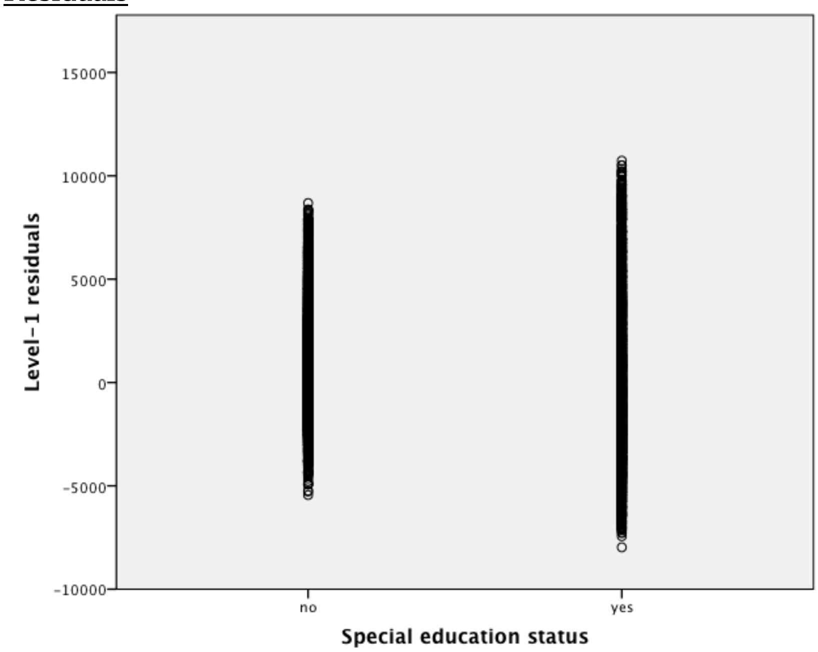


Figure 10: Evidence of Relationship Between Special Education Status and Level-1 Residuals



Given the violations of these three assumptions, it may be the case that the level-1 and level-2 models are mis-specified and that relevant variables that predict per-pupil TREs are missing from the models. In conclusion, MLM results should be interpreted with caution, and these assumption violations should be considered when generalizing results.

Regression models with continuous dependent variables. For each school, multiple linear regression (MLR) models are employed to evaluate the equity of the allocation of per-pupil TREs, core-academic TREs per pupil, and both class sizes and peer achievement in students' English and math classes. MLR models assume that the residuals of the model are independently and normally distributed and that the variance of the residuals does not depend on the values of the independent variables. For the models that gauge the equity of the allocation of per-pupil TREs and core-academic TREs per pupil, scatterplots of the predicted values v. the residuals demonstrated that the assumptions of homogeneity of variance and independence of observations were met. However, when examining histograms of the residuals for these models, it appeared that some deviations from normality existed. For this reason, the models were estimated with standard errors that are robust to non-normality. Hence, the standard errors are unbiased despite the potential violation of the assumption that the residuals are normally distributed. For the models with class sizes and peer achievement as the outcome variables, all MLR assumptions appear to have been met.

Regression models with binary dependent variables. To gauge model fit for the models that predicted binary dependent variables–new English teacher flag and new math teacher flag–R squared values of the models were examined because R squared values are one indicator of model utility. For models with R squared values that were less than 0.10, noted in Table 54, the results from these models were excluded from the study's findings. No other model fit indices were available for these models in M*plus*.

Table 54: Models With Binary Outcome Variables and Low R Squared Values

School	Dependent Variable	R Squared
School 15302	New Math Teacher Flag	6.5%
School 15319	New English Teacher Flag	2.5%
School 21314	New English Teacher Flag	2.5%
School 13327	New Math Teacher Flag	6.8%
School 6303	New Math Teacher Flag	6.7%

Regression models with a count dependent variable. For the model with the count dependent variable–the number of AP courses–Mplus only provides Akaike Information Criteria (AIC) values, which indicate relative model fit and are most appropriate for comparing two or more models. However, no AIC value appears unusually large, and these AIC values are provided in Table 55.

Table 55: AIC Values for Models With AP as the Outcome Variable

School	AIC
14323	2340
11303	802
15302	398
9308	884
15319	1325
21314	2849
5311	981
12309	1577
13327	1450
13314	710
10308	1016
6303	878
12317	1154
14309	1001
6331	384
18310	480
12320	590
18306	406
1302	1363
19309	1130
17308	1567
2308	1221

Dependent variable: AP

References

Abbott v. Burke, No. 710 A.2d 450 (Supreme Court of New Jersey 1994).

Archibald, S. (2006). Narrowing in on Educational Resources that Do Affect Student Achievement. *Peabody Journal of Education*, *81*(4), 23–42.

Baird, K. (2008). Federal Direct Expenditures and School Funding Disparities, 1990-2000. *Journal of Education Finance*, *33*(3), 297–310.

Baker, B. (2001). Balancing Equity for Students and Taxpayers: Evaluating School Finance Reform in Vermont. *Journal of Education Finance*, *26*(4), 437–462.

Baker, B. (2012). Rearranging Deck Chairs in Dallas: Contextual Constraints and Within-District Resource Allocation in Urban Texas School Districts. *Journal of Education Finance*, *37*(3), 287–315.

Baker, B., & Duncombe, W. (2004). Balancing District Needs and Student Needs: The Role of Economies of Scale Adjustments and Pupil Need Weights in School Finance Formulas. *Journal of Education Finance*, *29*(3), 195–221.

Baker, B., & Green, P. (2008). Conceptions of Equity and Adequacy in School Finance. In *Handbook of Research in Education Finance and Policy* (pp. 203–221). New York, NY: Routledge.

Barnes, G., Crowe, E., & Schaefer, B. (2007). *The Cost of Teacher Turnover in Five School Districts*. National Commission on Teaching and America's Future.

Bastian, K., Henry, G., & Thompson, C. (2013). Incorporating Access To More Effective Teachers Into Assessments Of Educational Resource Equity. *Education Finance and Policy*, *8*(4), 560–580.

Belfield, C., & Levin, H. (2013). The Cumulative Costs of the Opportunity Gap. In *Closing the Opportunity Gap* (pp. 195–206). New York, NY: Oxford University Press.

Berne, R., & Stiefel, L. (1984). *The Measurement of Equity in School Finance*. Baltimore, MD: Johns Hopkins University Press.

Berne, R., & Stiefel, L. (1994). Measuring Equity at the School Level: The Finance Perspective. *Educational Evaluation and Policy Analysis*, *16*(4), 405–421.

Bickel, R. (2007). *Multilevel Analysis for Applied Research: It's Just Regression!* New York, NY: The Guilford Press.

Bifulco, R. (2005). District-Level Black-White Funding Disparities in the United States, 1987-2002. *Journal of Education Finance*, *31*(2), 172–194.

Boozer, M., & Rouse, C. (1995). *Intraschool Variation in Class Size: Patterns and Implications* (No. 5144) (pp. 1–30). Cambridge, MA: National Bureau of Economic Research.

Borman, G., & Dowling, M. (2010). Schools and Inequality: A Multilevel Analysis of Coleman's Equality of Educational Opportunity Data. *Teachers College Record*, *112*(5), 1201–1246.

Boucher, V., Bramoulle, Y., Djebbari, H., & Fortin, B. (2010). *Do Peers Affect Student Achievement? Evidence from Canada Using Group Size Variation*. Bonn, Germany: Institute for the Study of Labor (IZA).

Boyd, D., Lankford, H., Loeb, S., Rockoff, J., & Wyckoff, J. (2007). *The Narrowing Gap in New York City Teacher Qualifications and Its Implications for Student Achievement in High-Poverty Schools* (Working Paper No. 10). Washington, D.C.: Center for Analysis of Longitudinal Data in Education Research.

Boyd, D., Lankford, H., Loeb, S., & Wyckoff, J. (2005, May). Explaining the Short Careers of High-Achieving Teachers in Schools with Low-Performing Students. American Economic Association. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=ehh&AN=18617407&site=ehost-live

Brent, C., Roellke, C., & Monk, D. (1997). Understanding Teacher Resource Allocation in New York State Secondary Schools: A Case Study Approach. *Journal of Education Finance*, *23*(2), 207–233.

Brewer, D., & McEwan, P. (Eds.). (2010). *Economics of Education*. San Diego, CA: Elsevier Ltd.

Brigham v. State, No. 692 A.2d 384 (Supreme Court of Vermont 1997).

Brown v. Board of Education of Topeka, No. 347 U.S. 483 (Supreme Court of the United States 1954).

Buckley, L. (2010). Unfulfilled hopes in education for equity: redesigning the mathematics curriculum in a US high school. *Curriculum Studies*, *42*(1), 51–78.

Bundt, J., & Leland, S. (2001). Wealthy or Poor: Who Receives and Who Pays? A Closer Look at Measures of Equity in Iowa School Finance. *Journal of Education Finance*, *26*(4), 397–413.

Burke, M., & Sass, T. (2008). *Classroom peer effects and student achievement* (Working Paper No. 18). Washington, D.C.: National Center for Analysis of Longitudinal Data in Education Research.

Burke, S., & White, G. (2001). The influence of district characteristics on intra district resource allocation. *Journal of Education Finance*, *26*(3), 259–280.

Caldas, S., & Bankston, C. (1997). Effect of School Population Socioeconomic Status on Individual Academic Achievement. *The Journal of Educational Research*, *90*(5), 269–277.

Card, D., & Krueger, A. (1998). School Resources and Student Outcomes. *Annals of the American Academy of Political and Social Science*, *559*, 39–53.

Carey, K. (2002). *State Poverty-Based Education Funding: A Survey of Current Programs and Options for Improvement*. Washington, D.C.: Center on Budget and Policy Priorities.

Carter, P. (2013). Student and School Cultures and the Opportunity Gap. In *Closing the Opportunity Gap* (pp. 143–155). New York, NY: Oxford University Press.

Carter, P., & Welner, K. (2013). Building Opportunities to Achieve. In *Closing the Opportunity Gap* (pp. 217–227). New York, NY: Oxford University Press.

Chambers, J. (1999). *Measuring Resources in Education: From Accounting to the Resource Cost Model Approach* (Working Paper No. NCES-WP-19-16). American Institutes for Research.

Clotfelter, C., Ladd, H., & Vigdor, J. (2003). Segregation and Resegregation in North Carolina's Public School Classrooms. *North Carolina Law Review*, *81*, 1463–1512.

Clotfelter, C., Ladd, H., & Vigdor, J. (2005). Who teaches whom? Race and the distribution of novice teachers. *Economics of Education Review*, *24*, 377–392.

Clotfelter, C., Ladd, H., & Vigdor, J. (2006). Teacher-Student Matching and the Assessment of Teacher Effectiveness. *Journal of Human Resources*, *41*(4), 778–820.

Clotfelter, C., Ladd, H., & Vigdor, J. (2007). *How and Why do Teacher Credentials Matter for Student Achievement?* Cambridge, MA: National Bureau of Economic Research.

Clotfelter, C., Ladd, H., Vigdor, J., & Wheeler, J. (2007). *High Poverty Schools and the Distribution of Teachers and Principals* (CALDER Working Paper No. 1). Washington, D.C.: Urban Institute.

Cohen, J., Cohen, P., West, S., & Aiken, L. (2003). *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences* (Third.). New Jersey: Lawrence Erlbaum Associates, Inc.

Condron, D., & Roscigno, V. (2003). Disparities Within: Unequal Spending and Achievement in an Urban School District. *Sociology of Education*, *76*(January), 18–36.

Conger, D. (2005). Within-School Segregation in an Urban School District. *Educational Evaluation and Policy Analysis*, *27*(3), 225–244.

Corcoran, S., Evans, W., Godwin, J., Murray, S., & Schwab, R. (2003). *The Changing Distribution of Education Finance: 1972 -1997*. New York, NY: Russell Sage Foundation.

Darling-Hammond, L. (2007). Third Annual Brown Lecture in Education Research: The Flat Earth and Education: How America's Commitment to Equity Will Determine Our Future. *Educational Researcher*, *36*(6), 318–334.

Deke, J. (2003). A study of the impact of public school spending on postsecondary educational attainment using statewide school district refinancing in Kansas. *Economics of Education Review*, *22*, 275–284.

Demeuse, M., Crahay, M., & Monseur, C. (2001). Efficiency and Equity. In *In Pursuit of Equity in Education* (pp. 66–91). Dordrecht, The Netherlands: Kluwer Academic Publishers.

Donaldson, M. (2013). Principals' Approaches to Cultivating Teacher Effectiveness: Constraints and Opportunities in Hiring, Assigning, Evaluation, and Developing Teachers. *Educational Administration Quarterly*, *49*(5), 838–882.

Driscoll, L., & Salmon, R. (2008). How Increased State Equalization Aid Resulted in Greater Disparities: An Unexpected Consequence for the Commonwealth of Virginia. *Journal of Education Finance*, *33*(3), 238–261.

Duncombe, W., & Yinger, J. (2004). *How Much More Does a Disadvantaged Student Cost?* (No. 60). Syracuse, NY: Center for Policy Research.

Education Week. (2005). Quality Counts 2005: No Small Change: Targeting Money Toward Student Performance. *Education Week*, *24*(17).

Elliott, M. (1998). School Finance and Opportunities to Learn: Does Money Well Spent Enhance Students' Achievement? *Sociology of Education*, *71*(July), 223–245.

Enders, C. (2001). A Primer on Maximum Likelihood Algorithms Available for Use With Missing Data. *Structural Equation Modeling*, *8*(1), 128–141.

Enders, C., & Tofighi, D. (2007). Centering Predictor Variables in Cross-Sectional Multilevel Models: A New Look at an Old Issue. *Psychological Methods*, *12*(2), 121–138.

Ewijk, R., & Sleegers, P. (2010). The effect of peer socioeconomic status on student achievement: A meta-analysis. *Educational Research Review*, *5*(2), 134–150.

Feng, L. (2010). Hire Today, Gone Tomorrow: New Teacher Classroom Assignments and Teacher Mobility. *Education Finance and Policy*, 278–316.

Feng, L., & Sass, T. (2011). *Teacher Quality and Teacher Mobility* (Working Paper No. 57). Washington, D.C.: National Center for Analysis of Longitudinal Data in Education Research, The Urban Institute.

Ferguson, R., & Ladd, H. (1996). How and Why Money Matters: An Analysis of Alabama Schools. In *Holding Schools Accountable: Performance-based reform in education* (pp. 265–298). Brookings Institution.

Figlio, D. (1999). Functional form and the estimated effects of school resources. *Economics of Education Review*, *18*, 241–252.

Figlio, D. (2005). *Boys Named Sue: Disruptive Children and Their Peers* (Working Paper No. 11277). Cambridge, MA: National Bureau of Economic Research.

Fortune, J., & O'Neil, J. (1994). Production Function Analyses and the Study of Educational Funding Equity: A Methodological Critique. *Journal of Education Finance*, *20*(1), 21–46.

Friedman, B., & Solow, S. (2013). The Federal Right to an Adequate Education. *The George Washington Law Review*, *81*(92), 92–156.

Gamoran, A. (1987). The Stratification of High School Learning Opportunities. *Sociology of Education*, *60*(3), 135–155.

Goertz, M., & Stiefel, L. (1998). School-Level Resource Allocation in Urban Public Schools: Introduction. *Journal of Education Finance*, *23*(4), 435–446.

Goldhaber, D. (2009). *Teacher Quality and Value-added Measurement*. Seattle, WA: Center on Reinventing Public Education.

Goldhaber, D. (2009, April 28). *Teacher Quality and Value-added Measurement*. Presented at the TQ Center and REL Midwest Technical Assistance Workshop, University of Washington.

Goldhaber, D., & Brewer, D. (1997a). *Evaluating the Effect of Teacher Degree Level on Educational Performance* (Proceedings/Conference Report No. 97535) (pp. 199–210). Washington, D.C.: National Center for Education Statistics.

Goldhaber, D., & Brewer, D. (1997b). Why Don't Schools and Teachers Seem to Matter? Assessing the Impact of Unobservables on Educational Productivity. *Journal of Human Resources, 32*(3), 505–523.

Greene, K., Huerta, L., & Richards, C. (2007). Getting Real: A Different Perspective on the Relationship Between School Resources and Student Outcomes. *Journal of Education Finance*, *33*(1), 49–68.

Grubb, N. (2006). When money might matter: Using NELS88 to examine the weak effects of school finance. *Journal of Education Finance*, *31*(4), 360–378.

Hanushek, E. (1981). Throwing Money at Schools. *Journal of Policy Analysis and Management*, *1*(1), 19–41.

Hanushek, E. (1992). The Trade-off between Child Quantity and Quality. *Journal of Political Economy*, *100*(1), 84–117.

Hanushek, E. (2006, April 26). Money Matters: An Interview with Eric Hanushek. Retrieved from http://www.educationsector.org/publications/money-matters

Hanushek, E., Kain, J., Markman, J., & Rivkin, S. (2003). Does Peer Ability Affect Student Achievement? *Journal of Applied Econometrics*, *18,* 527–544.

Hanushek, E., Kain, J., & Rivkin, S. (2004). Why Public Schools Lose Teachers. *Journal of Human Resources*, *39*(2), 326–354. doi:Article

Hanushek, E., & Rivkin, S. (2006). Teacher Quality. In E. Hanushek & F. Welch (Eds.), *Handbook of the Economics of Education* (Vol. 2). Elsevier.

Hanushek, E., & Woessmann, L. (2006). *Does Educational Tracking Affect Performance and Inequality? Differences-in-Differences Evidence across Countries* (NBER Working Paper No. 11124). Cambridge, MA: National Bureau of Economic Research.

Harris, D. (2006). *Lost Learning, Forgotten Promises*. Washington, D.C.: Center for American Progress.

Hartman, W. (1999). Education funding disparities: What do the dollars buy? *Journal of Education Finance*, *24*(3), 389–408.

Hawley, W., & Wolf, R. (2012). Diversity-Responsive Schools. In J. Banks (Ed.), *Encyclopedia of Diversity in Education*. Thousand Oaks, CA: Sage Publications, Inc.

Hedges, L., Laine, R., & Greenwald, R. (1994). An Exchange Part I: Does Money Matter? A Meta-Analysis of Studies of the Effects of Differential School Inputs on Student Outcomes. *Educational Researcher*, *23*(3), 5–14.

Heuer, R., & Stullich, S. (2011). *Comparability of State and Local Expenditures Among Schools Within Districts: A Report From the Study of School-Level Expenditures*. Washington, D.C.: U.S. Department of Education.

Hill, P., & Roza, M. (2008). Financing Schools for Results. *School Business Affairs*, *74*(8).

Hirth, M., & Eiler, E. (2005). Horizontal and Vertical Equity Analysis of Indiana's 2001 Reward-for-Effort Formula. *Journal of Education Finance*, *30*(4), 382–398.

Hogrebe, M., Kyei-Blankson, L., & Zou, L. (2008). Examining Regional Science Attainment and School Teacher Resources Using GIS. *Education and Urban Society*, *40*, 570 – 589.

Holmes, D. (2001). Equality of Educational Opportunity: A Student-Level Analysis of the Distribution of Teacher Resources. Retrieved from ProQuest Dissertations and Theses Database (UMI Number 3001665).

Hoxby, C. (2000). *Peer Effects in the Classroom: Learning from Gender and Race Variation* (No. 7867). Cambridge, MA: The National Bureau of Economic Research.

Huang, Y. (2004). Appendix B: A guide to state operating aid programs for elementary and secondary education. In J. Yinger (Ed.), *Helping children left behind: State aid and the pursuit of educational equity* (pp. 331–351). Cambridge, MA: MIT Press.

Hussar, W., & Sonnenberg, W. (2000). *Trends in Disparities in School District Level Expenditures per Pupil*. Washington, D.C.: National Center for Education Statistics.

Iatarola, P., & Stiefel, L. (2003). Intradistrict equity of public education resources and performance. *Economics of Education Review*, *22*, 69–78.

Ilon, L., & Normore, A. (2006). Relative Cost-Effectiveness of School Resources in Improving Achievement. *Journal of Education Finance*, *31*(3), 238–254.

Ingersoll, R. (1999). The Problem of Underqualified Teachers in American Secondary Schools. *Educational Researcher*, *28*(2), 26–37.

Ingersoll, R. (2001). Teacher Turnover and Teacher Shortages: An Organizational Analysis. *American Educational Research Journal*, *38*(3), 499–534.

Ingersoll, R. (2004). *Why Do High-Poverty Schools Have Difficulty Staffing Their Classrooms with Qualified Teachers?* Center for American Progress and Institute for America's Future.

Institute of Education Sciences. (2013, December 30). National Center for Education Statistics Search for Public Schools. *Institute of Education Sciences National Center for Education Statistics*. Retrieved from http://nces.ed.gov/ccd/schoolsearch/

Jefferson, A. (2005). Student Performance: Is More Money the Answer? *Journal of Education Finance*, *31*(2), 111–124.

Kalogrides, D., & Loeb, S. (2013). Different Teachers, Different Peers: The Magnitude of Student Sorting Within Schools. *Educational Researcher*, *42*(6), 304 – 316.

Kalogrides, D., Loeb, S., & Beteille, T. (2013). Systematic Sorting: Teacher Characteristics and Class Assignments. *Sociology of Education*, *86*(2), 103–123.

Kao, G., & Thompson, J. (2003). Racial and ethnic stratification in educational achievement and attainment. *Annual Review of Sociology*, *29*, 417–442.

Kelly, S. (2004). Are teachers tracked? On what basis and with what consequences. *Social Psychology of Education*, *7*, 55–72.

Kimball, R. (2009). Where does the money go? An analysis of student level resource allocation at the school level (Doctoral dissertation). Retrieved from ProQuest Dissertations and Theses Database (ISBN-978-1-1095-6163-0).

Klein, C. (2008). Intradistrict Public School Funding Equity, Community Resources, and Performance in Nashville, TN. *Journal of Education Finance*, *34*(1), 1–14.

Knoeppel, R., Verstegen, D., & Rinehart, J. (2007). What is the Relationship Between Resources and Student Achievement? A Canonical Analysis. *Journal of Education Finance*, *33*(2), 183–202.

Koedel, C., & Betts, J. (2009). *Does Student Sorting Invalidate Value-Added Models of Teacher Effectiveness?* (Working Paper). Columbia, MO: University of Missouri.

Konstantopoulos, S., & Borman, G. (2011). Family Background and School Effects on Student Achievement: A Multilevel Analysis of the Coleman Data. *Teachers College Record*, *113*(1), 97–132.

Koski, W., & Horng, E. (2007). Facilitating the Teacher Quality Gap? Collective Bargaining Agreements, Teacher Hiring and Transfer Rules, and Teacher Assignment Among Schools in California. *Education Finance and Policy*, 252–300.

Koski, W., & Reich, R. (2006). When “Adequate” Isn’t: The Retreat from Equity in Educational Law and Policy and Why It Matters. *Emory Law Journal*, *56*(3), 545–618.

Krueger, A. (2002). Understanding the Magnitude and Effect of Class Size on Student Achievement. In *The Class Size Debate* (pp. 7–33). Washington, D.C.: Economic Policy Institute.

Ladd, H. (2008). Reflections on Equity, Adequacy, and Weighted Student Funding. *Education Finance and Policy*, *3*(4), 402–423.

Ladd, H., Chalk, R., & Hansen, J. (1999). *Equity and Adequacy in Education Finance: Issues and perspectives*. Washington, D.C.: National Academy Press.

Ladson-Billings, G. (2013). Lack of Achievement or Loss of Opportunity? In *Closing the Opportunity Gap* (pp. 14–22). New York, NY: Oxford University Press.

Lankford, H., Loeb, S., & Wyckoff, J. (2002). Teacher Sorting and the Plight of Urban Schools: A Descriptive Analysis. *Educational Evaluation and Policy Analysis*, *24*(1), 37–62.

Lee, V., Croninger, R., & Smith, J. (1997). Course-Taking, Equity, and Mathematics Learning: Testing the Constrained Curriculum. *Educational Evaluation and Policy Analysis*, *19*(2), 99–121.

Lefgren, L. (2004). Educational Peer Effects and the Chicago Public Schools. *Journal of Urban Economics*, *56*(2), 169–191.

Leithwood, K., Louis, K., Anderson, S., & Wahlstrom, K. (2004). *How Leadership Influences Student Learning* (pp. 1–88). New York, NY: The Wallace Foundation.

Levin, B. (2003). *Approaches to Equity in Policy for Lifelong Learning*. Washington, D.C.: Education and Training Policy Division for the Equity in Education Thematic Review.

Levin, H. (2009). The Economic Payoff to Investing in Educational Justice. *Educational Researcher*, *38*(1), 5–20.

Levin, J. (2001). For whom the reductions count: A quantile regression analysis of class sizes and peer effects on scholastic achievement. *Empirical Economics*, *26*, 221–246.

Liu, G. (2006). Interstate Inequality in Educational Opportunity. *New York University Law Review*, *81*, 2044 – 2128.

Loeb, S., Darling-Hammond, L., & Luczak, J. (2005). How Teaching Conditions Predict Teacher Turnover in California Schools. *Peabody Journal of Education*, *80*(3), 44–70.

Luca, B., Takano, K., Hinshaw, S., & Raisch, D. (2010). Are the "Best" Teachers in the "Neediest" Schools? An Urban Intradistrict Equity Inquiry. *Education and Urban Society*, 1–19.

Lucas, S., & Berends, M. (2007). Race and track location in U.S. public schools. *Research in Social Stratification and Mobility*, *25*, 169–187.

Ludwig, J., & Bassi, L. (1999). The Puzzling Case of School Resources and Student Achievement. *Educational Evaluation and Policy Analysis*, *21*, 385–403.

Madigan, T. (1997). *Science Proficiency and Course Taking in High School* (No. NCES 97-838). Washington, D.C.: U.S. Department of Education, National Center for Education Statistics.

Maiden, J., & Evans, N. (2009). Fiscal Equity of Teacher Salaries and Compensation in Oklahoma. *Journal of Education Finance*, *34*(3), 231–246.

Maryland State Department of Education. (2010). *The Fact Book 2009-2010*. Baltimore, MD: Maryland State Department of Education.

McNeish, D., & Stapleton, L. (2013). The effect of the number of clusters on multilevel model estimates: A review and illustration. Presented at the American Educational Research Association (AERA) Annual Convention, San Francisco, CA.

Mickelson, R. (2005). The incomplete desegregation of the Charlotte-Mecklenburg schools and its consequences, 1971-2004. In B. Boger & G. Orfield (Eds.), *School resegregation: Must the South turn back?* (pp. 87–110). Chapel Hill, NC: University of North Carolina Press.

Miller, L., & Rubenstein, R. (2008). Examining the Nature and Magnitude of Intradistict Resource Disparities in Mid-Size School Districts. *Public Budgeting & Finance*, 26–51.

Miller, R. (2010). *Comparable, Schmomparable Evidence of Inequity in the Allocation of Funds for Teacher Salary Within California's Public School Districts*. Washington, D.C.: Center for American Progress.

Muller, P., Stage, F., & Kinzie, J. (2001). Science Achievement Growth Trajectories: Understanding Factors Related to Gender and Racial-Ethnic Differences in Precollege Science Achievement. *American Educational Research Journal*, *38*(4), 981–1012.

National Center for Education Statistics. (2013). Glossary. *NCES*. Retrieved from http://nces.ed.gov/ccd/bat/glossary.asp?letter=I

National Council on Teacher Quality. (2013). Class Size. *National Council on Teacher Quality*. Retrieved from http://www.nctq.org/districtPolicy/ourApproach/supportingResearch/index.jsp?sectionId=15

National Education Access Network. (2014). Retrieved from http://schoolfunding.info/

Nyhan, R., & Alkadry, M. (1999). The Impact of School Resources on Student Achievement Test Scores. *Journal of Education Finance*, *25*(2), 211–227.

Oakes, J., & Guiton, G. (1995). Matchmaking: The Dynamics of High School Tracking Decisions. *American Educational Research Journal*, *32*(1), 3–33.

Odden, A. (2000). The New School Finance: Providing Adequacy and Improving Equity. *Journal of Education Finance*, *25*(4), 467–487.

Odden, A., & Archibald, S. (2001). *Reallocating Resources*. Thousand Oaks, CA: Corwin Press.

Odden, A., Archibald, S., Fermanich, M., & Gross, B. (2003). Defining School-Level Expenditure Structures That Reflect Educational Strategies. *Journal of Education Finance*, *28*(3), 323–356.

Odden, A., & Borman, G. (2004). Assessing Teacher, Classroom, and School Effects, Including Fiscal Effects. *Peabody Journal of Education*, *79*(4), 4–32.

Odden, A., & Picus, L. (2008). *School Finance* (4th ed.). New York, NY: McGraw-Hill.

Okpala, C. (2002). Educational Resources, Student Demographics and Achievement Scores. *Journal of Education Finance*, *27*(3), 885–907.

Owens, T., & Maiden, J. (1999). A Comparison of Interschool and Interdistrict Funding Equity in Florida. *Journal of Education Finance*, *24*(4), 503–518.

Palardy, G. (2013). High School Socioeconomic Segregation and Student Attainment. *American Educational Research Journal*, *50*(4), 714–754.

Park, J. (2004). More Different Than Alike: State Strategies for Funding Education. *Journal of School Business Officials*, *16*(2), 315–336.

Patacchini, E., Rainone, E., & Zenou, Y. (2011). *Dynamic Aspects of Teenage Friendships and Educational Attainment* (CEPR Discussion Paper No. DP8223). London, England: Centre for Economic Policy Research. Retrieved from http://ssrn.com/abstract=1758432

Perez, M., & Socias, M. (2008). *Highly Successful Schools: What Do They Do Differently And At What Cost?* (pp. 109–129). Columbia, MO: American Education Finance Association.

Picus, L. (2000). Student-level Finance Data: Wave of the Future? *The Clearing House*, *74*(2), 75–80.

Picus, L., McCroskey, J., Robillard, E., Yoo, J., & Marsenich, L. (2002). Using Student Level Data to Measure Finance Adequacy. In *Fiscal Policy in Urban Education*. Greenwich, Connecticut: Information Age Publishing, Inc.

Player, D. (2010). Nonmonetary Compensation in the Public Teacher Labor Market. *Education Finance and Policy*, *5*(1), 82–103.

Raitano, M., & Vona, F. (2013). Peer heterogeneity, school tracking and students' performances: evidence from PISA 2006. *Applied Economics*, *45*(32), 4516–4532.

Raudenbush, S., & Bryk, A. (2002). *Hierarchical Linear Models*. Thousand Oaks, CA: Sage Publications, Inc.

Raudenbush, S., Fotiu, R., & Cheong, Y. (1998). Inequality of Access to Educational Resources: A National Report Card for Eighth-Grade Math. *Educational Evaluation and Policy Analysis*, *20*(4), 253–267.

Rawls, J. (1971). *A Theory of Justice*. Cambridge, MA: Harvard University Press.

Rice, J. (2002). Making the Evidence Matter: Implications of the Class Size Research Debate for Policy Makers. In *The Class Size Debate* (pp. 89–94). Washington, D.C.: Economic Policy Institute.

Rice, J. (2003). *Teacher Quality*. Washington, D.C.: Economic Policy Institute.

Rice, J. (2004). Equity and Efficiency in School Finance Reform: Competing or Complementary Goods. *Peabody Journal of Education*, *79*(2), 134–151.

Rice, J. (2010). *The Impact of Teacher Experience* (No. 11). Washington, D.C.: National Center for Analysis of Longitudinal Data in Education Research, The Urban Institute.

Rice, J., Monk, D., & Zhang, J. (2010). School Finance: An Overview. In *Economics of Education*. San Diego, CA: Elsevier Ltd.

Rice, J., & Schwartz, A. (Eds.). (2008). Making Money Matter. In *Handbook of Research in Education Finance and Policy* (pp. 131 – 183). New York, NY: Routledge.

Rivkin, S., Hanushek, E., & Kain, J. (2005). Teachers, Schools, and Academic Achievement. *Econometrica*, *73*(2), 417–458.

Robillard, E. (2001). The collection and use of student-level resource data in K-12 education (Doctoral dissertation). Retrieved from ProQuest Dissertations and Theses Database (UMI Number 3027769).

Rodriguez, G. (2004). Vertical Equity in School Finance and the Potential for Increasing School Responsiveness to Student and Staff Needs. *Peabody Journal of Education*, *79*(3), 7–30.

Rolle, A., & Liu, K. (2007). An Empirical Analysis of Horizontal and Vertical Equity in the Public Schools of Tennessee, 1994-2003. *Journal of Education Finance*, *32*(3), 328–351.

Rothstein, J. (2008). *Teacher Quality in Educational Production: Tracking, Decay, and Student Achievement* (Working Paper No. 14442). Cambridge, MA: National Bureau of Economic Research.

Rothstein, R. (2013). Why Children From Lower Socioeconomic Classes, on Average, Have Lower Academic Achievement Than Middle-Class Children. In P. Carter & K. Welner (Eds.), *Closing the Opportunity Gap* (pp. 61–74). New York, NY: Oxford University Press.

Roy, J. (2011). *Impact of School Finance Reform on Resource Equalization and Academic Performance: Evidence from Michigan* (pp. 137–167). Columbia, MO: Association for Education Finance and Policy.

Roza, M. (2005). Apples-to-Apples Fiscal Comparisons. In *Hopes, Fears, & Reality: A Balanced Look at American Charter Schools in 2005*. Seattle, WA: University of Washington.

Roza, M. (2008). *Allocation Anatomy: How District Policies That Deploy Resources Can Support (Or Undermine) District Reform Strategies.* Seattle, WA: Center on Reinventing Public Education.

Roza, M. (2009). Breaking Down School Budgets. *Education Next*, 29–33.

Roza, M. (2010). *Educational Economics: Where Do School Funds Go*. Washington, D.C.: The Urban Institute Press.

Roza, M., Guin, K., & Davis, T. (2008). *What is the Sum of the Parts?* Seattle, WA: Center on Reinventing Public Education.

Roza, M., Hill, P., Sclafani, S., & Speakman, S. (2004). How Within-District Spending Inequities Help Some Schools to Fail. *Brookings Papers on Education Policy*, *7*, 201–227.

Roza, M., & Miles, K. (2002). *Moving toward Equity in School Funding within Districts: A Comparison of Traditional Funding Policies and More Equitable Formulas*. Providence, RI: Brown University.

Rubenstein, R. (1998). Resource Equity in the Chicago Public Schools: A School-Level Approach. *Journal of Education Finance*, *23*(4), 468–489.

Rubenstein, R., Doering, D., & Gess, L. (2000). The Equity of Public Education Funding in Georgia, 1988-1996. *Journal of Education Finance*, *26*(2), 187–208.

Rubenstein, R., Schwartz, A., Stiefel, L., & Amor, H. (2007). From districts to schools: The distribution of resources across schools in big city school districts. *Economics of Education Review*, *26*, 532–545.

San Antonio Independent School District v. Rodriguez, No. 411 U.S. 1 (Supreme Court of the United States 1973).

Scafidi, B., Sjoquist, D. L., & Stinebrickner, T. R. (2007). Race, Poverty, and Teacher Mobility. *Economics of Education Review*, *26*(2), 145–159.

Serrano v. Priest, No. 18 Cal.3d 728 (Supreme Court of California 1976).

Slavin, R. (1999). How Can Funding Equity Ensure Enhanced Achievement? *Journal of Education Finance*, *24*(4), 519–528.

Snijders, T., & Bosker, R. (2012). *Multilevel Analysis* (2nd ed.). Thousand Oaks, CA: Sage Publications, Inc.

Southworth, S. (2010). Examining the Effects of School Composition on North Carolina Student Achievement Over Time. *Educational Policy Analysis Archives, 18*(29), 1–45.

Spatig-Amerikaner, A. (2012). *Unequal Education: Federal Loophole Enables Lower Spending on Students of Color*. Washington, D.C.: Center for American Progress.

Speakman, S., Cooper, B., Holsomback, H., May, J., Sampieri, R., & Maloney, L. (1997). The Three Rs of Education Finance Reform: Re-Thinking, Re-Tooling, and Re-Evaluating School-Site Information. *Journal of Education Finance*, *22*(4), 337–367.

Springer, M., Houck, E., & Guthrie, J. (2008). History and Scholarship Regarding United States Education Finance and Policy. In *Handbook of Research in Education Finance and Policy* (pp. 3–22). New York, NY: Routledge.

Stiefel, L., Rubenstein, R., & Berne, R. (1998). Intra-District Equity in Four Large Cities: Data, Methods, and Results. *Journal of Education Finance*, *23*(4), 447–467.

Stiefel, L., Schwartz, A., Portas, C., & Kim, D. (2003). School Budgeting and School Performance: The Impact of New York City's Performance Driven Budget Initiative. *Journal of Education Finance*, *28*(3), 403–424.

Talbert, J., & Ennis, M. (1990). *Teacher Tracking: Exacerbating Inequalities in the High School*. Stanford, CA: Center for Research on the Context of Teaching, Stanford University.

Taylor, L. (2006). Comparable Wages, Inflation, and School Finance Equity. *Education Finance and Policy*, 349–371.

Taylor, L., Alexander, C., Gronberg, T., Jansen, D., & Keller, H. (2002). Updating the Texas Cost of Education Index. *Journal of Education Finance*, *28*(2), 261–284.

The Education Trust. (2008). *Their Fair Share: How Texas-Sized Gaps in Teacher Quality Shortchange Low-Income and Minority Students*. Washington, D.C.: The Education Trust.

Theobald, N., & Gritz, M. (1996). Allocating Resources to Influence Teacher Retention. In *Where Does the Money Go?* (pp. 132–155). Thousand Oaks, CA: Corwin Press, Inc.

Timar, T. (1994). Politics, Policy, and Categorical Aid: New Inequities in California School Finance. *Educational Evaluation and Policy Analysis*, *16*(2), 143–160.

Toutkoushian, R., & Michael, R. (2007). An Alternative Approach to Measuring Horizontal and Vertical Equity in School Funding. *Journal of Education Finance*, *32*(4), 395–421.

Toutkoushian, R., & Michael, R. (2008). The Impacts of School Funding Formula Modifications on Equity, Fiscal Neutrality, and Adequacy. *Journal of Education Finance*, *33*(4), 352–380.

Tyson, K. (2013). Tracking, Segregation, and the Opportunity Gap. In *Closing the Opportunity Gap* (pp. 169–180). New York, NY: Oxford University Press.

U.S. Department of Education. (2010). *Race to the Top Program Guidance and Frequently Asked Questions*. Washington, D.C.: U.S. Department of Education.

Verstegen, D. (2002). Financing the New Adequacy: Towards New Models of State Education Finance Systems That Support Standards Based Reform. *Journal of Education Finance*, *27*(3), 749–781.

Verstegen, D. (2011). *A Quick Glance at School Finance: A 50 State Survey of School Finance Policies*. Reno, NV. Retrieved from http://schoolfinancesdav.wordpress.com/

Verstegen, D., & King, R. (1998). The Relationship Between School Spending and Student Achievement: A Review and Analysis of 35 Years of Production Function Research. *Journal of Education Finance*, *24*, 243–262.

Wayne, A., & Youngs, P. (2003). Teacher Characteristics and Student Achievement Gains: A Review. *Review of Educational Research*, *73*(1), 89–122.

Welner, K., & Carter, P. (2013). Achievement Gaps Arise from Opportunity Gaps. In *Closing the Opportunity Gap* (pp. 1–10). New York, NY: Oxford University Press.

Wenglinsky, H. (1998). Finance Equalization and Within-School Equity: The Relationship Between Education Spending and the Social Distribution of Achievement. *Educational Evaluation and Policy Analysis*, *20*(4), 269–283.

Wilson, K., Lambright, K., & Smeeding, T. (2006). School Finance, Equivalent Educational Expenditure, and the Income Distribution: Equal Dollars or Equal Chances for Success? *Education Finance and Policy*, 396–424.

Young, G. (2003). An analysis of per pupil resource allocation at an urban elementary school (Doctoral dissertation). Retrieved from ProQuest Dissertations and Theses Database (UMI Number 3116809).