EXPLORING SCHOOL SEQUENCES AS A NEW UNIT OF ANALYSIS FOR INTRADISTRICT SCHOOL FINANCE EQUITY STUDIES

By

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For Allison:

She opens her mouth with wisdom,
and the teaching of kindness is on her tongue.

Her children rise up and call her blessed;
her husband also, and he praises her:

"Many women have done excellently,
but you surpass them all."

- Proverbs 31:26, 27-29

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CHAPTER I

INTRODUCTION

Increasing interest in school-level productivity - brought on my *No Child Left Behind* as well as technological changes that make micro-level data collection more efficient and cost effective - has resulted in a related interest in school-level finance equity. Termed *intradistrict equity*, this research field has been dominated by methods adapted from interdistrict and intrastate equity studiers. This dissertation proposes a new unit of analysis for intradistrict school finance equity studies – student sequences of schools attended. It further adopts a new method in assessing equity within the intradistrict context – quantile regression. Through a series of steps, this dissertation examines whether sequence-based intradistrict equity analysis provide additional insight into intradistrict equity than those that arise from school-based analysis. Additionally, this dissertation assesses the use of quantile regression as a tool for examining equity within the intradistrict context.

This introductory section addresses the characteristics of intradistrict finance analysis compared to interdistrict and interstate school finance analyses. It specifies the research questions, and reviews methods and techniques for answering those questions. Finally, this section provides an overview of the organization of this dissertation. Taken together, these sections of the introduction present a rationale for analysis of intradistrict school finance equity via school sequences.

Purpose of the Research

This research examines the use of school sequences as units of analysis when conducting intradistrict resource equity analysis. Understanding the role of sequences is aided by an understanding of the larger enterprise of intradistrict school finance studies. The following section describes intradistrict finance before describing the contribution that a sequence-based analysis will make to the field.

*Intra*district resource studies examine the distribution of resources across schools within a district. This type of study is different from *inter*district or *inter*state school finance studies. Interdistrict and interstate finance studies assume variation in property wealth and effort as reflected in assessments and tax rates (Berne and Stiefel, 1984). Interdistrict analysis examines the relationship between a district's wealth, ability to pay, and levels of funding to determine if property poor districts, for example, are receiving funding to compensate for their poverty. Evaluation of interdistrict and interstate analysis is based upon a concept – formulated in California's *Serrano v. Priest* case – that has become know as school finance's proposition number one: "The quality of a child's schooling should not be a function of wealth, other than the wealth of the state as a whole." (*Serrano v. Priest*, 1971; Guthrie, et al., 2006). These studies further assume that students are allocated into schools by market forces such as Tiebout sorting (Tiebout, 1956; see also Bayer, Ferreira, and McMillan, 2004), and not through direct state intervention.

The intradistrict context, however, is different. There is no variation in tax effort or valuation, since taxation occurs at the district level. Instead of analysis between wealth and spending, intradistrict analysis focuses more directly on relationships between race and funding, poverty and funding, or between geographic location and funding (Berne and Stiefel, 1994).

Compared to other topics within school finance such as adequacy, the role of the courts, and the appropriate construction of cost function and production methodologies, there have been few intradistrict school finance studies conducted over the last 12 years (Berne and Stiefel, 1994; Hertert, 1995; Rubenstein, 1998; Stiefel, Rubenstein and Berne, 1998; Burke, 1999; Owens and Maiden, 1999; Iatarola and Stiefel, 2003; Condron and Roscigno, 2003; Roza, Hill and Miller, 2004; Stiefel, Rubenstein and Schwarz, 2004; Roza and Evans, 2005). A number of those conducted, however, have found substantial variation in funding across schools within the same district. They have also found variation in funding related to teacher salaries, and have found conflicting associations between student characteristics such as poverty or minority status and funding levels. While these studies examined variance in funding across schools with and without pupil weighting, none of these studies explicitly took into account the sequences of schools a student may attend and resulting disparities in funding.

School sequences develop as a result of district policies in three ways. First, students may be assigned directly to schools by district policy. Secondly, students may take advantage of choices – such as magnet schools – provided to them by the district. Finally, students can change schools regardless of district policy by changing their residence. Such changes may be made for familial reasons, or intentionally made to game the student assignment system.[1]

Under the first scenario, families face constrained choice in schools provided to them. Since school assignment is usually determined by neighborhood or by street address, families are essentially assigned into specific sequences of schools that extend from kindergarten until the twelfth grade.[2]

[1] A fourth option, here unaddressed, is that students and families create school sequences by exiting the public system and entering into charter, private or home school arrangements. Students taking this option may have sequences that are combinations of public and private schools.
[2] Technically, houses are assigned to schools by the district, and the families that reside in those houses follow suit.

In the second scenario, families may have magnet schooling options available through application, lottery or audition. Alternately, districts may present students with school attendance options based on geography; for example, a student may be able to choose between two middle schools geographically proximate to the student's home. In this scenario, school sequences might reflect student or parental efforts to determine a specific educational course through a specific sequence of schools.

In the third scenario, students and parents choose schools either indirectly (through moves within district made necessary by economic or vocational circumstances) or directly, by relocating within a district to take advantage of a better school assignment. Students and families can also resort to dishonesty in an effort to game the system and attend a different school by using a false home address.

School assignment sequences under any of the three scenarios, since they are direct or indirect creations of district policy, may change over time. For the purposes of understanding the manner in which schools are resourced and the levels of resources experienced by students attending those schools, a district may better be conceived as a collection of school sequences – and types of school sequences – rather than as a collection of schools.

It follows, then, that resource levels for school sequences would exist as averages or sums of the individual school resources that comprise that school sequence. One implication of the differences between examinations of interdistrict equity and intradistrict equity is that, in the intradistrict context, important variation may lie between these school assignment sequences. For example, sequence may exacerbate slight inequities between schools if students are assigned into consecutive schools with lower levels of resources available to them. Conversely, additional resources available at a student's subsequent school may ameliorate lower levels of resources at one individual school. Researchers examining intradistrict equity using schools as a unit of analysis may, consequently, under- or over- estimate levels of equity present in a system.

School sequences can be examined cross-sectionally or longitudinally. School sequence analysis conducted with one year of data is a cross-sectional study that would examine levels of funding equity present across sequences in a given district for a given year. No student actually experiences these sequences since a student can only be in one grade in any given academic year; they are more profitably considered a reflection of district intention and district policy. In any given year, districts may seek to privilege diversity in school-level student populations, they may seek to privilege geographic proximity when assigning students to schools, or they may seek additional policy priorities through student assignment.[3]

Assuming sequences for any one year are stable over time, draw from the same geographic area over time, and operate at the same levels of efficiency and effectiveness over time, they may be used as indicators of the equity impact of district policy on resource allocation. A cross sectional analysis can only present sequences as designed by district policy; it cannot represent the possible trajectories that any given student might take. As such, these cross sectional analyses are "static" sequences. While static sequences provide insight into equity of resources provided across specific schools, and while findings from an analysis of static sequences may provide different results than those analyses conducted across schools, they will not be able to provide information on the levels of resources experienced by students through time, and thus have less relation to the levels of resources confronted by students over time as district policies and priorities change.

[3] These values are often opposed to each other, since many large school districts display patterns of residential segregation.

An alternate method for examining school sequences – one to be tested in this dissertation – is to use student level data and district level data to construct assignment sequences over time. These sequences, unlike the static sequences described above, reflect changing district policies, since a student's school assignment in any one year will be determined by the policy in place in that year. As a student moves through multiple years, he or she also progresses through multiple assignment policies. An individual student may take different sequences than those assigned to him or her, by opting into magnet or alternative programs, by changing residence, or (in rare cases) by deliberately gaming the system. To the extent that district assignment policies are framed around a larger policy goal (such as a move towards neighborhood schools or a commitment to diverse school-level student populations), these "dynamic" sequences will indicate the long-term impact of district policy on resource allocation. Using student assignment sequences as a unit of analysis may also provide a clearer picture of resource equity across students as they matriculate through a school district. For these reasons, the use of school sequence represents a methodological contribution to the literature on intradistrict school finance as well as student assignment policy.

This dissertation explores the use of student school assignment sequences as a unit of analysis for intradistrict school finance studies. Insights from this work will guide researchers in determining if districts provide horizontally or vertically equitable opportunities for students over time. In addition, this proposed research may aid policymakers in their construction of student assignment sequences via district-level policy.

Research Questions

There is increasing interest in intradistrict school finance studies. Many studies, conducted at the school level, do not account for the manner in which district policies may contribute to the distribution of resources over time and across different students. This study investigates the effects of school sequences in intradistrict resource allocation studies. Student sequences represent district level policy decisions that may mediate or interact with district level finance policies. As such, they represent an intriguing new unit of analysis that may contribute to larger discussions about the role of district policy in providing resources and opportunities equitably to students. This dissertation seeks to analyze such school sequences within a school finance equity framework. Specifically, this dissertation asks:

1. Are measures of intradistrict equity different when measured across school sequences than when measured across schools?
2. Do school sequences for poor and minority students differ from school sequences for other students? If so, do poor and minority students attend sequences with greater or fewer resources than their non-poor, non-minority peers?

Methodological overview

Studies of intradistrict resource allocation rely on a framework developed by Berne and Stiefel (1984; see Berne and Stiefel, 1994 for an application of the framework in intradistrict analysis). This framework provides a methodology for examining the distribution of resources across sub-units of a larger governing entity (i.e., states within a country, districts within a state, or schools within a district). The Berne and Stiefel equity analysis framework includes measures of horizontal equity and vertical equity.

Horizontal equity as a concept seeks to measure the equal treatment of students regardless of student characteristics. Vertical equity as a concept seeks to measure the treatment of students accounting for student characteristics that may justify additional spending. An adaptation of this framework for school sequence analysis provides the best method at arriving at answers to the research questions posed above. Application of the Berne and Stiefel framework also allows for more direct comparisons between findings from school sequence analyses and findings from school level analyses. There will have to be significant changes in the manner in which vertical equity is modeled, however. As will be discussed below, quantile regression applications are necessary to account for variation across the distribution of dependent variables.

Analytic techniques

Techniques for analyzing levels of horizontal equity within the Berne and Stiefel framework include the computation of indices to reflect distribution of resources such as the coefficient of variation, the McLoone Index and the Gini coefficient. Techniques for analyzing levels of vertical equity and equality of opportunity within the Berne and Stiefel framework include correlations and multivariate regression. Regression coefficients will isolate the direction, strength, and significance of relationships between an independent and dependent variable net of the effects of other independent variables.

This dissertation will use quantile regression to obtain vertical equity regression coefficients at the school sequence level, and will therefore use quantile regression to analyze vertical equity using both schools and sequences as the unit of analysis. Quantile regression is a new application in school finance analysis, but has a longer history in econometric and ecological research. Quantile regression will allow for a test of the differential impact of student characteristics on resource distribution. These methods will address levels of inequity present across school sequences as a whole, clarify shifting relationships between independent and dependent variables across 5 quantiles of the distribution of the dependent variable (.10, .25, .50, .75, .90), and assess the strength and direction of change in one independent variable holding all other independent variables constant.

Since the purpose of this research is to examine what additional information is available from intradistrict school finance analysis conducted across school sequences, this research will compare results with results from traditional models of intradistrict school finance analysis.

Limitations

This study will use multiple years of data to examine the effect of using school sequences on intradistrict school finance. The use of student level data, while rich, presents challenges. Not all student data collected for the 1999-2004 timeframe will contain all years of data. More importantly, not all students will enter into the database at grade K or leave at grade 12. In this sense, students will enter the database with unknown histories and leave the database with unknown trajectories. Analysis of this database will take care to distinguish students by their time in the database when constructing sequences.

Additionally, regression models may fail to account for relevant variables in the creation of models. Through the use of year fixed effects in school-level analysis and the adaptation of year fixed effects for use in sequence models, this research will seek to control for external factors that may disproportionately impact regression-based findings.

Overview of the dissertation

An examination of school-level data by school sequence presents researchers with an alternative method for assessing levels of distributional inequity across schools within a district. This dissertation will examine the use of school sequences by constructing the aforementioned sequences of schools, populating those sequences with spending and demographic variables, and assessing degrees of inequity relative to more traditional analyses of intradistrict school finance.

This proposal will proceed in the following manner: Chapter two will review insights gained from equity research as well as findings from previous intradistrict school finance studies. Chapter two will end with a critique of current methods and an explanation of the potential value of using student assignment sequences as a unit of analysis. Chapter three will review the specific data to be used as well as methods for constructing variables and answering the questions posed above. Chapter three will also propose an analytic framework within which to apply these methods to answer the research questions above, and describe the selection and operationalization of five resource-related dependent variables. Chapter three will address limitations and problems posed by the data and proposed methods for addressing those issues and problems. Chapter four will present finding from analysis of horizontal and vertical equity using five resource-related dependent variables, and compare findings from horizontal and vertical equity analysis across schools (as it is traditionally conducted) and across sequences of schools. Finally, chapter five will review findings, discuss the methodological and research implications this research holds for the field of school finance, and chart directions for additional inquiry.

CHAPTER II

LITERATURE REVIEW

Overview

This chapter reviews prior work on school finance equity. First, this chapter presents an historical overview that describes the state of equity-based school finance research over time. This chapter then focuses on a review of prior research in intradistrict finance, addressing theoretical perspectives, data and methods used, and empirical findings. This chapter then addresses the need for an analysis of school sequences as a unit of analysis for examining levels of intradistrict horizontal and vertical equity by reviewing the challenges posed to school finance research by research on school segregation and peer effects. Overall, this chapter describes key insights, methods, and findings as a prelude to framing this study around school sequences.

Equity research – from state-level to school-level

Equity, variously defined, has been a topic of interest in the field of education administration and policy for a century. Although Elwood P. Cubberly was one of the first academics to examine equity as a dimension of school funding (Cubberly, 1906; Guthrie, Garms and Pierce, 1988; Guthrie, et al, 2006), a rash of court cases in the 1970s brought more intense interest in resource equity (Berne and Stiefel, 1994; *Serrano v. Priest*, 1971). The examination of resource distribution begun in the 1970s as a result of school finance litigation helped to bring the study of school finance into the modern era (Guthrie, 2006) through the development of measures, methods and theories of school finance equity.

Berne and Stiefel's book *The Measurement of Equity in School Finance* (1984) defined a framework for examining levels of equity within a school finance system. Berne and Stiefel's framework described the subjects of equity analysis, objects of equity concern, principles for determining equity, and measures for assessing levels of equity. This framework has survived over time with surprisingly little alteration or challenge (see Berne and Stiefel, 1994), and has framed equity studies of single states and groups of states, as well as national comparisons. These studies find that resource inequity has decreased over time both within state and between states, often as a result of finance litigation and reform (Murray, Evans and Schwab, 1998; Springer and Liu, 2005). Recently, the primary emphasis in school finance research has moved from considerations of input equality to considerations of appropriate levels of resources necessary to meet accountability requirements. This move has been termed the shift from equity to adequacy (see Clune, 1993; Ladd, Chalk and Hansen, 1999). Despite this conceptual shift, researchers still confront issues about the manner in which educational funds are distributed. Often, knowledge of equity conditions is a precursor to understanding the role of resources in education production. Equity studies, therefore, still have a part to play in education finance research.

Additionally, a parallel but smaller body of research has focused on the distribution of resources across schools within districts. These intradistrict finance studies often rely on school level data that were, until the school-level analysis demanded by *No Child Left Behind*, uniquely available. These studies apply the methods of analysis commonly used in interdistrict studies to assess level of equity across schools. Although some studies were conducted throughout the 1970s (Owen, 1972; Hornby and Holmes, 1972; Summers and Wolfe, 1976), renewed interest in intradistrict equity studies formed during the 1990s.[4] This renewed interest was fueled by three developments in intradistrict study: a court case, a research article, and one journal's dedication to the topic. The sections that follow review each in turn.

In 1992, plaintiff parents in the Los Angeles Unified School District brought suit against the school system, claiming that students in the district were denied rights because of inequitable intradistrict funding. A component of the plaintiff's case was that schools with high minority populations had, on average, teaching staffs with less experience and less training other schools across the district (*Rodriguez v. Los Angeles Unified School Distric*t, 1992; Warner-King and Smith-Casem, 2005).

In 1994, Berne and Stiefel published an article applying their 1984 equity framework to an examination of intradistrict resource allocation in New York City schools. Berne and Stiefel cited three reasons for an increased interest in intradistrict study, as well as reasons for receding interest in interdistrict study. According to Berne and Stiefel, the "dominance of the district as the unit of analysis in school finance equity" was challenged by:

- A belief that the most critical educational activities are those closet to the student;
- A developing interest in studying the relationship between inputs, process and outcomes, which were assumed to more effectively studies at the school level; and,
- Technical advancements making the collection and review of school level data both possible and palatable (p.405).

Berne and Stiefel conceptualized their work as the first of a long line of intradistrict studies, and were correct in that assumption, as a review of pertinent studies below will attest.

[4] Although intriguingly titled, the 1988 American Education Finance Association Yearbook, *Microlevel School Finance: Issues and Implications for Policy*, yielded little information on intradistrict finance issues.

Finally, editors dedicated a special edition of the *Journal of Education Finance* to exploring the issue of school-level data and intradistrict finance research. In the introduction, Busch and Odden (1997) reviewed issues that school level analysis could help address "governance, efficiency and productivity of resource utilization, accountability, equity, adequacy, comparability of data, and longitudinal analysis" (p.228). In the same issue Berne, Stiefel and Moser (1997) assessed the field of intradistrict finance:

> School-level analysis is a relatively new area and as such it is worthwhile to continue to let a thousand flowers bloom…it is too early to cut off potentially productive ways to gather and analyze data…We eventually need a good sense of the kinds of analyses that are used for decision making and the kinds of data necessary for analyses (p.253).

Roza and Hill (2004) advance the theory (further developed in Roza, 2005) that the district practice of allocating teachers positions to schools – regardless of actual teacher costs – contributes to intradistrict disparities as teachers with more experience (and higher salaries) move away from high-minority, high-poverty schools.

Finally, in a most recent analysis of the state of intradistrict finance, Stiefel, Rubenstein, and Schwartz (2004) summarize the current state of intradistrict equity analysis:

> First, though evidence directly comparing school-level and district-level disparities is limited, the resource disparities found across schools within districts are often large and, in some cases, may be larger than the more widely-recognized disparities across districts. Second, these disparities are generally perversely related to school and student characteristics; schools with greater student needs often find themselves disadvantaged relative to other schools in the same district, particularly in terms of the quality of teacher

> resources. Third, these patterns are not caused by the intentional targeting of resources to lower-need schools…. these resource disparities are frequently the result of intradistrict funding formulas that allocate positions, rather than dollars, to schools, and teacher sorting patterns that allow higher paid teachers to systematically opt into lower need schools without financial ramifications for the schools to which they transfer (p.11).

The following section reviews the data, methods and findings of important work in intradistrict finance that led Rubenstein, Schwartz and Stiefel to this conclusion. Although most intradistrict finance studies have applied some variation of the Berne and Stiefel framework, and found substantially similar relationships between funding and school-level characteristics (especially poverty), there has been some variation in both methodology and findings, which will be highlighted.

Review of intradistrict studies

Intradistrict studies of resource equity have most often been conducted in large, urban school districts. Findings from these studies often reflect patterns of inequity. For example, all studies find that a majority of district funding is allocated at the school level (59 to 68 percent across studies) and that the largest piece of school level expenditures is staffing costs, specifically teacher salaries.

All studies report disparities across schools within districts, and all studies find relationships between school-level variables such as racial composition and poverty and costs per pupil at the school level. Stiefel, Rubenstein and Schwarz (2004) caution that funding disparity patterns are unique across four urban school systems in their study, attributing this dynamic to the variety of school-level data available for specific districts. Indeed, the field of intradistrict study is necessarily a case-based endeavor, as there exists little regulation regarding the manner by which districts provide school-level revenue and expenditure data. This section will review key studies of intradistrict equity as a frame for the methods needed to answer the research questions.

In an early study, Summers and Wolfe (1976) provided an early analysis of school level resource equity in the Philadelphia schools. Using two years of data, Summers and Wolfe used regression analysis to examine the distribution of school characteristics and school-level funding. Summers and Wolfe controlled for percentage of a schools' students that were African American and percentage of a school's students that were impoverished through two separate regressions. While Summers and Wolfe found evidence of compensatory spending at the local, state and federal levels (an additional 7% of total spending was targeted to African American students; an additional 13% was targeted to poor students), as well as lower student/teacher ratios for schools with greater proportions of African-American students, they also found that schools with higher proportions of poor and African American students were likely to have less experienced principals, higher teacher vacancy rates, and teachers with lower exam scores and lower quality undergraduate educations than schools with smaller proportions of poor and African American students. The Summers and Wolfe study was an early effort at exploring the relationships between school level composition characteristics and school resource allocation.

As described above, Berne and Stiefel (1994) adapted their school finance equity framework for intradistrict analysis. In addition to their adaptations (reviewed above) Berne and Stiefel applied their methods in a study of New York schools. They examined 32 New York geographic sub-district budgets and 800 school level budgets, and found significant disparities between high-wealth and low-wealth sub-districts within New York City. Berne and Stiefel used five outcome measures as dependent variables in their vertical equity regressions: general education budget per pupil, general education expenditures per pupil, teacher salary budgeted per pupil, average teacher salary per pupil and student/teacher ratio. The results of the study provide baseline information that would serve as comparatives for further studies. Berne and Stiefel report that 86.5% of district allocations were direct to schools. They further report that 74% of school budgets were dedicated to teacher salaries. Berne and Stiefel reported that the percent of students in poverty was associated with decreased teacher salary at the elementary school level, but was associated with increased teacher salary at the middle school level.[5] In addition, Berne and Stiefel found significant differences in resource allocation between elementary and middle schools, with middle schools spending more on additional staff to compensate for teachers with lower salaries (salary being a proxy for experience) at high poverty schools.

Most important for this proposed study is that Berne and Stiefel compared findings of analysis conducted at the school level to analysis conduced across New York's 32 school sub-districts. Each sub-district functioned more or less as an independent district, so sub districts are not the same as attendance sequences. However, this study represents the only review of the literature that examines units of aggregated schools within districts. Berne and Stiefel found that the relationships between poverty and general education spending were no different when analyzed across schools or across sub-districts. However, when conducting school level analysis, Berne and Stiefel were only able to assign each school the sub-district mean teacher salary. Because Berne and Stiefel were not able to use school-level teacher salary data in their analysis, it is possible that their work underestimated the effect of independent variables on the teacher salary dependent variable.

[5] The R-squared values in these models were modest; the highest r-squared value achieved was .115.

Hertert (1995) examined the distribution of educational funds across and within California districts. Hertert used a sample of California school districts, which accounted for 31% of the school-age population, 1,042 schools and 926,740 students. Hertert used regular expenditures as a dependent variable, net of federal and state categorical funding. Following Berne and Stiefel's 1984 framework, Hertert used the range, restricted range, federal range ratio, coefficient of variation, Gini coefficient and McLoone Index to assess levels of horizontal equity and stepwise multiple regression to assess vertical equity. In her assessment of levels of horizontal equity, Hertert reported 19 of 25 districts with coefficients of variation above .15 and 13 of 25 districts with Gini coefficients greater than .10.[6] When assessing vertical equity, Hertert found little effect of ethnicity variables. Most variation in expenditures was explained by school type – elementary, middle or high school. Hertert's assessment was that the horizontally equitable distributions in California came as a result of changes to statewide school finance policies that increase state responsibility and decrease local discretion in providing educational funds, thereby increasing horizontal equity. These policies were viewed as a direct result of school finance litigation California.

Rubenstein (1998) analyzed spending within the Chicago Public Schools utilizing school-level budgets at an incredible level of detail (157,000 line items per school). Rubenstein finds that base funding per pupil, defined as the core amount allocated by the district net of additional funding streams, was equally distributed across schools. Inequity occurred when additional funding streams were added, so that total funding per pupil exhibits horizontal inequity. Rubenstein found that high schools are more equitably funded than elementary schools, and that funding became more horizontally equitable as more narrow budget categories were used as

[6] Although Hertert stated her use of .10 as a threshold for the coefficient of variation, as suggested by Odden and Picus (1992), she assessed equity within districts with a coefficient of variation threshold of .15, a more conservative estimate.

dependent variables. Rubenstein's vertical equity analysis found weak, significant and positive relationships between funding and poverty save for Title I and Chapter I funds. As expected, Title I and Chapter I funds were distributed to schools with higher percentages of students in poverty.

Rubenstein's models did not adequately control for the effects of teacher salary or prior performance on fund allocation. For example, to assess the relationship between Tile I funding and poverty, Rubenstein models

$$TitleI = \alpha + \beta_1 Lowincome + \varepsilon \qquad (2.1)$$

To examine relationships between total budget and spending, Rubenstein modeled

$$Budget = \alpha + \beta_1 Lowincome + \beta_2 Enrollment + \varepsilon \qquad (2.2)$$

with little regard for interactions with race, the influence of teacher salary, or prior year performance that may cloud the estimates of the independent variables. To analyze teacher salary, Rubenstein places it as a dependent variable in equation (2.1) above, and finds that schools with higher percentage of low-income students employed teachers with smaller salaries. However, Rubenstein failed to use multiple regression to examine the impact of enrollment and poverty simultaneously. These controls would have made interpretation of his findings more clear.

Stiefel, Rubenstein and Berne's 1998 study used Berne and Stiefel's 1994 intradistrict framework and compared equity of school funds across four cities: Chicago, Fort Worth, New

York and Rochester. For horizontal equity analysis, the authors relied upon the coefficient of variation and used regression analysis to examine vertical equity relationships. Because each city represented a different a socio-political context and a different district-level capacity to collect and organize information, data were not parallel across the four cities, and not even across the same academic year. Nonetheless, Stiefel, Rubenstein and Berne found coefficients of variation in three cities to be below .15 across budget subcategories in three cities; Rochester consistently scored a coefficient of variation above .15 in all budget categories.[7] This finding indicated that spending was horizontally equitable within three of the four districts.

When assessing vertical equity, Stiefel, Rubenstein and Berne found positive relationships between poverty and total budget in New York and Rochester, but negative relationships between poverty and general fund expenditures in Chicago. Findings from all four cities revealed the relationships between race and funding to be weak and only occasionally significant. Rochester was the only city that indicated vertically equitable funding; center-city schools comprised mostly of impoverished students received additional funding from the district. Data limitations across the four sites hampered the researchers' abilities to draw strong conclusions about these relationships.

Burke's 1999 study deviates from the traditional use of the Berne and Stiefel framework, instead using the Gini coefficient to examine differences between inter-state, intra-state and intra-district funding disparities using a national dataset. Burke used the pupil/teacher ratio as a proxy for educational resource allocation to examine resource distribution across 1,204 school districts in 37 states. When evaluating districts without state boundaries, Burke finds that only 75 of the 1,204 districts had Gini coefficients above .10 (a standard metric for evaluating Gini

[7] Although Stiefel, Rubenstein and Berne used a cut off of .15 to assess he coefficient of variation, this proposed dissertation will evaluate the coefficient of variation with a cutoff of .10 (Odden and Picus, 2000).

coefficients).[8] When evaluating all districts and imposing state boundaries, Burke reports significant variation in Gini coefficients for all 37 states in her study. In her intra-state analysis, Burke finds Gini coefficients that range from .068 to .12, with an unweighted mean of .09. In all, 37.8% of states having Gini coefficients above .10. In her inter-district analysis, Burke reports Gini coefficients that range from .019 to .078 with an unweighted mean of .042. Burke interprets these findings as an indication that district level practices matter in the distribution of educational resources, specifically pupil/teacher ratios.

Adopting a methodology from Lambert and Aronson, Burke decomposes state-level Gini coefficients to account for inter- and intra-district disparities.[9] Burke finds that intradistrict Gini's demonstrate sometime substantial levels of inequity while state and district level examinations reveal relatively stable Gini coefficients that represent horizontal equity. Burke's interpretation of these findings is that, while there is substantial distributional inequity within a district, school-wide disparities are not that great once district boundaries are removed. This finding places the role of the district in a more important light than in previous studies. It also provides support for the use of teacher-level variables as appropriate proxies for resource distribution.

Owens and Maiden's examination of school spending in Florida examined all elementary schools net of district boundaries (1999). Owens and Maiden used four measures of instructional expenditures as a dependent variable (per-pupil, basic program only; per pupil, program adjusted, basic program only; per pupil, compensatory programs included, and per pupil, program adjusted, compensatory programs included) to examine the distribution of resources across Florida schools. At the school level, Owens and Maiden report substantial inequity across

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[8] A description of the Gini coefficient is provided in chapter two.

[9] The formula for this decomposition is $Gini_{intrastate} = Gini_{interdistrict} + (Weight \bullet Gini_{intradistirct}) + \varepsilon$

elementary schools with some evidence that Title I funds may be "supplanting" regular instructional funds. Regression analysis results indicated that increases in percentages of African American and impoverished students resulted in decreased spending across all four dependent variables. Owens and Maiden interpret this finding to demonstrate that although compensatory spending dampens inequities, it does not remove them. An additional level of analysis revealed that none of the significant effects were apparent using district level analysis. Owens and Maiden conclude that school-level analysis is an important addition to the school finance researchers' toolbox.

Iatarola and Stiefel (2003) examined intradistrict equity among New York City schools. Their study represents a careful application of the Berne and Stiefel framework, and represents the direction intradistrict finance can take as school-level data become more available and as technological innovation makes more complicated multiple regression analysis possible. This study examined equity across five measures: operating funds per pupil, direct service funds per pupil, pupil/teacher ratio, teacher salary and percent of teachers who were certified. Data were cross sectional for the 1997-1998 school year. Iatarola and Stiefel examined horizontal equity using the mean, coefficient of variation and range. Across 664 elementary schools, the coefficient of variation for the five dependent variables ranged from .09 to .19. Across 186 middle schools the coefficient of variation on dependent variables ranged from .08 to .20. For both elementary and middle schools, the coefficient of variation on teacher salary was the only variable which did not exceed the traditional threshold of .10, indicating some inequity in the distribution.

Iatarola and Stiefel assessed vertical equity through regression analysis using each measure as a dependent variable. Independent variables included percent of students on free and reduced price lunch, percent of students who were limited English proficient, percent of students who were immigrants, percent of students who did not complete the academic year in the same school, and the percent of special education students at the school. The percentage of students receiving free and reduced price lunch at a school was associated with decreased operational funds per pupil, decreased pupil/teacher ratio, decreased teacher salary and a decrease in the percentage of certified teachers at a school. These findings were the same across elementary and middle schools and were significant at the $p<.05$ level. Other variables were also influential, although not as consistently significant as the variable for free-and-reduced price lunch. Using traditional thresholds for horizontal equity (Rubenstein, 1998; Odden and Picus, 1992; 2000; also see explication on evaluation of horizontal equity methods in the data and methods section below), the study reported inequitable spending levels across elementary and middle schools.

Iatarola and Stiefel also examined outcome equity through regressions using two different test results as dependent variables in a production function. Outcome equity was defined as an analysis of the distribution of test scores across schools and the relationship between school level student body composition variables and those test scores. Each of these analyses was run separately for elementary and middle schools. Outcome equity analysis run by Iatarola and Stiefel reported negative and statistically significant coefficients on independent variables for percent of student who received free lunch, percent of students who were Limited English Proficient (LEP), percent of students who were immigrants, and percent of students who were mobile, i.e. did not attend one school for the entire academic year. In a replication of Berne and Stiefel (1994), Iatarola and Stiefel, when examining sub district equity in New York City schools, were able to account for New York's 32 sub districts, but only used this information to examine variation when sub districts bordered on another state.

Another examination of intradistrict equity used data from 89 Ohio elementary schools within one district. Condron and Roscigno (2003) used production function regressions to determine the impact of school composition and funding on academic achievement. Condron and Roscigno's regressions controlled for achievement three years prior to the year of available finance data, used five subject specific achievement measures, separated the effects of local spending, federal Title I supplemental spending, and maintenance spending, and included independent variables from the school system reports that addressed broad topics of school adequacy, safety, healthfulness and appearance as well as school level measures of racial composition and poverty. The study found significant correlations between local spending (total spending per-pupil with Title I funding per pupil subtracted) and school-level race and class variables. Regression models demonstrated positive and significant relationships between spending and achievement through instructional spending (spending per pupil without Title I funds) and maintenance spending. Coefficients on independent variables in which math and science scores were the dependent variable were smaller and less often significant than with subjects such as reading and writing.

In a policy brief prepared for the Pioneer Institute, West and Shen (2003) examined intradistrict equity using the Boston area's seven largest school districts. According to West and Shen's derived inequity measure, intradistrict inequity across all seven districts was reported to range from .12 to .20, above their threshold for inequity of .10. In addition, West and Shen used instructional expenditure per pupil as a dependent variable in a regression to assess relationships between school-level characteristics and expenditures. In six non-Boston districts, West and Shen found positive and significant relationships between spending and percentage of minority students in schools. Boston schools exhibited negative relationships between percent of minority students and expenditures. West and Shen also found that higher enrollments were associated with decreased instructional expenditures per pupil.

Stiefel, Rubenstein and Schwarz (2004) use better-specified multivariate regressions controlling for enrollment, special education, English Language Learners, 4th grade achievement in their analysis of intradistrict spending in New York, Cleveland and Columbus, Ohio. For New York, Stiefel, Rubenstein and Schwarz found significant relationships between the percentage of students eligible for free and reduced lunch and expenditures, between 4th grade reading achievement and expenditure variables between enrollment and expenditure variables, between percentage of special education student and expenditure variables. Expenditures include school-level and classroom-level spending per pupil, as well as teacher salary. Both the free lunch and special education variables were associated with increased school and classroom level spending but decreased teacher salary, as well as fewer teachers with a master's degree. In Columbus, Stiefel, Rubenstein and Schwarz found significant relationships between enrollment and school-level expenditures. Free lunch and middle school status were associated with decreased teacher salary, and school-level free lunch percentage was associated with a smaller percentage of teachers with a master's degree. In Cleveland, only elementary school enrollment was associated with decreased school-level spending; middle school achievement was associated with increased teacher salaries and percentage of teachers with a master's degree. Stiefel, Rubenstein and Schwarz's conclusion sums up the findings of previous intradistrict analyses well:

> Overall, the comparison of the three cities confirms that there is a trade-off in which, as poverty increases, schools receive more funds but exhibit lower teacher quality and teacher salaries…No clear pattern emerges in the relationship between school

characteristics and teacher salaries and the relationship between school size and resources is complex (p.10).

Finally, Schwartz, Stiefel and Amor (2005) use three years of panel data and cost function analysis to examine the efficiency of Ohio schools (n=6,963). Stiefel, Schwartz and Amor used school-level fixed effects estimators as efficiency proxies in addition to holding teacher characteristics, enrollment, school level academic performance, and school level demographics constant. The resulting cost function equation was:

$$\ln E_{sdt} = \rho + \sum_{m=1}^{M} \beta_m \ln W_{msdt} + \sum_{r=1}^{R} \theta_r \ln Y_{rsdt} + \sum_{p=1}^{P} \gamma_p SD_{pdst} + \sum_{s=1}^{S} \nu_s S_s + \sum_{t=1}^{T} \lambda_t YEAR + e_{sdt} \qquad (2.3)$$

where S was the school fixed effect, W is the set of input prices, Y is a set of school-level outputs, SD are a set of school and district characteristics, YEAR is a dummy variable for year, M is the number of inputs, R is the number of outputs, P is the number of school and district characteristics, S is the number of schools, and T is the number of years. Stiefel, Schwartz, and Amor used this same model with additional lagged achievement variables as well.

Across four separate model specifications using different combinations of independent variables in equation 2.3, Stiefel, Schwartz, and Amor found that enrollment was associated with increased expenditures at a decreasing rate, with a threshold enrollment of 90, at which point increases in enrollment are associated with decreasing per pupil expenditures. In these cost function regressions, which controlled for individual school effects, neither race nor poverty were significantly associated with changes in the natural log of total expenditures per pupil. Each specification accounted for approximately 30% of the variation in log of total expenditures per pupil.

Additionally, Stiefel, Schwartz and Amor were able to use school level fixed effects estimates – again, as proxies for school efficiency – as a dependent variable to better understand the role of time invariant school level characteristics in education production. In these regressions, race and poverty were positively and significantly associated with increased costs at the school level. Although they did not set out to do so, Stiefel, Schwartz and Amor found indications of vertically equitable spending patters in Ohio schools.

These key studies of intradistrict resource distribution provide a broad foundation for analysis of school sequences and district resource allocation patterns. Taken together, these studies provide a basic framework for assessing levels of horizontal and vertical equity, a basis from which to construct a theoretical model and select independent variables and a framework for extended analysis using cost function analysis. The following section will describe the data available, the analytic tools to be used and potential problems and solutions in framing answers to questions about the role of school sequences in intradistrict resource distribution.

Discussion of existing methods

The studies reviewed above contributed to researchers' understanding of the manner in which district allocation policies to schools may contribute to the measured inequity of resources. These studies further illuminate the role that teacher salaries play in these inequities, and further still point to disturbing negative associations between race and poverty on one hand and resources allocated on the other. Nevertheless, these studies do not account for the manner in which students move through a school district over time. Using school sequences as a unit of analysis is a new method for analyzing intradistrict equity that accounts for total resources expended on students throughout multiple years of education. The need for this new methodology is twofold: it is motivated by both methodological and policy considerations.

The first reason for examining school sequences as a unit of analysis is a methodological one. By holding the level of analysis to the school level, current intradistrict studies cannot account for the resources allocated to students in schools in prior or subsequent years. While a school may receive additional funds in a given year, little is known about resources allocated to students in previous or subsequent years. Theoretically, then, a student receiving adequate or compensatory funds at a school in one year my not have received such funds in previous years. In production function equations, this would lead to underestimation of the relationship between spending and an educational outcome. In addition, student assignment creates peer conditions that, in turn, influence the movement of experienced teachers away from schools thought to be difficult teaching environments. Peer conditions are also thought to influence student performance.

Peer effects as a resource

Peer effects, described above, occur when a student's classmates and schoolmates exert an influence on individual student learning. Research on peer effects has focused on issues of integration and segregation of schools, a well as more recent interest in the specific role peers play in school-specific measurements of performance and achievement. Wells and Crain (1994) find long-term benefits of desegregation on economic performance and educational attainment as well as mixed results in the short term. Trent (1997) found longitudinal impacts of desegregation for minority youth, but also found increasing concentrations of poor and minority youth in schools, using the Youth Longitudinal Survey (YLS) and High School and Beyond (HSB). Gary Orfield and colleagues (1999) find a relationship between resegregation and increased dropout rates for minority populations. Lee and Bryk (1989), also using HSB, found direct effects of social composition on student academic achievement. Hoxby (2000) used Texas statewide data and found peer effects even when controlling for enrollment trends by randomizing the years of her dataset. Other economists have reached similar conclusions. Using the same Texas data, Hanushek, Rivkin and Kain (2001) found a significant impact for African-American elementary school students of .024 standard deviation increase in test scores associated with a 10 percent decrease in African-American classmates. Additionally, Hanushek, Rivkin and Kain (2004) found peer effects using panel data of Texas students over time; specifically, African American student achievement was most impacted by percentage of African American students in classes. The percentage of African American students in classes, however, seemed to have little impact on the performance of white students. These findings occurred independently of achievement or school quality differences.

Teacher mobility

In addition to finding peer effects on student achievement, research also suggests that peer factors such as race may be a factor in teacher mobility between schools. One study reports Georgia teachers leaving high-minority schools at increasing rates through the 1990s (Freeman, Scafidi and Sjoquist, 2002). Hanushek, Kain and Rivkin (2001) used panel data from Texas to examine relationships between teacher salary, school level characteristics such as racial composition, and teacher transition decisions. Hanushek, Kain and Rivkin found teacher preferences for low-minority, low-poverty and high achieving schools. Teachers in Texas who made a transition to a school that was, on average, populated by 2.5% fewer African American students, 5% fewer Hispanic students, and 6.6% fewer students who receive free and reduced price lunch. Additionally, teachers moved to schools that scored 3 percentile points, or 0.8

standard deviations, higher on academic achievement tests than the schools they had vacated (p.12). Lankford, Loeb and Wyckoff (2002) found similar patterns among teachers in New York State. Among four New York districts, Lankford, Loeb and Wyckoff found a negative association between school levels of nonwhite and poor students and teacher quality. Lankford, Loeb and Wyckoff defined teacher quality as training and skills observed trough traditional record keeping. The question of teacher quality, i.e., what specific teacher characteristics impact student academic achievement, is a question very much under debate in the field.[10] Teachers who are under qualified are often those that are new to the profession (Ingersoll, 2001). This relationship between school racial characteristics and teacher mobility has been observed in Nashville as well. Goldring and Houck (2005) reported that Nashville schools with greater than 60% African American students were staffed by less experienced teachers as well as higher proportions of new teachers (no years of prior experience) and non-tenured teachers (0 to 3 years of experience).

If a school's level of poor and minority students affects teacher mobility, then there is a link between student assignment and levels of school funding, specifically the allocation of teachers – by far the largest item in instructional expenditure budgets.

The second reason for examining school sequences as a unit of analysis is policy driven. The need to clearly understand the equity implications of policy decisions has become increasingly important as districts find greater freedom in crafting student assignment policies and greater freedom is distributing students across schools. Recent court decisions in large urban districts such as Atlanta (*Mills v. Freeman*, 1996), Charlotte, NC (*Capacchione v. Charlotte-Mecklenburg*, 1999), Denver (*Keyes v. Denver School District No. I,* 1995*),* Nashville (*Kelly v. Metropolitan Board of Education*, 1998), and San Diego (*Board of Education v. Superior Court,*

[10] For competing perspectives on this question, see Loeb and Page (2000) and Ballou and Podgursky (2000).

1998) have declared large urban school systems to be unitary, thereby freeing them from court ordered desegregation plans focusing on the manner by which students are assigned to schools. Unitary status decisions have additional impact on neighboring or peer districts, which have responded by altering their student assignment policies as well. (See *Making Choices*, 2003 for a review of this dynamic among North Carolina school districts). One outcome of these changing policies is a resegregation of schools in these districts (Orfield, Frankenberg, and Lee, 2003; Orfield, 2001). Unlike the racist practices of *de jure* segregated school systems, which chronically and intentionally under-funded segregated schools (see Walker, 1996; Anderson, 1988), today's segregating school districts have introduced a number of compensatory spending measures. Nashville officials, for example, created special school types – designed to provide additional resources and located in impoverished neighborhoods – as one method of blunting the negative effects of concentrations of poor and minority students. Charlotte-Mecklenburg officials provided additional instructional resources for schools with high concentrations of poor and minority students and paid teachers additional salary for teaching in those schools (Charlotte-Mecklenburg Schools, 2006; Goldring and Smrekar, 2002).

Urban districts have enacted polices which provide compensatory spending as a remedy for resegregation. There is debate among researchers about the extent to which school resources (in this case, spending) contribute to school productivity and efficiency (Hanushek, 1981; 1986; Hanushek, Kaine and Rivkin, 1999; Hedges, Laine, and Greenwald, 1994; Greenwald, Hedges and Laine, 1996). There is also a line of thinking that district offices may be more of an impediment than a help in implementing policy effectively (Chubb and Moe, 1990; Galvin, 2000; Walberg and Walberg, 1994). Therefore, it is important to know if – through the combination of student assignment and compensatory spending – students of minority background or impoverished circumstances matriculate in sequences of schools where the additional educational resources intended for them are available.

Analysis of intradistrict equity across schools will only partially answer these questions. Since the relationships between student racial and economic characteristics and funding carry over time across a student's matriculation within a school system, it becomes important to determine if districts are committed to providing resources equitably across schools across a student's time in the district.

CHAPTER III

DATA AND METHODS

Overview

The purpose of this chapter is to review the data and analytic techniques used to answer the following research questions:

1. Are measures of intradistrict equity different when measured across school sequences than when measured across schools?
2. Do school sequences for poor and minority students differ from school sequences for other students? If so, do poor and minority students attend sequences with greater or fewer resources than their non-poor, non-minority peers?

Answers to these questions will be tested using one district as a case – the Goodville Public Schools (GPS). Goodville is an unnamed metropolitan Southern city school system that has recently moved into unitary status. The Goodville context is one that involves a move to unitary status, compensatory spending and student assignment shifts that make it appropriate for study. Subsequent sections describe the data collection and management, including the construction of dependent and independent variables; the methodology to be applied and the specific techniques to be used in this analysis. This section presents the specific models used at each level of analysis.

The Goodville context

This research examines school sequences using data from the Goodville Public Schools (GPS). Goodville represents an appropriate case for studying the effects of school sequences on intradistrict finance studies. Goodville moved voluntarily into unitary status in 1998. In moving to neighborhood based student assignment policies, the Goodville community committed itself to providing resources to dampen the effects of high concentrations of poor and minority students. Goodville therefore represents a case of a district making direct policies to use additional resources to address segregating schools. The final year of student assignment (2003-2004) should reflect policy changes made over the last five years to provide vertically equitable resources to schools based on student demographic variables. Finally, the move to neighborhood-based student assignment policy was a gradual one; Goodville student assignment policy changed slightly over five years to arrive at the current configuration of schools and student assignment sequences.

Anticipating resegregation, Goodville created s series of school types to be located in comminutes that would address the needs of poor and minority students. These school types were to provide additional resources to a resegregating student body. Additionally, students in Goodville were often held harmless as the district changed student assignment policies. That is, students, or their siblings were allowed to remain in school sequences although the district had changed those sequences as a matter of policy. In addition to strengthening their magnet school program, Goodville created enhanced option and design center schools.

Figure 3.1 demonstrates the changes in GPS school configurations and assignments over time. In the 2000-2001 academic year, GPS supported 18 separate school/grade configurations. In the 1999-2000 academic year, GPS provided 788 separate pathways for s students to progress from kindergarten to the twelfth grade. This variation allows for an examination of patterns of resource allocation over time to see if Goodville schools provided systemic levels of resource allocation. Taken together, these dynamics make Goodville an attractive site to study school attendance sequences as a unit of analysis over multiple years of student assignment.

Table 3.1: Grade configurations and student assignment sequences, GPS, 1998-2005

Year	**97-98**	**98-99**	**99-00**	**00-01**	**01-02**	**02-03**	**03-04**	**04-05**
Grade Configurations	K-K	K-K	K-K	K-K	K-K	K-K	K-4	K-4
	1-2	1-2	1-1	K-2	K-2	K-4	5-6	K-5
	1-3	1-3	1-2	K-3	K-4	3-4	5-7	5-8
	1-4	1-4	1-3	K-4	3-4	5-6	5-8	6-8
	1-6	1-6	1-4	K-6	5-5	5-7	7-8	9-12
	3-6	3-6	1-6	3-4	5-6	5-8	8-8	
	4-6	4-6	2-2	3-6	5-7	7-7	9-12	
	5-6	5-6	3-4	4-4	5-8	7-8		
	7-8	7-8	3-6	4-6	6-6	8-8		
	9-12	9-12	4-6	5-5	7-7	9-12		
			5-6	5-6	7-8			
			5-8	5-8	8-8			
			7-8	6-6	9-12			
			8-8	6-12				
			9-12	7-7				
				7-8				
				8-8				
				9-12				
School configurations	**10**	**10**	**15**	**18**	**13**	**10**	**7**	**5**
School sequences	**564**	**564**	**788**	**514**	**377**	**280**	**154**	**68**

Goodville's policy shift, occurring over five years, allows for the construction of data that capture the historically accurate sequences of schools attended by GPS students. Creating this database involves pulling data from three main sources: students, teachers, and street level school assignments.

Data

Prior work in the area of intradistrict finance has decried the difficulty in obtaining relevant data that capture school by school variation in staffing costs and supplemental funding, in addition to more easily captured data about school level demographics and performance (Stiefel, Rubenstein and Berne, 1998; Guthrie, 1997; Berne, Stiefel and Moser, 1997; Farland, 1997; Busch and Odden, 1997; Roza, 2005). Often, school level data in the literature come through district-directed policy initiatives such as the data collection systems set up in the state of New York. Researchers have attempted to more clearly categorize school level data by function code or other organizational schemes, to little visible effect (Cooper, at al, 1997; Speakman, et al, 1997). Although these efforts have met with limited success, intradistrict studies find that a majority of funds go to varieties of instructional expenditures, the largest category of which is teacher salaries.

Data for this analysis comes from three major sources: student enrollment data, street-level student assignment data, and teacher level salary and experience data. Each of these three datasets contributes to a more complete understanding of the manner in which student assignment sequences contribute to the levels of resources provided to students. Consequently, each will be discussed in turn.

The first source of data is student enrollment data from GPS. Records in this database cover the 1998-1999 academic year to the 2004-2004 academic year. Student racial, gender and free and reduced price lunch information was aggregated across all six years to arrive at independent variables describing students.[11] In addition, each student's grade level and school of

[11] These are reported with school type information in Table 3.5 below.

record were included in the files. An identifier number matched students across years. This resulted in a database of 123,537 observations, representing students who moved through GPS between 1998-1999 and 2003-2004.

Students who attended preschool or post-12th grade special programs were removed from the database, resulting in 118,698 observations. This database was used to construct peer variables of percent minority and percent free lunch for each school within GPS over the time of the study. Finally, because the goal of this study is to examine the impact of successions of schools, students were dropped from the database unless they were present in GPS for three academic years. This reduced the database to 69,274 observations. For descriptive purposes, each student in this database was assigned a cohort based on the numbers of specific grade/year combinations possible within that cohort. Table 3.2 illustrates the configuration of the sequences along with the population of each cohort. For example, a student was assigned to cohort five if they were in first grade in the 1999-2000 academic year, second grade in the 2000-2001 academic year, third grade in the 2001-2002 academic year, fourth grade in the 2002-2003 academic year or fifth grade in the 2003-2004 academic year, or any three-year combination thereof.

Table 3.2: Student cohorts in GPS, 1999-2004; all students with 3+ years in system.						
Cohort (n)	**1998-99**	**1999-00**	**2000-01**	**2001-02**	**2002-03**	**2003-04**
1 (3,876)	-	-	-	K	1	2
2 (4,498)	-	-	K	1	2	3
3 (4,872)	-	K	1	2	3	4
4 (6,220)	K	1	2	3	4	5
5 (6,128)	1	2	3	4	5	6
6 (6,038)	2	3	4	5	6	7
7 (5,757)	3	4	5	6	7	8
8 (5,581)	4	5	6	7	8	9
9 (5,243)	5	6	7	8	9	10
10 (5,133)	6	7	8	9	10	11
11 (4,977)	7	8	9	10	11	12
12 (4,272)	8	9	10	11	12	-
13 (3,741)	9	10	11	12	-	-
14 (2,938)	10	11	12	-	-	-
Total	69,274					

The next data source consisted of GPS student assignment data files. These data also originated with GPS. The student assignment files for the 1998-1999 through the 2004-2005 academic year consist of 32,259 street-level student assignments. Each record consists of a street name, an address range, school identifier and grade range. These data were combined to reflect every unique pattern of school attendance available to students within a given cohort. Table 3.1 shows that for the 2004-2005 academic year, GPS students who made no school choice by applying to a magnet or other school could be assigned into one of 68 distinct sequences of schools for grades K-12. Similar data files exist for academic years from 1998-1999 to 2003-2004.[12] These records were combined over time to reflect the number of student assignment sequences available to each cohort of students. Conceptually, a student could fall into one of three broad categories:

- Students whose sequences of schools within a cohort match with the school sequences in the district student assignment data files are aligned with district student assignment policies.
- Students whose sequences of schools within a cohort do not match with the school sequences in the district student assignment data files but who attended magnet schools are aligned with district choice policies.
- Students whose sequences of schools within a cohort do not match with the school sequences in the district student assignment data files and do not contain magnet schools are assumed to have transferred residence, obtained an administrative waiver such as a grandfather provision or (perhaps) gamed the system in order to attend a different sequence of schools than anticipated by school district policy.

Coding of students in this manner isolates those students who most directly represent the intentions of district assignment policy and those who make magnet choices in schools.

The next source consisted of data on individual teachers and instructional staff. Staff level data files exist for the academic years 1998-1999 to 2003-2004, and were also provided by GPS. Each teacher file contains individual records, which describe each teacher's race and

[12] Although magnet schools are filled through a lottery process, some neighborhoods were actually zoned to attend a magnet school. These assigned magnets are reflected in the school sequences.

gender, credentials, years of experience, salary and work location.[13] Categories of professional staff in these files include classroom teachers, art and music teachers, librarians, guidance counselors and principals. When aggregated to the school level, these records provides school-level average teacher salary value. These school-level teacher salary variables represent an improvement over the traditional use of district average teacher salary, as recent research has shown that disparities in teacher salaries across school represent a key source of intradistrict inequity.

Teacher salaries as inequitably distributed resources

Marguerite Roza and Paul Hill, working with the Center for Reinventing Public education (CRPE) have conducted a number of intradistrict school finance studies. In a 2004 Brookings Education Paper, Roza and Hill review the role of teacher salary in assessing intradistrict disparities, Their review of the literature suggests that, although teacher salary is a tenuous proxy for teacher quality, the demands of the teacher labor market are such that schools with aggregate higher teacher salaries will usually have more capable or experienced teachers, as schools with more teacher applicants will be able to hire more highly paid (and perhaps, more highly effective) teachers. Roza and Hill found variation around the district mean teacher salary across schools within districts in Baltimore, Cincinnati, and Seattle. However, since all of these districts (and 16 other alluded to in the study) report district-wide average teacher salaries, this variation is lost to school finance researchers. In Baltimore City schools, for example, Roza and Hill found an average monetary discrepancy of $101,786 per school based on comparisons of

[13] Experience is measured as years working in the district. Experienced teachers who transfer into the district will have artificially low years of experience. In these cases, each teacher's salary would be a more accurate reflection of years of experience. Therefore, all teachers will have their salary and highest degree held compared to district salary schedules to determine actual years of teaching experience.

school-level mean teacher salary to district level mean teacher salary. That figure was $120,612 in Baltimore County, $106,974 in Cincinnati, and $72,576 in Seattle.

Since one flaw with many intradistrict studies addressed in the literature is the use of district mean salary at the school-level (Roza, 2005), and teacher salary represents a majority of school-level instructional funding, this information provides important variation across schools.

Goodville teacher salaries were computed with administrative and professional staff included, to provide a measure of "other professional salary" and without administrative staff to reflect a "teacher salary."[14] These school level data were imported into the student records database, so that every student, for every year, is assigned her or his school's average teacher salary. These data were also aggregated to the school level to provide data on teacher quality characteristics at the school level. Since students attended the district for different years (even within the same cohort), the new teacher and salary variables were weighted by student years of attendance to provide comparable percentage values. Table 3.4 provides an overview of select teacher salary and quality calculations by cohort. Teacher salary is positively statistically correlated with teacher experience at the $p<.05$ level with a coefficient of .802.

Finally, each school was coded by school type as reflected on the Tennessee Department of Education report cards and GPS data for a given year. These school types included: enhanced option, design center and magnet schools. These school types are supposed to receive additional funding and should be controlled for later in the analysis. Table 3.5 provides an overview of demographic characteristics and school types for each cohort in the dataset.

[14] All salary figures were adjusted for inflation using the consumer price index; all dollars are 2004 dollars.

Table 3.3: Teacher characteristics by cohort, all salary figures in 2004 dollars

Cohort	**Percent non-tenured**	**Mean teacher experience**	**Mean teacher salary**	**Mean salary**	**Salary difference**
1	.19	13.15	43,788.18	44,484.44	696.26
2	.20	12.96	43,455.33	44,294.97	839.64
3	.21	12.83	43,210.27	44,135.75	925.48
4	.23	12.31	42,801.15	43,797.43	996.28
5	.24	12.15	42,920.82	44,004.01	1,083.19
6	.26	11.86	42,729.23	43,842.43	1,113.20
7	.27	11.66	42,763.73	43,960.99	1,197.26
8	.26	11.81	43,097.67	44,381.39	1,283.72
9	.25	12.07	43,579.79	44,891.55	1,311.76
10	.23	12.74	44,399.93	45,688.42	1,288.49
11	.21	13.66	45,518.99	46,767.31	1,248.32
12	.20	14.18	46,141.30	47,452.07	1,310.77
13	.20	14.41	46,451.52	47,857.09	1,405.57
14	.20	14.33	46,293.02	47,803.85	1,510.83
Mean	.23	12.87	44,082.21	45,240.12	1,157.91

Combining these three datasets allows for close comparison of a student's actual sequence through the system versus the district level idea of students progress through the system. In addition, each student can be assigned the values of his or her total enrollment and total teacher salary over all years for comparison across cohorts, or the mean of the same variables for the same analysis within cohorts.

Table 3.4: School type characteristics, by cohort				
Cohort	**Mean enrollment**	**Percent years magnet**	**Percent years design center**	**Percent years enhanced option**
1	491.64	.025	.058	.038
2	499.21	.029	.063	.042
3	510.94	.028	.050	.043
4	527.68	.049	.037	.040
5	557.81	.056	.023	.028
6	576.98	.074	.014	.012
7	595.63	.097	.006	.006
8	718.61	.111	.003	.003
9	825.74	.133	.001	.003
10	957.17	.137	.0001	.0002
11	1,064.15	.131	0	0
12	1,163.81	.167	0	0
13	1,255.17	.177	0	0
14	1,234.19	.179	0	0
Mean	784.20	0.10	0.018	0.015

Methods

This dissertation makes use of traditional framework of school finance equity to assess the equity of student school sequences as a unit for analysis in intradistrict school finance studies. As outlined by Berne and Stiefel (1984), the procedure for assessing the equitable distribution of resources involves both horizontal and vertical analysis. Because of the data available and the nature of the research questions posed, vertical equity analysis will utilize quantile regression, a technique that estimates relationships at differing percentiles of the dependent variable (Koenker and Hallock, 2001). Specific methods for assessing levels of horizontal and vertical equity are described below.

Horizontal equity is popularly conceived as measures of the equal treatment of equals across a population. Although Berne and Stiefel note that it is readily obvious that not all children are equal and caution that horizontal measure should only be used to assess distribution of resources across like subgroups, horizontal equity analysis is traditionally presented as a foundational analysis for understanding the degree of inequity present in a system across variables of interest (Berne and Stiefel, 1994; Rolle and Liu, in press; Iatarola and Stiefel, 2003). Measures of horizontal equity are calculated as indices or ratios. While Berne and Stiefel list eleven measures of horizontal equity, this analysis will be concerned with three: the coefficient of variation, the McLoone Index and the Gini coefficient. The following section discusses each in turn.

The coefficient of variation is a simple measure of dispersion, calculated by dividing the standard deviation of a distribution by its mean. The formula for the coefficient of variation is:

$$\sigma / \mu \qquad (3.1)$$

The greater the inequity in the system, the larger the coefficient of variation. As outlined by Odden and Picus (1992), coefficients of variation greater than .1 reflect some degree of undesirable inequity across a distribution. For reference, Iatarola and Stiefel found coefficients of variation ranging from .08 to .195 in the dependent variables of their intradistrict equity analysis of New York City schools. Stiefel, Rubenstien and Berne (1998) reported coefficients of variation ranging from .09 to .26 in their review of intradistrict equity in four cities: Chicago, New York, Rochester, and Fort Worth.

The McLoone Index is a more recent development in econometrics, designed to provide a measure of the impact of inequity within a distribution on those located below the median within that observation. The McLoone index is a ratio of the total amount of funding allocated to the bottom 50% of a distribution expressed as a ratio to the total amount of hypothetical funding that same bottom 50% of a distribution would receive if each were funded at the median level. The formula for this ratio is:

$$(\sum_{i=1}^{J} P_i X_i) \Big/ (M_p \sum_{i=1}^{J} P_i) \qquad (3.2)$$

where J is the number of schools in district below the median value (M) , P is the per pupil amount of revenue for school J, M is the median value of revenues, where values between 1 and J are less than M_p. McLoone values reach zero in inequity and one in equity. Again, a guide from Odden and Picus is that McLoone values below .9 are generally considered equity concerns. Although the McLoone index has not been used often in academic research, it has been highlighted in recent work. In an examination of Tennessee districts, Rolle and Liu report McLoone indices that range from .88 to .93 across the years of 1994 and 2001 (Rolle and Liu, in press).

The Gini coefficient is a standard economic measure of dispersion. It expresses the ratio between the percentage of any given population and the cumulative percentage of resources expended. The Gini coefficient is calculated by:

$$(\sum_{i=1}^{N} \sum_{j=1}^{N} P_i P_j \left| X_i - X_j \right|) \Big/ \left[2(\sum_{i=1}^{N} P_i)^2 \overline{X}_p \right] \qquad (3.3)$$

and represents the ratio between a hypothetical situation in which each percent of a distribution receives that same percentage of revenue (i.e., 1 percent of the population receives 1% of total funding, 2% of the population receives 2% of total funding, etc.), and the actual distribution of revenue by percent of population. The Gini coefficient approaches zero in an equitable distribution and one in an inequitable distribution. P_i represents the number of pupil per school, P_j represents the number of pupil across all schools, X represents mean revenues, and X_p represents mean revenues across all pupils. For this analysis, pupils and schools will be replaced with schools and district level measures. Some intradistrict analysis has reported Gini coefficients, with Burke (1999) making extensive use of the measure; decomposing it to demonstrate inter- versus intra- district sources of disparity across Chicago schools as described above. As reported by Odden and Picus, a Gini coefficient of .1 is a desirable representation of equity.

Taken together, measures of horizontal equity provide information about inequalities in resources across a distribution. It may be case (and often is) that spending is horizontally inequitable for appropriate reasons – additional funds are being expended to assist traditionally low-performing groups. Additional vertical equity analysis can assist in determining the relationships between spending and student and school characteristics.

Recent work in school finance vertical equity analysis has eschewed the correlational analysis called for by Berne and Stiefel (1984) in favor of multivariate regression. The results of regression present an overview of strength, sign, and significance between school and community factors and school spending. Interdistrict analysis utilizes vertical equity to assess relationships between spending, outcome and property wealth. Since intradistrict analysis examines schools within an area that is similarly valued and similarly taxed (i.e., there is no variation in the relationship between property wealth and taxes raised), intradistrict school finance research uses vertical equity regression to assess relationships between school-level cost, school student body composition and schooling outcomes (Condron and Roscigno, 2003; Iatarola and Stiefel, 2003; Schwartz, Stiefel and Amor, 2005). In most cases of vertical equity analysis, input costs are excluded, and multiple school characteristics are regressed against cost. An example of a regression used in intradistrict finance analysis would be:

$$TS = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ...\beta_n X_n + \varepsilon \qquad (3.4)$$

where TS = teachers' mean salary at a given school (or any other pupil weighted cost dependent variable, such as total instructional expenditures, etc.), X_1 through X_n represent relevant independent variables such as student population characteristics; e is a randomly distributed error term, and β_1 through β_n represent estimates of the impact of a one unit change in the relevant independent variable on teacher salaries at the school level.[15]

Although this type of vertical equity regression has been used to provide insight into resource distribution across schools, it will not suffice in an assessment of resource distribution across school sequences. Measures of resource distribution for school sequences are averages of school-level variables within that sequence. Since regression coefficients provide insight into the relationship between the average value of an independent variable and the average value of a dependent variable, and since sequence level variables are simply arithmetically transformed school level variables, results from sequence level regressions will be substantially the same as results from school level regressions.

One way to address this issue is with quantile regression. Quantile regression builds upon the insights of maximum likelihood (ML) estimation to create a method to assess changing relationships between dependent and independent variables across a distribution. Originally

[15] This model represents the model used in Iatarola and Stiefel, 2003.

designed a more robust method for estimating relationships between variables in populations where the distribution of the error term did not meet the Gaussian assumptions of ordinary least squares (OLS) based methods (see Koenker and Bassett, 1978), quantile regression has gained popularity as a method to gain information about relationships between independent variables and a dependent variable at different points in the distribution than the conditional mean used by OLS (Eide & Showalter, 1998; Koenker, 2005).

To do this, the τ th quantile of a variable Y is defined as the inverse function of the of the probability distribution of Y. That is, if Y is a random variable with a probability distribution function of

$$F(y) = \Pr obability(Y \leq y) \qquad (3.5)$$

then the τ th quantile of Y is the inverse function such as

$$Q(\tau) = \inf\{y : F(y) \geq \tau\} \qquad (3.6)$$

The median in this case is Q(.5), while the 25th percentile would be Q(.25). Optimizing this equation yields a different regression equation; similar in form to an OLS equation that expresses relationships between independent variable and a specified quantile. The bivariate quantile regression equation is

$$Q_y(\tau \mid x) = \beta_0 + x_1\beta_1 + F_u^{-1}(\tau) \qquad (3.7)$$

where Q is the given quantile and F_u is the distribution function term of the errors (Koenker, 2005). This assumes that the errors are identically distributed and independent.[16] Quantile regression provides robust estimates that are also equivariant under monotonic transformations (see Cade & Noon, 2003) and are not overly sensitive to outliers in the distribution. Quantile regression has been used in economics (see, for example, Martins and Pereira, 200),

[16] A model in which error terms are heteroskedastic is described more fully in the section to follow.

environmental research (see, for example, Schröder, Andersen and Kiehl, 2005), and medical research (see, for example, Austin and Schull, 2003) but has only rarely been used in assessing education questions (see Eide & Showalter, 1998 as well as Levin, 2001 for examples).

Levin uses quantile regression to estimate marginal effects of the role of class size in student achievement along different points in the distribution. Levin states, “the researcher asks not what the effect…is on average, but for whom such effects are significant and how large they might be” (p.223). Levin further notes the suitability of quantile regression as a methodology to assessing equity questions in education research (p.223). From this perspective, the use of quantile regression in conducting vertical equity studies – regardless of the unit of analysis – will provide important information about the status of the marginal student at different points along the distribution of a dependent variable. Inequity in a quantile regression framework can take many forms. For example, if the funding gap between minority and white students is wider at the .8 quantile of resource distribution than at the .2 quantile, then inequity is assessed as the race gap at higher quantiles of the distribution.

Consequently, this research will use quantile regression to estimate relationships between student characteristics and school level resources: teacher and other professional salary, percentage of racial minorities, and students eligible for free lunch, and percent of teachers in a school who have 3 or fewer years of experience.

Each of the methods in assessing horizontal and vertical equity described above will be employed to aid in understanding the role that student assignment plays in the levels of resources provided to students. The section that follows outlines the specific analytic steps that will be employed to determine the role that school sequences pay in the distribution of educational resources.

Analytic strategy

Because no assessment of intradistrict equity using school sequences has been conducted, this dissertation will examine intradistrict inequity at both the school level and the sequence level and compare findings from the two analyses. The following sections outline a proposed analytic strategy to identify levels of equity across GPS schools, to examine equity across school sequences with special emphasis on those sequences that are aligned with district policy as written.

This analysis will occur in three steps. The first step will seek to describe the characteristics of students within the database by sequence characteristics - such as students in sequence, transfer students, magnet school attendees - and compare mean values for these students controlling for cohorts and for student years in the system. This description will provide insight into the type of sequences encountered by GPS students between 1999 and 2004 and the frequency with which those sequences were encountered.

The second step will consist of a traditional school-level finance equity study. Results from this analysis: coefficients of variation, McLoone indices and Gini coefficients as well as estimated regression coefficients will be compared to findings from a sequence-level analysis. In order to obtain apples to apples comparisons between regression coefficients, quantile regression will also be applied in this “school level” analysis to demonstrate the manner in which the relationships between student characteristics and resources varies across a distribution.

The third step of analysis will replicate the of quantile regression second step using the accounting for student school sequences. Once the base comparison has been made, this step will also control for sequence type in order to provide a better understating of the sources of variation in dependent variables. Each step is discussed more fully below.

Description

An appropriate first step in an analysis with a large student database and a new proposed unit of analysis is to describe the variables in the database: their attributes and variation across the data. Analysis of key variables across cohorts, across years of enrollment, across transfer status, grad retention status and magnet school attendance will be presented and interpreted before conducting horizontal and vertical equity analysis. Description of this sort will allow for a closer examination of issues that arise from the database, while still anchoring the focus on the comparison of findings between school sequences and school level analysis of the equitable distribution of resources. Key questions at this stage of analysis will be:

- How many students attended schools in district created sequences, attended district provided magnet choices, or attended school sequences that were not developed by district policy?
- How were in-sequence, magnet and transfer students resourced? Did any group of students "trade up" by making different school decisions?

Dependent variables

This analysis will therefore focus on five resource variables. Each is described more fully below. Dependent variables are:

- teacher salary;
- other professional salary;
- school-level percent of minority students;
- school-level percent of free and reduced price lunch eligible students; and,
- teacher quality as measured by non-tenure status.

Prior research has shown teacher salary variable to represent a high percentage of instructional spending (Berne and Stiefel, 1994), and to have a relationship with school racial and economic characteristics (Roza, 2004). Teacher and other professional salary best represent the dynamics of intradistrict school finance this study seeks to capture.

School-level percentages of minority or poor students are traditionally used as independent variables to predict the provision of a more pecuniary dependent variable. However, the literature on peer effects suggests that school composition variables such as the percentage of minority or free lunch eligible students at a schools may represents resources that impact student attainment and achievement. The structure of the data set and the application of quantile regression allows for more interesting analysis. In this case, vertical equity models using quantile regression provide information on the manner in which individual race and poverty characteristics interact with school-level concentrations of poor and minority students. It is natural to expect a student's race to predict school levels of racial composition; but the difference in these relationships across quantile can provide insight into the intensity of segregation across schools.

Finally, teacher inexperience exists as a purchased input that may operate differently from teacher and salary. A measure of the percentage of non-tenured teachers at a student's school represents a degree of teacher quality present for that student (see, for example, Rice, 2003; Hanushek, et al, 2005).

Traditional (school-based) analysis – horizontal equity

The next step of inquiry is to conduct a standard analysis of resources as distributed across Goodville schools, as is found in many intradistrict school finance studies. Three measures of horizontal equity – the coefficient of variation, the McLoone index and the Gini coefficient will be calculated across students for two cost variables per year: teacher salary per pupil and other professional staff salary per pupil across GPS schools. In addition, assessments of horizontal equity have often also applied measures of distribution to student racial and economic characteristics (Rolle and Liu in press; Rolle, McColl and Houck, in review). Some have even begun applying this analysis to outcomes (see Iatarola and Stiefel, 2003).

Traditional (school-based) analysis – vertical equity

Vertical equity at the school level will be assessed in this step using multiple regression. Conceptually, vertical equity regressions will utilize two classes of variables: demographic variables and school type variables – to determine the impact of school characteristics the teacher and other professional staff salary dependent variables.

One insight from the literature review is that the strength of relationship (expressed by the slope) between enrollment and spending may change as output changes, thereby necessitating the use of a polynomial term (Studenmund, 2001). Because concentrations of poor and minority students were a concern for Nashvillians during the move to unitary status and because of the confluence of race and class variables that often occurs in educational research, the proposed model will include an interacted term of race and class. Specifically, the interacted term is the multiplicative product of the non-white and free and reduced price lunch variables. Using an interacted term of this sort allows for interpretation along three race/class dimensions: the impact of minority students who are not poor; the impact of poor students who are non minority, and the impact of students who are both poor and minority on spending (see Rolle, McColl and Houck, in review, for an example of using an interacted term to tease out separate funding effects for urban and rural minority students). In a separate regression, school type variables will account for any changes in funding due to a school's designation as an enhanced option, design center, middle school, or magnet school, net of student demographic characteristics. The final two models of a school-level vertical equity regression will be:

$$S_x = \beta_0 + \beta_1 E + \beta_2 E^2 + \beta_3 MIN + \beta_4 FRPL + \beta_5 (MIN \times FRPL) + \\ \beta_6 2000 + \beta_7 2001 + \beta_8 2002 + \beta_9 2003 + \beta_{10} 2004 + \varepsilon \qquad (3.8)$$

and

$$S_x = \beta_0 + \beta_1 E + \beta_2 E^2 + \beta_3 DC + \beta_4 EO + \beta_5 MAG + \\ \beta_6 2000 + \beta_7 2001 + \beta_8 2002 + \beta_9 2003 + \beta_{10} 2004 + \varepsilon \qquad (3.9)$$

where S is one of five resource variables, E is enrollment, E^2 is the squared term of enrollment, *MIN* is the minority status of an individual student, *FRPL* is the free lunch status of an individual student, *DC* is a dummy variable taking the value of 1 if a school is a design center, *EO* is a dummy variable taking the value of 1 if a school is an enhanced option school, *MAG* is a dummy variable taking the value of 1 if a school is a magnet school, and the variables 2000,2001,2002, 2003 and 2004 are variables which account for individual year fixed effects, and e is a randomly distributed error term. The coefficients represent estimated relationships between a unit change in the appropriate independent variable on the percent change in the dependent variable – one of the five resource measures described above. Separate equations are used to explain maximum variation related to either student characteristics or school types. Appendices will present finding of fully specified models containing both student characteristic and school type variables.

This vertical equity analysis across schools represents an application of traditional methods of intradistrict analysis across GPS schools. On its own, it represents a contribution to the larger literature on intradistrict school finance by providing sharper analysis of resource distribution across an urban Southern system. Findings from this step of analysis can be compared with findings from other studies to sharpen researchers' understanding of across school resource distributions.

If vertical equity appropriately asks about the unequal treatment of students under unequal conditions, then the use of the average relationship between changes in an independent variable on the mean of the dependent variable is a weak method to answer these questions. This is illustrated through an examination of figures 3.1 and 3.2, below.

Figure 3.1 presents a graphic illustrating traditional OLS regression analysis. In this figure, a hypothetical example is developed using average teacher salary as a dependent variable. Values of teacher salary run along the y-axis. The x-axis has values of 0 and 1, representing a dummy variable for student minority status (0=White, 1= minority). The two vertically oriented normal curve represent the hypothetical distribution of teacher salary for only White students (over the 0 on the x-axis) and for only minority students (over the 1 on the x-axis). The asymmetrically shifted normal curves demonstrate that minority students, hypothetically, receive fewer average teacher salary dollars than White students do; the curve for minority students is shifted down from the similar distributional curve for majority students. The line from the mean value of the majority distribution to the mean value of the minority distribution represents a regression coefficient, the slope of a line expressing the average difference in teacher salary between majority and minority students. This aligns with a traditional interpretation of a regression coefficient on the dummy variable of minority status: "minority status is associated with decrease in teacher salary dollars of β_1."

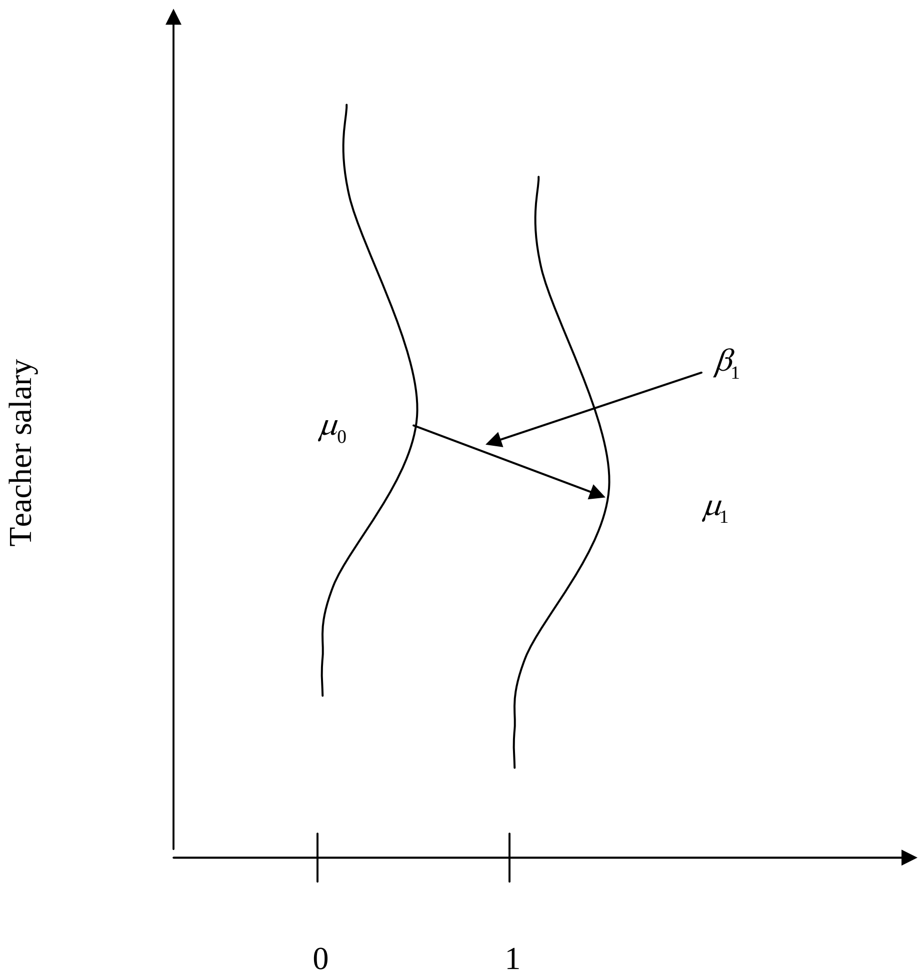

Figure 3.1 – hypothetical OLS regression

However, Figure 3.1 explains very little about racial difference in teacher salary across the distributions of majority and minority students. Perhaps the average difference is slight, but a greater discrepancy exists between minority and majority students and very low teacher salaries, or very high salaries. Figure 3.2 represents a quantile regression approach to examining this same issue. Rather than one line representing the entire difference between teacher salary levels for majority and minority students, there are now three lines – representing this relationship at the .25, .5 and .75 quantiles of the distribution of teacher salary.

Figure 3.2 is more illuminating. Although the slope of the line connecting the median (Q_{50}) points of the majority and minority distributions ($\beta_{1,Q50}$) of teacher salary is similar to line representing the relationship between racial differences in average teacher salary shown in figure 3.1, the line representing the relationship between minority and majority students at the 25% quantile of the distribution ($\beta_{1,Q25}$) is steeper, indicating a larger racial gap in the provision of the very lowest teacher salaries. This represents a beta coefficient in a regression equation that is larger than the coefficient on the same variable at the median.

At the .75 quantile, representing high teacher salaries, the line representing the relationship between majority and minority students ($\beta_{1,Q75}$) is relatively flat, indicating that minority students receive roughly the same exposure to highly paid teacher than their majority peers.

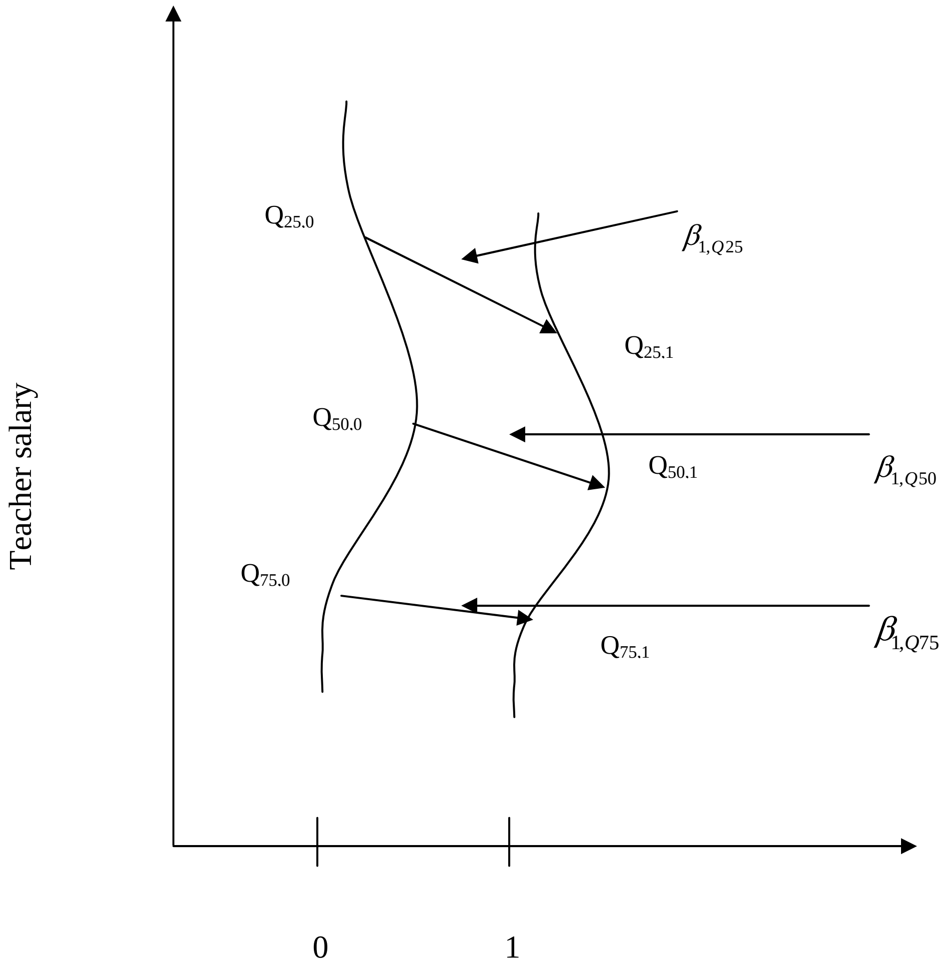

Figure 3.2 – hypothetical quantile regression, quantiles 25, 50 and 75

When taken together, the picture in figure 3.2 illuminates how inequity works its way across a distribution and provides for a more nuanced interpretation of results. Minority students are more impacted when they are at the low end of the distribution of teacher salary than at the median or at the high end of the distribution. Minority status has a greater impact among low-paid teachers than among other teachers. In interpretation of quantile regression results, inequity can be described both in magnitude (all coefficients in figure 3.2 point towards an inequitable relationship between race and salary) and in the location of greatest impact along the distribution of the dependent variable.

It should be noted that figure 3.2 could be composed using either school-based or sequence-based analysis. In this dissertation, quantile regression will be used in computing relationships at the school level and the sequence level. The comparison between the two methods will determine if the relationships between the two sets of results are statistically different, and in which direction.

Determining the changing relationships between independent and dependent variables across each distribution, as provided by quantile regression, will allow greater insight into the manner by which educational resources are distributed for a number of reasons.

Because quantile regression represents a powerful new way to understand relationships between funding, student racial and economic characteristics and school types, it will be used in addition to standard OLS regression for vertical equity analysis. Models at this stage of analysis will follow conventions of vertical equity analysis, but will conduct the analysis using quantile regression. The basic quantile equation for a quantile regression model with a heteroskedastic error term is

$$Q_y(\tau \mid x) = \beta_0 + \beta_1 X_1 ... + \beta_n X_n + \sigma(x) F^{-1} \tau \qquad (3.10)$$

where Q is the x^{th} quantile of the distribution of dependent variable Q, and the error term is the inverse function of the variance for quantile x. School type variables will account for any changes in funding due to a school's designation as an enhanced option, design center, middle school or magnet school, net of student demographic characteristics. The final models of a school-level vertical equity quantile regression will be:

$$Q\ (\tau \mid x) = \beta_0 + \beta_1 E + \beta_2 E^2 + \beta_3 MIN + \beta_4 FRPL + \beta_5 (MIN \times FRPL) + \beta_6 2000 + \beta_7 2001 + \beta_8 2002 + \beta_9 2003 + \beta_{10} 2004 + \sigma(x) F^{-1} \tau \tag{3.11}$$

and

$$Q\ (\tau \mid x) = \beta_0 + \beta_1 E + \beta_2 E^2 + \beta_3 DC + \beta_4 EO + \beta_5 MAG + \beta_6 2000 + \beta_7 2001 + \beta_8 2002 + \beta_9 2003 + \beta_{10} 2004 + \sigma(x) F^{-1} \tau \tag{3.12}$$

where Q is one of five dependent variables and $(\tau \mid x)$ is the specified quantile of the distribution of the dependent variable,[17] *E* is enrollment, *MIN* is the minority status of an individual student, *FRPL* is the free lunch status of an individual student, *DC* is a dummy variable taking the value of 1 if a school is a design center, *EO* is a dummy variable taking the value of 1 if a school is an enhanced option school, *MAG* is a dummy variable taking the value of 1 if a school is a magnet school, and $\sigma(x)F^{-1}\tau$ is a randomly distributed error term. Year-by-year fixed effects will also be included in these models to control for the effects of time. The coefficients represent estimated relationships between a unit change in the appropriate independent variable on the change in the dependent variable – one of the five dependent variables described above. Analysis will be conducted across a standard range of quartiles (.10, .25, .50, .75, .90) using quantile regression with resampling to determined confidence intervals, F values and p values.[18]

[17] This analysis will utilize what have come to be the “conventional” quantiles: .10, .25, .50, .75, .90. See Levin (2003) for an example.
[18] The SAS PROC QUANTREG procedure uses a newer bootstrap method called the Markov chain marginal bootstrap (MCMB). This procedure, developed by He and Hu (2002), is more efficient in resampling for quantile regression because it is designed to compute *p* one-dimensional solutions instead of computing *p* dimensional solutions within the matrix.

Sequence-based analysis

The main question addressed by this research is a determination of the manner in which school sequences used as a unit of analysis might alter findings from intradistrict school equity studies. Equity analysis will therefore be conducted with school sequences, using aggregates of teacher salary and other professional staff salary variables. Horizontal equity measures will include the coefficient of variation, McLoone Index and Gini coefficient. Vertical equity will be assessed using quantile regression, although the model will be modified to account for the longitudinal nature of sequences.

Year by year fixed effects will be computed by creating a weighted variable for each year in the data sequence for each student. For example, a student in the database for three years, 2001, 2002 and 2003 will have a fixed effect for each year with a value of .33. A student in the database for four years would have each of the years of her inclusion weighted by a factor of .25. In this manner, sequence based analysis can still account for the vagaries of time while providing apples to apples equations for comparisons of effects between school-based and sequence-based analysis.

As Table 3.2 illustrates, the database for this analysis consists of 69,024 records distributed across 14 cohorts. By taking the weighted averages of dependent variables salary, analysis across all 14 cohorts can be conducted. In some cases, simply expressing the variable as a mean across all years for the number of years a student was enrolled.

In other cases, the dependent variable will be expressed as a weighted dummy variable much like the weighted fixed effects for year. For example, a student who is enrolled for 3 years and is free lunch eligible for two years will have a free-lunch percentage of 2/3, or roughly 66%. A student enrolled for all six years and free lunch eligible for two years will have a free lunch variable value of 2/6, or roughly 33%. The purpose of this type of analysis is to determine overall levels of equity across six years of data and to locate them within the horizontal equity statistics computed at the school level for all six years of the study. Vertical equity across all student sequences will be conducted using quantile regression. The initial model for this analysis will be:

$$\begin{aligned} Q\ (\tau \mid x) &= \beta_0 + \beta_1 MEANE + \beta_2 MEANE^2 + \beta_3 MIN + \beta_4 \%FRPL + \\ &\beta_5 (MIN \times \%FRPL) + \beta_6 2000w + \beta_7 2001w + \beta_8 2002w + \\ &\beta_9 2003w + \beta_{10} 2004w + \sigma(x) F^{-1} \tau \end{aligned} \tag{3.13}$$

and

$$\begin{aligned} Q\ (\tau \mid x) &= \beta_0 + \beta_1 MEANE + \beta_2 MEANE^2 + \beta_3 \%DC + \beta_4 \%EO + \beta_5 \%MAG + \\ &\beta_6 2000w + \beta_7 2001w + \beta_8 2002w + \beta_9 2003w + \beta_{10} 2004w + \sigma(x) F^{-1} \tau \end{aligned} \tag{3.14}$$

where Q is the specified quartile of the dependent variable, MEAN*E* is average enrollment and *MIN* is the minority status of a student. Because this analysis occurs across sequences, the variable *%FRPL*, *%DC*, *%EO*, and *%MAG* indicate the percentage of years a student received free or reduced price lunch or was assigned to a design center, enhanced option, middle or magnet school. Year fixed effects are weighted as described above and noted as 2000w, 2001w, 2002w, 2003w, 2004w.

A final step of analysis will be to compare the findings from those studies conducted at the school level to those conducted at the sequence level. Horizontal equity statistics, since they are population specific, can be directly compared. Clear interpretation of coefficients will allow for a determination of the impact of sequences level analysis as compared to school level analysis. Sets of coefficients from regression equations can be compared using a graphical comparison developed by Basset, Tam and Knight (2002) to assess whether sequence-based estimates fall outside of the 95% confidence interval of similarly derived school-based independent variable coefficients.

Conclusion

Equity in the provision of educational resources remains a concern for educators and policymakers, despite growing concerns about adequacy of resources in producing educational outcomes. With greater availability of data and greater technical sophistication, increasing interest has developed in assessing the degree to which districts distribute resources to schools and relationships between traditional markers of at-risk student populations and the follow of resources into schools with high proportions of those populations. Intradistrict finance equity study places a premium on school composition variables such as race and poverty. It follows, then, that consideration the manner in which school composition is created, and the consequences of school composition over time, be a consideration of equity analysis at the intradistrict level. This dissertation research poses two research questions:

1. Are measures of intradistrict equity different when measured across school sequences than when measured across schools?
2. Do school sequences for poor and minority students differ from school sequences for other students? If so, do poor and minority students attend sequences with greater or fewer resources than their non-poor, non-minority peers?

In answering these two research question, this research will conduct school wide equity analysis using horizontal and vertical equity measures across all students in GPS for the years 1998-1999 to 2003-2004 and within 14 cohorts of those students. This research will contribute to a better understanding of the manner in which district assignment, choice and teacher transfer policy interacts with funding policies. It will provide a framework for using quantile regression to assess vertical finance equity. Finally, this research contributes to the literature on quantile regression as a tool for evaluating levels of equity within school finance frameworks.

CHAPTER IV

ANALYSIS

Introduction

Analysis of school sequences in intradistrict resource allocation analysis introduces several new concepts to the field of school finance equity studies, and intradistrict finance studies in particular. Therefore, this analysis will work through a number of necessary steps in order to arrive at satisfactory conclusions to the research questions. First, student sequences need to be created and classified using available data. Second, traditional equity analysis, undertaken across schools, will determine a baseline of results against which to judge sequence-based analysis. Third, quantile regression (QR), conducted across schools, will demonstrate how QR results differ from ordinary least squares (OLS) results. Finally, QR using school sequences will provide the comparison between school-level and sequence-level analysis of vertical equity. The analytic strategy section below reviews each of these steps. Each of these steps generates findings that are relevant to the field of intradistrict school finance and relevant to answering the research questions posed by this dissertation.

Consequently, this chapter will unfold in the following manner. An initial section will review the analytic strategy used to find answers to research questions posed in chapter one. Next, an overview of key findings will provide a guide to the sections of analysis to follow. Finally, additional sections will expand on each research finding, including methods, findings, and conclusions.

Analytic strategy

The purpose of this research is to examine the role that school sequences play in the distribution of educational resources across students within districts. Since most intradistrict equity studies focus on examining the distribution of resources across schools, they may fail to account for the manner in which student school attendance mediates or moderates resource distribution. School sequence analysis will examine the equity of resource distribution across a student's entire academic career. Specifically, this research addresses two questions:

1. Are measures of intradistrict equity different when measured across school sequences than when measured across schools?
2. Do school sequences for poor and minority students differ from school sequences for other students? If so, do poor and minority students attend sequences with greater or fewer resources than their non-poor, non-minority peers?

To answer question one, school sequences will be constructed and described for available data. Once constructed, horizontal equity statistics between schools and sequences can be compared.[19]

To answer question two, regression coefficients for poor and minority students will be compared across five regression models: (1) school-level ordinary least squares (OLS) regression using pooled data with year fixed effects with student characteristics as independent variables; (2) school-level ordinary least squares (OLS) regression using pooled data with year fixed effects with school types as independent variables; (3) quantile regression (QR) on pupil-weighted school-level data using the same regression models as OLS analysis (2) and (3); (4) QR

[19] Horizontal equity statistics were created using the 'inequal' subroutine in Stata 9.0. McLoone indices were hand calculated in Stata.

using school sequences with weighted year controls and student level characteristic as independent variables; and, (5) QR using school sequences with weighted year controls and school type characteristic as independent variables.[20]

Why so many steps? The use of quantile regression introduces a new method for assessing vertical equity into the school finance framework. As discussed in chapter three, QR is the chosen method for this analysis because 1) OLS would provide similar results between school-based and sequence based analysis and 2) QR provides information about the pattern of relationships between independent variables and resource allocation along different points of the distribution as illustrated in figures 3.1 and 3.2.

Since quantile regression has not been used in a vertical equity application within the field of school finance, it is necessary to calibrate QR findings relative to OLS findings. That is, since quantile regression will be the method for assessing any differences between school-based and sequence-based analysis, it is important to know how to interpret school-based QR relative to school-based OLS analysis. Once established, QR results can be compared between school-based and sequence-based analyses in order to determine whether sequence-based analysis provides different results from school-based analysis. This process will both provide answers to a comparison of sequence-based versus school-based analysis, it will also provide findings that are comparable to traditional vertical equity analysis.

The following steps will be taken: Results from steps 1 and 2 will be compared with results from step 3 in order to determine what additional information is provided by QR that is not provided by OLS. Coefficient estimates from step 3 will be compared to results from steps 4

[20] OLS regression estimates were calculated using "PROC REG" in SAS 9.1. QR estimates were obtained using "PROC QUANTREG" in SAS 9.1. PROC QUANTREG is a SAS experimental procedure updated in January of 2006. Additional information about proc quantreg and downloads can be found at http://support.sas.com/rnd/app/da/quantreg.html.

and 5 to determine whether sequence-based analysis yields statistically different estimates from school-based analysis.

Overview of findings

The purpose of this section is to describe key findings from each step of the analysis. This overview will provide an orientation to the steps of analysis as described in chapter two as well as above. These findings are listed in order of their discovery throughout the analytic process. The list below summarizes findings from each step of analysis.

Findings from school sequences

Although school sequence creation yielded over 32,000 distinct sequences and parts of sequences, only 27% of students in the database were classified as “in sequence.” After accounting for students who repeated grades and chose to attend magnet schools, there were still 40% of student who were not accounted for. Descriptive analysis revealed that students not in sequences were no different from students in sequences vis-à-vis the distribution of five resources: teacher experience minority and free lunch peers, and teacher and other professional staff salaries. Magnet students, however, seemed to experience higher percentages of non-tenured teachers and considerably lower percentages of free lunch peers.

Findings from horizontal equity analysis

Horizontal equity analysis determined that each of the five resource variables were inequitably distributed across students. Horizontal equity analysis conducted across sequences of schools yielded horizontal equity statistics that were often less than school-based analysis. That is, although sequence based horizontal equity analysis still showed the distribution of resources to be unequal, those findings were of a lesser magnitude than findings from school-based horizontal equity analysis.

Findings from OLS vertical equity regressions

Standard OLS regression vertical equity analysis confirmed that vertical inequity was related to both student characteristics such as race and class, as well as school types such as design center, enhanced option and magnet schools. Overall, poor and minority students experienced higher percentages of non-tenured teachers, less average teacher and other professional staff salary, and higher percentages of poor and minority peers in the schools they attended. Among school types, enhanced option schools functioned more like magnet schools – they both provided higher levels of salary and higher percentages of minority peers. However, enhanced option schools were associated with increases in free lunch peers while magnet schools were associated with decreases in free lunch peers.

Findings from school-based quantile regression vertical equity regressions

School-based quantile regression yielded estimates that were different from school-based vertical equity regressions using OLS. Quantile estimates allowed for greater interpretation of results across the distribution of each dependent variable.

Findings from sequence-based quantile regression vertical equity regressions

Finally, results from sequence-based quantile regression were often different from similar estimates using school-based QR. However, there was no systematic pattern of differences: 46% of coefficients were greater than school-based estimates, and 44% of sequence-based estimates were lower. Although school sequences provide different estimates of vertical equity than school-based quantile regression, the use of sequences may be specific to the research questions.

Overall, results confirm that sequence-based vertical equity analysis using quantile regression provide different estimates that may be useful in some contexts. In addition, systematic vertical inequity based on student characteristics in particular functions through school sequences as well as through schools. The sections that follow will describe the coding of data, the mechanics of horizontal and vertical equity analysis and results from each step.

Describing school sequences in GPS, 1999-2004

This section examines the role of school sequences in assessing levels of horizontal and vertical equity, using data from the GPS for the years 1999-2004. The idea of a school sequence is a common one: every student has a trajectory of schools he or she attends over time. In this sense, every student in the database has a school sequence, even if that sequence consists of only one school or one academic year. As outlined in the introduction, therefore, it is important to note and classify the types of sequences students can create as they move through a school system over time. Chapter one outlines three types of school sequences. These sequences occur when:

- Students are assigned directly to schools by district policy;
- Students take advantage of choices – such as magnet schools – provided to them by the district; or,
- Students change schools by changing residence, being grandfathered in by the system or otherwise finding a way to attend schools out of the mandated sequence.

This section will outline the operationalization of these sequences are within the dataset. It will provide descriptive statistics as well as a breakdown of students by cohort, by years enrolled, and by sequence. The number and types of sequences will be the focus of a final discussion before presenting two rounds of analysis comparing school-level and sequence levels of equity in the provision of five resources: teacher experience, school percent minority, school percent free lunch, teacher salary, and other professional staff salary. An important first step is to adjust the data to control for the varied number of years a student can attend schools. This is done by constructing cohorts of students based on the grade of entry and subsequent progress through schools.

Cohort construction

Table 3.2 (reprinted below as table 4.1) gives an overview of each cohort in the database, the years and grades attended by members of that cohort, and the number of observations in each cohort.

Within the dataset, a student received a cohort designation based on the grade and year combinations of a student's first year in the database. For example, in order to be placed in cohort six, a student's first year in the database could have been K in 1999, one in 2000, two in 2001, three in 2002, four in 2003, or five in 2004. In this manner, students who repeated or transferred were accounted for in cohort assignments.

Table 4.1: Student cohorts in GPS, 1999-2004; all students with 3+ years in system.						
Cohort (n)	**1998-99**	**1999-00**	**2000-01**	**2001-02**	**2002-03**	**2003-04**
1 (3,876)	-	-	-	K	1	2
2 (4,498)	-	-	K	1	2	3
3 (4,872)	-	K	1	2	3	4
4 (6,220)	K	1	2	3	4	5
5 (6,128)	1	2	3	4	5	6
6 (6,038)	2	3	4	5	6	7
7 (5,757)	3	4	5	6	7	8
8 (5,581)	4	5	6	7	8	9
9 (5,243)	5	6	7	8	9	10
10 (5,133)	6	7	8	9	10	11
11 (4,977)	7	8	9	10	11	12
12 (4,272)	8	9	10	11	12	-
13 (3,741)	9	10	11	12	-	-
14 (2,938)	10	11	12	-	-	-
Total	69,274					

Eight of the 14 cohorts (cohorts number 4 through 11 in figure 3.2) cover six years of school attendance and 45,077 (65%) observations. The remaining six cohorts (one through three; 11 through 14) cover fewer than six years of school and the remaining (35%) observations. Within each cohort, there are myriad possibilities for each student: they can be retained, transfer, opt into a magnet school, or continue in their district-assigned sequence of schools. A cohort, then, only represents a student's peer group as he or she moves through schools. A cohort is ideal for comparing students to those most like them in age and grade and for controlling the effects of time, but describes little else. Therefore, additional variables describe the types of students within each cohort and the sequences of schools available to students within each cohort. The following section will describe the creation of sequence variables.

Sequence construction

This research seeks to examine the effects of school sequences on resource distribution. Within each cohort, there can be three sequence types.[21] First, a student can attend all of the schools assigned to him or her by the school district for any or all of the available years in a sequence. Second, a student can fail to complete the schools in the sequence they were assigned, either by 1) exiting the entire school system or 2) otherwise attending schools in the system in a sequence that does not match a district prescribed sequence for the student's cohort. A student can, therefore, be an "in-sequence" student, or a "chooser." The sections below describe each variable in more below. Additional variables will trace the relationships between school sequences and magnet schools.

- In-sequence – A student was coded as "in sequence" if the series of schools attended matched a series of school outlined in district policy. School sequences were determined by analyzing the GPS street-level student assignment database. Once all possible sequences were determined for a cohort, those possible sequences (consisting of 3, 4, 5, and 6-year strings of schools) were expanded to include all possible 3, 4 and 5-year combinations. Duplicate strings were removed. Remaining were 32,259 distinct school sequences for students. Accounting for these partial strings of schools allowed students who moved into or out of the database to still be considered "in sequence."

[21] Specific choice policies in GPS provide for additional variations of these three sequences and will be discussed in a following section.

- “Choosers” were students who did not fit into a GPS school sequence for their years in the database, and accounted for 73%, or 50,570, students. One obvious reason for a student to be out of sequence is that he or she attended an GPS magnet school. Students who attended a magnet school but were not in sequence were labeled magnet choosers – they chose a magnet option and were able to attend through audition or lottery.

Overall, 18,704, or 27%, of students in the database were determined to be in-sequence. In the database, 17% of students – or 11,777 – chose a magnet school outside of their school sequence. Table 4.2 presents a breakdown of students in magnet schools across cohorts. This leaves 56% of students attending schools outside of GPS school sequences – a large percentage. Since some students could be retained and still fall into a defined school sequence, students were coded as “retained” based on their grade of record in each year. If the grade of record was the same for two years, the student was coded as retained. Descriptive statistics indicate that 16% of students in the database were retained; that is, they had the same grade variable for two consecutive years. Removing these students from consideration leaves a remaining 40% of students out of sequence. It may be that these students are mobile – they moved residences and therefore changed schools. It could also be the case that these students were allowed by the district to stay in a prior sequence through grandfathering. This would occur outside of their assignment sequence, it is difficult to tell. GPS reconfigures assignment by street and house address every year, adjusting for in-migration and out-migration of students. Consequently, short of a physical address linked to a student record, the decision-making of these 33,427 students is sketchy at best. In sum, 27% of student in the database were in district-designed sequences, and 40% were not. Sixteen percent were retained and 17% attended magnet schools for at least one year. Once conclusion drawn from these descriptive findings is that the system of student assignment is flexible, through a combination of district intention (such as grandfathering), lack of enforcement, or student mobility.

Figure 4.1 provides an overview of the manner in which sequence and magnet school type variables are related. The categories of transfer students, in-sequence students and magnet choosing students are almost mutually exclusive.

Table 4.2: Magnet school categories by cohort, 1999-2004

Cohort	Magnet –in-sequence	Magnet choosers
1	0 (0)	.039 (.19)
2	.0007 (.03)	.05 (.21)
3	.002 (.04)	.05 (.22)
4	.0002 (.01)	.12 (.32)
5	.004 (.06)	.15 (.35)
6	.003 (.05)	.17 (.38)
7	.006 (.07)	.21 (.40)
8	.02 (.14)	.22 (.41)
9	.03 (.18)	.25 (.44)
10	.03 (.16)	.23 (.42)
11	.02 (.13)	.20 (.40)
12	.0005 (.02)	.23 (.42)
13	0	.21 (.40)
14	0	.19 (.40)
Mean	.008	.165

Note: Standard deviations in parenthesis. Means may not total 100% due to rounding.

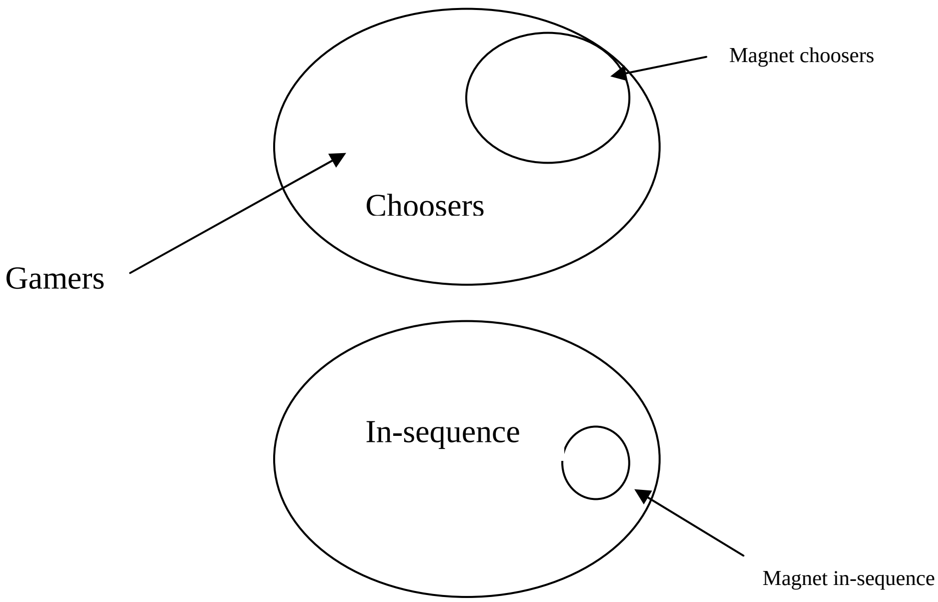

Figure 4.1: Sequence types

School sequence and magnet school variables, as described above, provide an overview of the role that school sequence analysis will play in determining levels of horizontal and vertical resource equity. The picture of GPS is one where students are highly mobile: 56% of students in the database were not in a district-assigned or a magnet school sequence, and only 27% of students remained in sequence, even accounting for students who attended school for only part of a given cohort.

A second finding is that GPS magnet schools function as a legitimate choice for students – 17% of whom take advantage of magnet options. Only .8% of students were assigned to magnet schools through district-assignment policies.

Having described the manner in which students are distributed across these sequence types, analysis can begin by asking whether different categories of students receive different treatment of resources. Specifically, do the values of teacher salary, other professional staff salary, percent of non-tenured teachers, percent of minority peers and percent of free lunch peers vary by student type? Perhaps students who are not in their assigned sequences "trade up" to maximize the resources available to them.

Table 4.3 provides the mean value of each of the five dependent variables by the student categories of in-sequence, magnet choosers and other choosers (whose decisions are not clear but are not in assigned sequences) of the system who were not retained.

Table 4.3: Comparisons of resources across sequence type

	In-sequence	Magnet chooser	Not-in-sequence
Percent non-tenured	22.0%	23.7%	22.8%
Percent minority peers	52.7%	56.5%	54.5%
Percent free lunch peers	50.6%	37.4%	47.2%
Mean teacher salary	$43,870.46	$43,815.10	$43,836.50
Mean other professional staff salary	$44,887.64	$44,898.37	$44,964.74

In-sequence students are those who conformed to district assignment policy. Their basket of resources is important, then, as a baseline representing the results of resources flowing to students as the district intended. In-sequence students were "treated" to faculty with an average of 22% non-tenured teachers. The average school for in-sequence students was 53% minority and 51% free lunch. Average teacher salary was almost $44,000 and average staff salary (including administrators) was just about $45,000.

Did magnet school choosers improve their lot vis-à-vis this basket of resource goods? Magnet-choosing students encountered 2% more non-tenured teachers than their in-sequence peers. They encountered schools with higher minority populations and relatively similar teacher and staff average salaries. However, magnet students encountered 13.2% fewer free lunch students in their schools than their in-sequence peers. For magnet students, the trade off in resources was slightly greater levels of non-tenured teachers and minority peers in exchange for considerably lower levels of peers in poverty. The magnet effect, as evidenced in Goodville, seems to be more about class than about race.

The majority of students in the sample, however, were neither in-sequence nor magnet choosing, leading to a conclusion that these students somehow created their own sequence of schools. Did these students trade up in resources over their in-sequence peers? A short answer is no. Even accounting for students who were retained and were therefore not exactly choosing their schools, students who were neither in-sequence nor in a sequence with a magnet experienced a .8% increase in non-tenured teachers, a 1.8% increase in minority peers, a 3.4% decrease in free lunch peers and similar teacher and other professional staff salaries than their in-sequence peers. This represents very little trade up for gamer students. A small gain occurs with the variable of free lunch peers; gamers attended schools with smaller numbers of free-lunch peers than in-sequence students.

An appropriate next question, encapsulated in research question one is: will an analysis of resource distribution across sequences provide substantively different findings than similar research conducted across schools? First, a traditional equity analysis needs to be conducted to set a baseline for comparison. The following section will present measures of horizontal equity computed across school and across sequences. Next, a section presents result of vertical equity OLS regression equations, and results of quantile regression vertical equity equations using school-level methods, to address the issue raised in research question two: what are the relationships between resource distribution across sequences and student racial and economic characteristics? A final section of analysis will provide results from quantile regression equations across sequences and sequence types.

Horizontal equity across schools and sequences

As described earlier, horizontal equity measures examine the equal distribution of resources across a population. Traditionally, horizontal equity measures treat each student as an equal, and measure the difference in treatment both between and across students. The following tables present: 1) calculations of three horizontal equity statistics (the coefficient of variation, the McLoone Index and the Gini coefficient) for each academic year; 2) the average of each inequity measure across all four years; 3) sequence-based measures of each inequity statistic. The first two results are pupil-weighted, school-based measures of inequity for each dependent variable. The third result is a pupil-weighted, sequence-based measure of each inequity statistic. These calculations as presented allow for comparison of school-based and sequence based statistics of inequity for each dependent variable. Each of these measures includes all students in each year and all students with a sequence, respectively. As reviewed in chapter three, although there are numerous horizontal equity measures available to researchers, these three provide a complete overview of inequity across a distribution and across the bottom half of any given distribution.

There is some question about comparison of horizontal equity statistics between school-based and sequence based analysis. From one perspective, since the database used consisted of all students in GPS over the time period studied with three or more years of attendance, horizontal equity statistics may be considered as the population of GPS students. From this perspective, any difference in the coefficient of variation, the McLoone Index, or the Gini coefficient can be considered a significant and reportable difference. However, if the database of GPS students is considered a sample – a historical sample – of all students that have been affected by GPS assignment policies, then horizontal equity statistics can similarly be viewed as sample statistics, and should be compared based on t-tests for difference of means. The analysis that follows will address both perspectives.

Horizontal equity statistics for each of five variables: teacher and other professional staff salaries, teacher experience, and school-level percentages of minority and free lunch students are used in creating these tables. The discussion for each variable will include an assessment of levels of equity and trends in equity over time, as well as a discussion of the statistical significance of any differences found between school-based and sequence-based analysis of horizontal equity.

Table 4.4: Horizontal equity measures, school percent minority, 1999-2004

Year	Measure of inequity		
	Coefficient of variation	McLoone Index	Gini coefficient
1999	.3222	.7423	.1829
2000	.3412	.6998	.1937
2001	.3441	.7112	.1955
2002	.3164	.7270	.1785
2003	.3060	.7328	.1729
2004	.3590	.6525	.2051
Mean 1999-2004	.3315	.7109	.1881
Sequence	.2732	.7883	.1539

Table 4.4 shows three measures of horizontal equity for school level percentages of minority students in GPS from 1999 to 2004. All three measures are well above thresholds that indicate inequity: the coefficient of variation is consistently above .10, the McLoone Index is consistently less than .80, and the Gini coefficient in consistently greater than .10. The coefficient of variation decreased from .344 in 2001 to .306 in 2003 before increasing again to .359 in 2004. The McLoone Index demonstrated more fluctuation, but had decreased to .653 in 2004 from .742 in 1999. The Gini coefficient grew from 1999 to 2001, decreased in 2002 and 2003 and increased considerably in 2004. When taken together, the average coefficient of variation was .332 across all four years, and the average Gini coefficient was .188. The trend from 1999 to

2004 demonstrates horizontal equity statistics that indicate increasing inequity across all students. This means that minority students are inequitably distributed across schools, and becoming more so. This finding supports findings in other studies of GPS that report increasing racial segregation.

Sequence-based analysis confirms the findings of inequity derived from school-based analysis. However, sequence based measures of inequity reported greater equity across sequences than was reported across schools. The average school-based coefficient of variation across all six years of data was .331; the coefficient of variation across all school sequences was .273. The average school-based McLoone Index was .711, whereas the sequence-based McLoone Index was reported as .788. Finally, the average school-based Gini coefficient was .188 while the sequence-based Gini coefficient was .154.

Although comparison of mean horizontal equity statistic values to sequence values indicates that sequence-based analysis results in lower levels of inequity, two-tailed t-tests run against school-based and sequence based statistics showed no significant differences. That is, in computing horizontal equity statistics for the percentage of each school's student body that is minority, sequence-based analysis shows no different results than school-based analyses.

Table 4.5: Horizontal equity measures, school percent free lunch, 1999-2004

Year	Measure of inequity		
	Coefficient of variation	McLoone Index	Gini coefficient
1999	.4786	.5995	.2738
2000	.4991	.5971	.2862
2001	.5173	.6049	.2960
2002	.4919	.5945	.2822
2003	.4589	.6614	.2619
2004	.4077	.6544	.2326
Mean 1999-2004	.4756	.6186	.2721
Sequence	.4357	.6518	.2498

Table 4.5 shows three measures of horizontal equity for school level percentages of students eligible for free and reduced price lunches in GPS from 1999 to 2004. All three

measures are well above thresholds for indicating inequity; free and reduced price lunch students are the most inequitably distributed resource of all five dependent variables. Each of the three measures of inequity indicates trends of improvement over time. The coefficient of variation increased slightly from .479 in 1999 to .517 in 2001 but decreased to .408 in 2004. Similarly, the McLoone Index increased from .600 in 1999 to .654 in 2004, indicating small improvements in the bottom half of the distribution of free and reduced price lunch eligible students across the district. The Gini coefficient decreased slightly from .274 in 1999 to .233 in 2004. These findings, although they indicate small improvements over time, show that GPS is segregated by income in addition to being segregated by race.

Sequence based analysis once again confirms the findings of school-based analyses and, although sequence based horizontal equity statistics seem to indicate that sequence based analysis indicates smaller degrees of inequity within the population of all GPS students with 3+ years in the system between 1999-2004, these differences were not statistically different from the average of school-based horizontal equity analysis. The sequence-based coefficient of variation was .436, compared to the six-year average coefficient of variation of .476. The McLoone Index for school-based averages and sequence-based analysis was .619 and .652, respectively. Finally, the Gini coefficient for the average of six years of school-based analysis was .272, while the sequence based Gini coefficient of .250. Overall, the distribution of poor students across schools remains inequitable, with slight improvements over time. Measuring inequity by sequence types reports similar levels of horizontal equity as the average of six years of school-based analysis.

Table 4.6: Horizontal equity measures, non-tenured teachers, 1999-2004			
Year	Measure of inequity		
	Coefficient of variation	McLoone Index	Gini coefficient
1999	.4585	.6495	.2515
2000	.4495	.6149	.2552
2001	.4486	.6684	.2496
2002	.5097	.5527	.2891
2003	.4703	.6381	.2647
2004	.4770	.6419	.2668
Mean 1999-2004	.4689	.6276	.2628
Sequence	.3401	.7216	.1934

Table 4.6 shows three measures of horizontal equity for school-level averages of non-tenured teachers in GPS from 1999 to 2004. The measure of non-tenure status is a proxy for teacher inexperience; research suggests that teachers with little experience (particularly no experience) are less effective than teachers with more experience. All three measures are well above their conventional thresholds for inequity, indicating that non-tenured teachers are inequitably distributed across GPS schools. Analysis of school-based findings across all six years indicates that the distribution of non-tenured teachers remained stable over time, with very slight increases in the inequity of the distribution. For example, the coefficient of variation increased from .459 in 1999 to .501 in 2002 before moderating to .477 in 2004. Similarly, the McLoone Index, indicating the impact of inequity on the bottom half of schools in the distribution of non-tenured teachers decreased from .650 in 1999 to .553 in 2002 before increasing to .642 in 2004. This means that the distribution of non-tenured teachers across all schools disproportionately impacted schools in the bottom half of the distribution between 1999 and 2002. The Gini coefficient declined from .2524 in 1999 to .267 in 2004. Sequence-based analysis of the same horizontal equity statistics reveals equity statistics that are smaller in the cases of the coefficient of variation and the Gini coefficients, but larger for the McLoone Index. This means that sequence-based analysis shows more equity in the distribution of non-tenured teachers across sequences than across schools. The coefficient of variation was .13 less for

sequences, the McLoone Index was .09 greater, and the Gini coefficient was .07 less in sequence-based analysis. However, these differences were not statistically significant with a two-tailed t-test reporting a p-value of .65. For horizontal equity in the distribution of non-tenured teachers at schools, sequence-based analysis reinforces, but is not different from, school-based analysis.

Table 4.7: Horizontal equity measures, teacher salary, 1999-2004 (in 2004 constant dollars)

Year	Measure of inequity		
	Coefficient of variation	McLoone Index	Gini coefficient
1999	.0690	.9433	.0391
2000	.0744	.9450	.0416
2001	.0682	.9550	.0379
2002	.0641	.9505	.0355
2003	.0703	.9563	.0378
2004	.0672	.9482	.0359
Mean 1999-2004	.0689	.9497	.0380
Sequence	.0619	.9621	.0316

Table 4.7 shows three measures of horizontal equity for average teacher salaries in GPS from 1999 to 2004. All three measures demonstrate an equitable distribution of teacher salaries, with statistics below the traditional thresholds for inequity. In addition, the trend over time indicates slight increases in the equitable distributions of average teacher salary. The coefficient of variation decreases from .069 to .067 between 1999 and 2004, which parallels similar decreases in the Gini coefficient from .039 in 1999 to .036 in 2004. The McLoone Index increased from .94 to .95 between 1999 and 2004. Sequence-based analysis of horizontal equity statistics is once again similar – and statistically the same as – findings from horizontal equity analysis conducted across schools. The sequence-based coefficient of variation - .062 – is less than the average across years of .069. The average school-based McLoone Index for mean teacher salary is .95, while the sequence-based statistic is .96, and the school-based Gini coefficient is .038 compared to the sequence-based Gini coefficients of .032. Again, when

interpreted as population-based computations, sequence-based analysis provide a more equitable snapshot of the distribution of teacher resources when compared to the average of four years of horizontal equity statistics.

Table 4.8: Horizontal equity measures, other professional staff salary, 1999-2004 (in 2004 constant dollars)			
Year	Measure of inequity		
	Coefficient of variation	McLoone Index	Gini coefficient
1999	.0668	.9447	.0375
2000	.0721	.9559	.0405
2001	.0650	.9590	.0362
2002	.0583	.9534	.0325
2003	.0612	.9558	.0330
2004	.0672	.9482	.0359
Mean 1999-2004	.0651	.9528	.0359
Sequence	.0600	.9643	.0304

Finally, Table 4.8 shows three measures of horizontal equity for average staff salaries in GPS from 1999 to 2004. All three measures demonstrate an equitable distribution of staff salaries within conventional thresholds for equity. Analysis over six years of school-based equity statistics indicates that the distribution of other professional staff salary stable over time. The coefficient of variation remained at .067 from 1999 to 2004, while the McLoone Index increased from .94 to .95 over the same period, and the Gini coefficient decreased slightly from .038 to .036.

Sequence-based analysis of horizontal equity in average staff salary was statistically the same as four-year averages of school-based horizontal equity statistics, but again indicted in real differences that sequence-based analysis provides more equitable results than school-based findings.

Taken together, these horizontal equity statistics indicate that expenditures for salary are equitably distributed across GPS; they are one of the few resources that are. The proportion of non-tenured teachers on staff is inequitably distributed across GPS schools, as are poor and minority student peers. Inequity in the distribution of free lunch students is the most pronounced across student types. The picture presented by these findings seems to be one in which teacher and other professional staff salary are invariant to school populations; that is, al school seem to have similar levels of expenditure for teacher and other professional staff salaries.

Educator salary schedules include a combination two factors: years of experience and degrees or certification held by teachers. Each contributes to increased salary. In a situation where teacher salary is distributed relatively equally across schools, but teacher experience (proxied by the percentage of non-tenured teachers at a school) is not, then the differentiating factor may be teacher experience. That is, in order to maintain equal spending on teacher and other professional staff salaries, schools may have more experienced, less credentialed teachers or more credentialed, less experienced teachers. For example, according to the GPS salary schedule for 2005-2006, a new teacher with a master's degree would earn the equivalent of a teacher with 4.5 years of experience and a bachelor's degree.

Horizontal equity analysis of five variables provides answers to two important questions. First, this analysis shows that horizontal equity analysis conducted across sequences of schools yields results that are not statistically different from horizontal equity analysis conducted across schools. Analysis of horizontal equity statistics for each academic year shows that these numbers showed small changes over time. If treated as population parameters; that is, if any finding of difference can be interpreted as actual differences, then sequence-based horizontal equity analysis consistently yields results that are more equitable than school-based analyses. That is, sequence-based analysis still yields findings of inequitable distribution of the five resources analyzed; however the sequence-based inequity is less extreme than inequity that arises from school-based analysis.

Another result of horizontal equity analysis is a view of the state of equity for five different variables in GPS over time. Findings here will inform vertical equity analysis to follow. Overall, horizontal equity is present in both mean teacher salaries and mean staff salaries across schools. However, minority peers, peers in poverty, and inexperienced teachers are inequitably distributed across both schools and sequences. The findings of inequitable distributions of minority and free lunch peers confirm earlier findings of segregation across GPS over time. Increasingly inequitable distributions of minority students illustrate greater segregation within the district over time. Inequity in the distribution of poor students is decreasing over time. This may be due to better integration of poor students across schools via district policy. However, the decline in inequitable distribution of poor students might also be due to increasing numbers of poor students entering into the system. If the range of poverty levels at schools ranged from 20% to 100%, and more poor students entered into the system, the number of schools with low percentages of poor students would decline, the ceiling of 100% would remain the same, resulting in less variation in percentages of poor students across schools and in a corresponding decrease in the inequitable distribution of poor students according to measures of horizontal equity.

In either case, vertical equity analysis will aid in better understanding the relationships between resource distribution, and student characteristics.

Vertical equity analysis – school-based OLS

There are two ways in which a situation may be determined to be inequitable. The first is where resources are obviously distributed inequitably as measured by traditional methods for assessing horizontal equity. This does not seem to be the case with school-level resources in

GPS when considering teacher and other professional staff salary. Although these are trends towards inequity, these figures remain within the accepted ranges of equitable distribution for the three statistics used.

Another way in which a situation may be determined to be inequitable is one where resources are distributed equally to groups that are patently unequal in circumstance. This seems more likely to be the case in GPS. Teacher and other professional staff salary resources seem to be impervious to changes in student school-level populations of poor and minority students. An example of vertical equity would be one in which teacher experience and salaries were inequitably distributed across schools, and there was a positive relationship between teacher salary and the percentage of poor or minority students at a school, i.e., schools with higher percentages of poor and minority students received the benefits of better paid, more experienced teachers. Vertical equity analysis via ordinary lest squares (OLS) regression has long been the accepted method for answering these types of questions. This research posits the idea that sequence level analysis, conducted via quantile regression, will better approximate true levels of intradistrict equity. For comparison, however, standard OLS regression should be conducted across schools to determine what relationships exist between students' race and poverty status, school type and school-level resources.

To conduct vertical equity analysis, student data for all six years was pooled to create a database of 329,133 observations. Models for this analysis, presented in equations 3.8 and 3.9 are:

$$
\begin{aligned}
S_x &= \beta_0 + \beta_1 E + \beta_2 E^2 + \beta_3 MIN + \beta_4 FRPL + \beta_5 (MIN \times FRPL) + \\
&\beta_6 2000 + \beta_7 2001 + \beta_8 2002 + \beta_9 2003 + \beta_{10} 2004 + \varepsilon
\end{aligned}
\qquad (4.1)
$$

$$S_x = \beta_0 + \beta_1 E + \beta_2 E^2 + \beta_3 DC + \beta_4 EO + \beta_5 MAG + \beta_6 2000 + \beta_7 2001 + \beta_8 2002 + \beta_9 2003 + \beta_{10} 2004 + \varepsilon \tag{4.2}$$

Table 4.9 presents the number of observations, mean, standard deviation, minimum and maximum value for each dependent and independent variable.

Although these results are presented in order to provide a baseline for comparison ins forthcoming quantile regression models, it is also important to take time to interpret these results within the Goodville context. These OLS regression findings present a picture of the inequitable distribution of resources across GPS students.

Table 4.9: Descriptive statistics for ordinary least squares vertical equity regression

Variable type	Variable	N	Mean	Std Dev	Minimum	Maximum
Dependent	Non-tenured teachers	328,856	.232	.113	0	1.0
	Percent minority	295,942	.548	.182	.10	.99
	Percent free lunch	326,407	.488	.238	.02	1.0
	Mean teacher salary	328,341	43,878.07	3,130.57	11,369.60	53,827.10
	Mean staff salary	328,341	45,228.89	3,022.26	18,093.83	54,528.37
Independent	Enrollment	326,980	747.41	458.427	16	2,464
	Enrollment^2	326,980	768,769.66	1,052,325.32	256	6,071,296
	Minority	329,133	.570	.495	0	1.0
	Free lunch	329,133	.468	.499	0	1.0
	Minority & Free lunch	329,133	.353	.478	0	1.0
	Design center	329,133	.016	.126	0	1.0
	Enhanced option	329,133	.015	.123	0	1.0
	Magnet	329,133	.104	.305	0	1.0
	2000	329,133	.167	.373	0	1.0
	2001	329,133	.186	.389	0	1.0
	2002	329,133	.186	.389	0	1.0
	2003	329,133	.167	.373	0	1.0
	2004	329,133	.147	.354	0	1.0

These variables provide a snapshot of the district and the students used to conduct this analysis. On average, 23% of GPS teachers are non-tenured. The average number of minority students at a school is 55%, and the average free lunch population is 49%. The average GPS teacher earns $43,878.07 in inflation-adjusted 2004 dollars. The average staff salary is a little less than $2,000 more at $45,228.89. The average GPS school has an enrollment of 747 students. Fifty-seven percent of GPS students are minorities and 47% of students in the database received free lunch. Thirty-five percent of students were both poor and minority. Only 2% of students were enrolled in enhanced option or design center schools, and 10% had attended a magnet school.

Results from this model for each of the five resource variables is shown in Tables 4.10 through 4.14. The sections to follow will address each dependent variable in turn, noting key findings from traditional analysis before performing a comparison analysis using quantile regression. A table illustrating results from a fully specified model including all independent variables can be found in Appendix A.

Table 4.10 – OLS vertical equity regression: percent of non-tenured teachers

Variable	Student	School
Intercept	0.26058	0.28309
Enrollment	-0.00007999	-0.00008174
Enrollment^2	2.48E-08	2.54E-08
Minority	0.02825	
Free lunch	0.02556	
Interaction	-0.01513	
Design Center		0.07857
Enhanced Option		0.06918
Magnet		0.00962
2000	0.02253	0.02026
2001	0.01007	0.00673
2002	-0.03874	-0.04186
2003	-0.00279	-0.00551
2004	-0.06239	-0.06383
F	3911.9	3626.77
Adjusted R^2	0.1069	0.0999

Note: All estimates significant at p<.0001.

Non-tenured teachers

The model as presented in equations 4.1 and 4.2 accounted for approximately 11% of the variation in the percentage of non-tenured teachers at a given school when student characteristics were used as independent variables, and 10% of variation when school type characteristics were analyzed. Although statistically significant, the effects of enrollment and the square of enrollment very small. Among student characteristics, a minority student was associated with a 3% increase in non-tenured, or inexperienced, teachers. A student's free lunch status also contributed to a 3% increase in non-tenured faculty. A poor and minority student was associated with a 4% increase in non-tenured teachers. The standard deviation on non-tenured teachers variable was .113. A 3% increase represents .25 of a standard deviation increase and a 4% increase represents 34% of a standard deviation. These positive and significant results indicate inequity in the distribution of teacher quality as proxied by non-tenured teachers among poor and minority students.

Considering school type, the similarly tiny effects of enrollment and the square of enrolment hold. Magnet schools were associated with small increased in non-tenured teachers – the effect was .9%, or .08 of a standard deviation. Design center schools are associated with an 8% increase in non-tenured teachers and enhanced option schools were associated with a 7% increase. These increases represent 70% and 62% of a standard deviation, respectively. Again, these findings present evidence of inequity. Design centers and enhanced option schools – schools planned around providing additional opportunity to struggling students employer higher numbers of inexperienced teachers, while magnet school employ only very slightly higher number of inexperienced teachers.

Table 4.11 – OLS vertical equity regression: school percent minority		
Variable	**Student**	**School**
Intercept	0.48576	0.57375
Enrollment	-0.00011122	-0.00011533
Enrollment^2	3.31E-08	3.41E-08
Minority	0.11147	
Free lunch	0.0822	
Interaction	-0.03574	
Design Center		0.23164
Enhanced Option		0.33813
Magnet		0.0314
2000	0.02175	0.01221
2001	0.03748	0.02499
2002	0.04839	0.03646
2003	0.06347	0.05391
2004	-0.02731	-0.03272
F	6280.05	3958.25
Adjusted R^2	0.175	0.1179
Note: All estimates significant at p<.0001.		

School percent minority

Table 4.11 presents OLS findings on the dependent variable of percentage of minority peers experienced by students. The model with student type characteristics explains 18% of the variation in the percent of minority peers, and the school type model accounts for 12% of the variation in the dependent variable.

The effects of enrollment and the square of enrollment are significant but small. Among student type variables, a student's minority status is associated with an 11% increase in minority peers. This is 61% of a standard deviation. Although this seems to be an overly simple relationship – minority students have more minority peers – it does point to the inequity effect of peer group composition for minority students. Free lunch students are associated with 8% greater minority peers, indicating relationships between the school assignment of poor and minority students. The interaction term indicates that a poor and minority student sees an increase of minority peer group at school of 15%. This means that a poor and minority students in GPS attends school with a peer group that is 64% minority as opposed to 49%.

All school types indicate increased minority student populations. The increase in minority peers for enhanced options and design centers are large: 34% and 23% respectively. Since these schools were designed to target students in poor minority neighborhoods, these findings make sense. Interestingly, even magnet schools are associated with a small but significant increase in minority student population of 3%. This indicates that students who choose or are assigned to enhanced option, design center, or magnet schools experience an increase in minority peers. These effects strengthen over time, as indicated by the significant and positive coefficients on the year-by-year fixed effect variables for 2000, 2001, 2002, and 2003. There seems to be a significant decline in minority peers in 2004.

School percent free lunch

Table 4.12 – OLS vertical equity regression: percent free lunch peers

Variable	Student	School
Intercept	0.57401	0.70851
Enrollment	-0.00043037	-0.00043012
Enrollment^2	1.04E-07	8.64E-08
Minority	0.07391	
Free lunch	0.18521	
Interaction	-0.05689	
Design Center		-0.03811
Enhanced Option		0.29986
Magnet		-0.21236
2000	0.0083	0.00722
2001	0.01383	0.01347
2002	0.03236	0.03521
2003	0.05447	0.06795
2004	0.19831	0.21677
F	22341.6	19449.3
Adjusted R^2	0.4063	0.3734

Note: All estimates significant at $p<.0001$.

Figure 4.12 presents OLS regression coefficients with the dependent variable as the percent of minority peers in a school. The student-level model accounts for 41% of the variance in peers in poverty, and the school type model accounts for 37%. Again, enrolment is a small but significant factor in the provision of free lunch students. Among student characteristics, minority status is associated with a 7% increase in free lunch peers, and an individual student's free lunch status is associated with a 19% increase in free lunch peers – 79% of a standard deviation. These findings indicate again that race and class do ride together in terms of school composition and that the distribution of free lunch students themselves is vertically inequitable. A poor and minority student is associated with a 21% increase in free lunch peers – or 88% of a standard deviation.

The relationship between free lunch peers and school types varies. Design center schools are associated with a slight – 4% - decrease in free lunch peers, while enhanced option schools are associated with a 30% increase in free lunch peers. It seems as though design centers are schools targeted for minority students but hot poor students, and that enhanced option schools are designed for students who are both poor and of minority status. Magnet schools are associated with decreases in free lunch peers discussed in the descriptive statistics above. As magnet school student may encounter greater numbers of minority peers, but far fewer peers from poverty backgrounds. Year fixed effect coefficients indicate that the district overall is becoming poorer – the free lunch percentages are associated with increases every year – from a small .8% increase in 2000 to a 20% increase in 2004.

Average teacher salaries

Table 4.13 – OLS vertical equity regression: average teacher salary		
Variable	**Student**	**School**
Intercept	40962	40247
Enrollment	5.02649	5.51499
Enrollment^2	-0.00133	-0.00146
Minority	-587.66982	
Free lunch	-748.92196	
Interaction	682.99568	
Design Center		-1072.99249
Enhanced Option		4489.39555
Magnet		499.39615
2000	132.21797	26.78936
2001	171.04114	84.51971
2002	2078.53449	1951.5022
2003	957.74472	830.18122
2004	261.68333	128.98275
F	7887.36	9235.48
Adjusted R^2	0.1946	0.2205
Note: All estimates significant at p<.0001.		

Table 4.13 provides OLS output for vertical equity models using teacher salary as a dependent variable. Again, enrollment has a small but significant effect on teacher salaries, perhaps reflecting the dynamic that secondary school teachers tend to make ore than elementary school teachers. The models account for 19% and 22% of the variation in teacher salaries, respectively. Among student characteristics, minority status is associated with a 19% of a standard deviation decrease in teacher salary, and free lunch status is associated with a 25% of a standard deviation decrease in teacher salary. These findings indicate an inequitable relationship between student characteristics and teacher salary, confirming studies that indicate that poor and/or minority students receive less “treatment” vis-à-vis teacher salary. A student who is both poor and minority received 654 dollars less teacher salary than non-minority, non-poor peers - approximately 20% of a standard deviation. Cost-adjusted teacher salaries have increased every year, as shown by year fixed effects. Teacher salary increased greatly in 2002 and 2003 but has

only increased modestly in other years. This can be due to increasing teacher salaries as well an increasingly credentialed and/or experienced teacher corps in Goodville.

School type is also associated with changes in teacher salary. Design center schools are associated with decreases in teacher salary of 34% of a standard deviation. Enhanced option schools, however, are associated with large increases in teacher salary – 140% of a standard deviation. Magnet schools are associated with a 16% increase in teacher salaries.

Taken together, the coefficients on student type and school type variables suggest that each factors contributes to the inequitable distribution of teacher salary – and teacher resources – across GPS.

Average professional staff salaries

Table 4.14 – OLS vertical equity regression: average staff salary

Variable	Student	School
Intercept	42448	41826
Enrollment	4.77503	5.22947
Enrollment^2	-0.00125	-0.00138
Minority	-482.52115	
Free lunch	-713.70469	
Interaction	633.30006	
Design Center		-1265.53262
Enhanced Option		3989.80462
Magnet		321.90892
2000	122.97468	34.84643
2001	304.06416	237.63731
2002	1820.83488	1718.8914
2003	747.6165	648.93246
2004	198.85083	93.59986
F	7091.14	8223.42
Adjusted R^2	0.1785	0.2012

Note: All estimates significant at p<.0001.

Table 4.14 presents results from OLS regression using other professional staff salary as a dependent variable. This variable included school-level administrators, librarians, and guidance counselors in the computation of school-level average salary. Staff salaries are generally higher than teacher salaries - as evidenced by the intercept - by 170 to 200 dollars. The model used describes slightly less of the variation in other professional staff salary than the model did for teacher salary – the student characteristics explain 18% of the variation and school type variables account for 20% of the variation in average staff salaries.

Student type variables account for smaller changes in staff salary, although these changes track in direction and magnitude with the teacher salary variable. For example, a student's minority status is associated with a 15% of a standard deviation decrease in staff salary, and a free lunch student is associated with a 23% of a standard deviation – or $714 - decrease in staff salary. School type variables also track with similar effect on teacher salary. Design centers schools are associated with considerably lower salaries - $1,265 dollars or 42% of a standard deviation. Enhanced option schools exhibit similarly large increases in staff salary, and magnet schools also show similar modest gains.

Conclusions from school-based OLS

These OLS models represent a traditional vertical equity analysis of student and school characteristics for the distribution of five dependent variables of interest: teacher and other professional staff salaries, percent of non-tenured teachers, and poor and minority peers. These results demonstrate inequity of resource distribution related to student ethnicity, student SES, and school type. Poor and minority students are associated with fewer teacher and staff dollars, greater numbers of poor and minority peers, and higher percentage of inexperienced teachers – exactly the opposite pattern of resource distribution that a vertically equitable system would wish. In addition, magnet schools seem to privilege students in the distribution of these resources. Schools designed to specifically address the needs of poor and minority students present a mixed bag – design center schools are associated with large decreases in teacher resources and experience, while enhanced option schools seem t provide increases in these resource variables. These models are not only presented to provide a vertical equity analysis of GPS between 1999 and 2004, however. These models establish a baseline with which to compare results from school-based quantile regression, which further opens the way for comparisons between school-level and sequence-level analysis using quantile regression.

Vertical equity analysis – school-based quantile regression

As discussed in chapter three, quantile regression (QR) provides point estimates of relationships between key independent variables and dependent variables at specific points along the distribution of the dependent variable. Because OLS analysis would provide the same answer in both school-based and sequence based analyses, this dissertation will utilize QR to determine how inequitable relationships present themselves along a distribution of the dependent variable.

Using QR will 1) provide QR estimates that are comparable to OLS estimates, allowing for a transition between traditional vertical equity analysis and a newer methodology and 2) provide a set of findings with which to compare sequence-based quantile regression. The following section will present results from school-based quantile regression models.

Equations for quantile regression will be the same as equations 4.1 and 4.2, above. For each dependent variable, relationships at five quantiles of interest will be assessed. These quantiles are .10, .25, .50, .75, and .90. Table 4.15 presents descriptive statistics at three quantiles (.25, .50, .75) for relevant variables in the model. This information serves as evidence that there is enough distribution across quantiles of the distribution to make quantile regression an appropriate tool.

Table 4.15 – Descriptive statistics for vertical equity quantile regression						
Variable type	**Variable**	**N**	**0.25**	**0.5**	**0.75**	**Standard deviation**
Dependent	Non-tenured teachers	326,740	.15	.22	.30	0.1125
	Percent minority	295,942	.41	.55	.67	0.1819
	Percent free lunch	326,407	.30	.46	.68	.2383
	Mean teacher salary	326,399	41,803	43,708	43,894.50	3,095.90
	Mean staff salary	326,399	43,260.60	45,039.80	45,245.70	2,982.80
Independent	Enrollment	326,980	456	625	911	474.4
	Enrollment^2	326,980	207936	390625	829921	1E+06
	Minority	329,133	0	1	1	0.4955
	Free lunch	329,133	0	0	1	0.4981
	Design center	329,133	0	0	0	0.1188
	Enhanced option	329,133	0	0	0	0.1206
	Magnet	329,133	0	0	0	0.306
	2000	329,133	0	0	0	0.389
	2001	329,133	0	0	0	0.4051
	2002	329,133	0	0	0	0.4051
	2003	329,133	0	0	0	0.3885
	2004	329,133	0	0	0	0.2198

Assessing differences between OLS and QR in school-based analysis

For researchers using quantile regression, there is an issue of distinguishing QR estimates from OLS estimates. For some researchers, the point is moot: they report OLS estimates alongside QR estimates and interpret numerical differences without performing any statistical test of difference (see, for example, Eide and Showalter, 1998). Another approach, cited is Koenker and Hallock’s 2001 overview of quantile regression – is that of Bassett, Tam and Knight (2002). These authors plot quantile regression estimates along with confidence intervals for the conditional mean of the estimate of each independent variable. Significance is determined if the regression quantile estimate falls outside of the conditional mean interval for each estimate. This method provides both a display of the significant of difference between quantile estimates and OLS estimates. It further graphically represents the direction of change in coefficients between any given quantile and the OLS estimate. An example of this is figure 4.2, below.

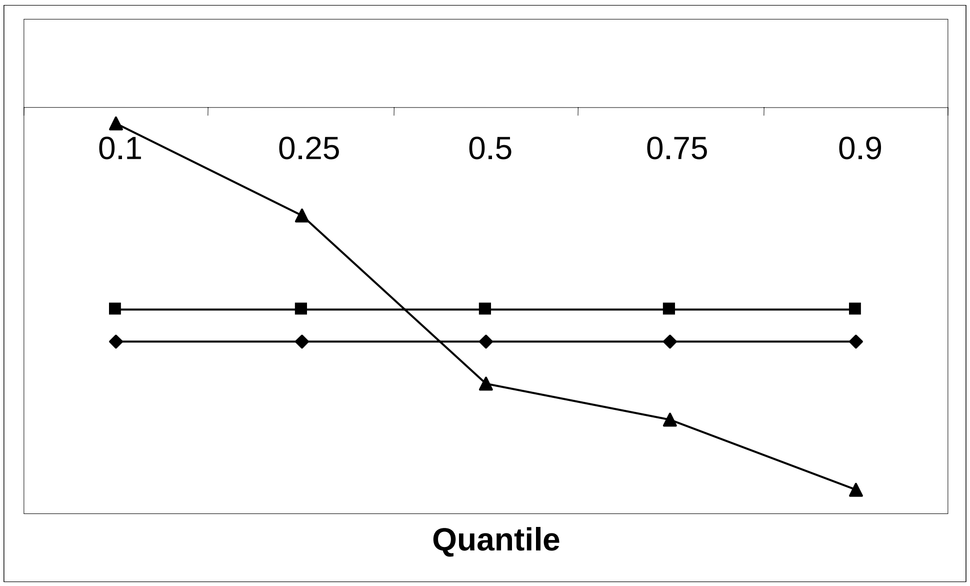

Figure 4.2: Generic comparison of OLS and QR results

Recall figures 3.1 and 3.2, where regression coefficients are displayed as lines with a slope (the regression coefficient) connecting similar spots on two distributions, one for each value of a binary variable. A larger coefficient results in a line with a steeper slope or larger effect; a smaller coefficient results in a line with a flatter slope. These same dynamics occur in figure 4.2. By representing slope coefficients as points on a line graph, we can compare the strength of association between the same independent and dependent variables at different quantile of the distribution of the dependent variable.

The two straight lines in figure 4.2 represent the upper and lower 95% confidence limits for the estimated relationship between an independent and dependent variable, obtained via OLS. Plotted along with these upper and lower confidence bands are the estimated relationship between the independent and dependent variable are specific points along the distribution of the dependent variable. In the case of figure 4.2, as is the case with the quantile regression analysis conducted in this dissertation, the quantiles of interest are .10, .25, .50, .75, and .90.

In the case of figure 4.2, any point along the quantile regression line that falls outside of the 95% confidence interval is determined to be a significant difference. The location of a point on the quantile regression line relative to the confidence bands reflects the direction of the difference. For example, the estimated relationship between the independent variable and the dependent variable at the .10 quantile of the distribution of the dependent variable is greater than the estimated relationship at the mean, and the difference is significant. The slope of the line, as expressed in figure 3.2, would be steeper at the .10 quantile of the distribution. The relationship at the .90 quantile of the distribution is also significantly different from the OLS estimated relationship at the mean, but in the opposite direction. In this case, the QR coefficient is smaller, resulting in a flatter line, and a smaller relationship between the independent and dependent variables.

The sections that follow will analyze results from school-based QR compared to results from school-based OLS fore ach of five dependent variables. This analysis will include an assessment of inequity expressed by QR models. This section lays groundwork for a forthcoming comparison of school-based QR and sequence-based QR. Results from fully specified models can be found in Appendix B.

Non-tenured teachers

Table 4.16 presents quantile regression estimates for student characteristics and school type variables regressed on the percentage of non-tenured teachers in schools. These findings confirm the general direction of relationships founds in the OLS vertical equity regressions presented above.

Graphically, the relationship between OLS and QR estimates demonstrates than QR results are often different. Among students who attend schools with very low percentages of non-tenured teachers (the .10 quantile) the difference between minority and majority students in exposure to non-tenured teachers is very small, but significantly different from OLS estimates. This could be interpreted as an equitable distribution of non-tenured teachers between minority and non-minority students who are most favored in the allocation of non-tenured teachers. For every other quantile of the distribution of non-tenured teachers, QR estimates are different from – and greater than – the estimated OLS relationship. That is, minority students see greater percentages of non-tenured teachers than estimated through OLS at the .25, .5, .75 and .90 quantiles of the distribution of non-tenured teachers.

Table 4.16 – Vertical equity quantile regression: percentage of non-tenured teachers										
	0.1		0.25		0.5		0.75		0.9	
	Student	School	Student	School	Student	School	Student	School	Student	School
Intercept	0.0994	0.1168	0.1647	0.1909	0.2533	0.2869	0.3461	0.3738	0.3991	0.4210
Enrollment	0.0000	0.0000	-0.0001	-0.0001	-0.0001	-0.0001	-0.0002	-0.0001	-0.0001	-0.0001
Enrollment^2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Design center		0.1209		0.0996		0.0673		0.0681		0.0262
Enhanced option		0.0808		0.1184		0.0696		0.0247		0.0370
Magnet		-0.0269		0.0053		0.0099		-0.0223		0.0424
Minority	0.0124		0.0386		0.0380		0.0395		0.0348	
Free lunch	0.0170		0.0350		0.0366		0.0375		0.0276	
Interaction	-0.0025		-0.0266		-0.0278		-0.0321		-0.0266	
2000	0.0051	-0.0011	0.0164	0.0168	0.0227	0.0198	0.0509	0.0337	0.0608	0.0480
2001	0.0093	0.0051	0.0042	-0.0042	0.0060	0.0065	0.0146	0.0080	0.0380	0.0310
2002	-0.0337	-0.0405	-0.0444	-0.0455	-0.0370	-0.0394	-0.0269	-0.0393	-0.0318	-0.0327
2003	-0.0206	-0.0205	-0.0062	-0.0001	-0.0057	-0.0064	0.0076	0.0151	0.0175	0.0030
2004	-0.0373	-0.0414	-0.0416	-0.0446	-0.0658	-0.0668	-0.0743	-0.0844	-0.0779	-0.0901
Note: All estimates significant at p<.0001, except *-p<.05 and **-p>.05.										

The pattern is similar in the relationship between free lunch students and non-tenured teachers, the only difference being that the difference between free lunch and non-free lunch students is within the confidence interval at the .9 quantile. This pattern is

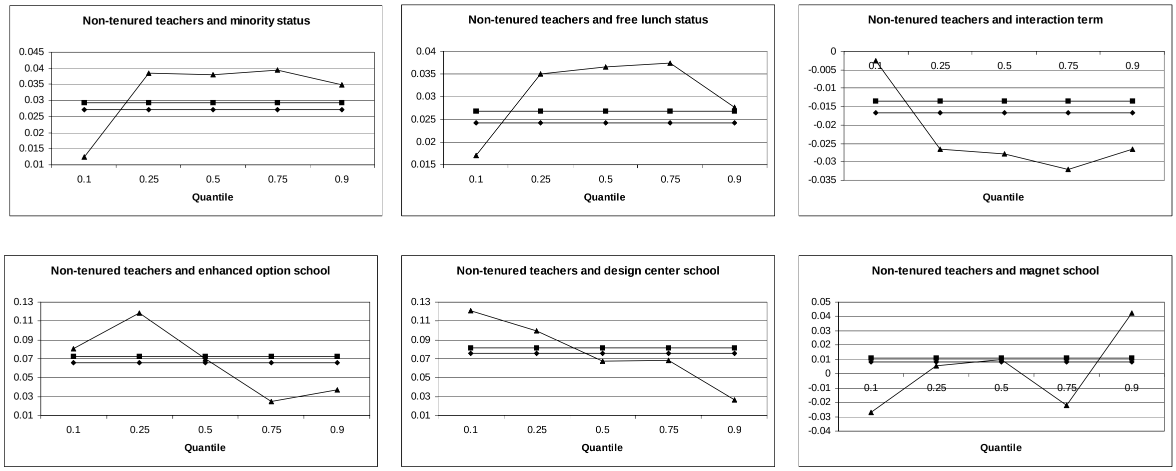

Figure 4.3 – Quantile estimates plotted against 95% confidence band for OLS estimates

inverted for the interaction effect of race and poverty. Recall that the appropriate interpretation of an interaction term is to combine arithmetically the coefficients on the interacted terms with the interaction effect itself. In the graph for the interacted term, no QR estimate is within the 95% confidence band of the OLS estimate. Although QR estimates indicate stronger negative interaction effects (thereby dampening the effect of the combination of race and class variables) that dampening still results in QR estimates that are larger than OLS estimates at every quantile save for quantile .10. This means that the differences between student type and access to non-tenured teachers is increased across the distribution of non-tenured teachers.

Quantile regression estimates for school type variables are also significantly different from OLS estimates. For students who encounter fewer non-tenured teachers; that is, more favored students, the gap between those who are in enhanced option schools and those who are not is greater than OLS estimates indicate. The coefficient for students with the median exposure to non-tenured teachers is not different from the OLS estimate, while the estimates at the .75 and .90 quantiles are less than OLS estimates. This indicates that the largest gap between enhanced option schools and other schools vis-à-vis non-tenured teachers is at the low end of the non-tenured teacher distribution. The pattern for design center schools is more of a diagonal line running from estimates at the .10 quantile that are greater than the OLS estimated relationship, to QR estimates at the .9 quantile that are less than the OLS estimates. Among students who are more favored with low percentages of non-tenured teachers, the teacher quality gap is greater for design center students. For those students who receive higher percentages of non-tenured teachers, design center students receive fewer non-tenured teachers than other students. Among favored students, magnet school students have significantly fewer non-tenured teachers. The same is true with less- favored students at the .75 quantile of the distribution of non-tenured teachers. Among the least favored students, however – those who experience the greatest percentages of non-tenured teachers, magnet students see significantly higher percentages of non-tenured teachers.

Note that the changes in estimates for the magnet school variable switch signs across quantile estimates. That is, although the OLS estimate of the impact of magnet schools is positive, two of the five quantile estimates are actually negative, and the highly positive coefficient at the .9 quantile looks as if it would bias an estimate at the mean up.

School percent minority

Table 4.17 presents quantile regression results with the percentage of minority peers as a dependent variable. As figure 4.4 demonstrates, results from quantile regression are often significantly different from OLS estimates. For student characteristic variables, the impact of being a minority student on the racial makeup of one's school peers is smaller than the OLS estimate among students who attend schools with lower percentages of minority peers. This relationship is the less at the .25 quantile, greater at the median, slightly less at the .75 and greater at the .9 quantile. For free lunch status, QR estimates are the same as – or slightly less than – OLS estimates, save for the .5 quantile, in which the relationship between free lunch status and percentage of minority peers is larger. Again, the coefficients on the interaction of these two terms results in a greater impact for students who are both poor and minority.

Table 4.17 – Vertical equity quantile regression: percentage of minority peers										
	0.1		0.25		0.5		0.75		0.9	
	Student	School	Student	School	Student	School	Student	School	Student	School
Intercept	0.1924	0.2745	0.3385	0.3892	0.4758	0.624	0.659	0.7494	0.7574	0.8217
Enrollment	0.0001	0.0001	0	0	-1E-04	-2E-04	-3E-04	-3E-04	-3E-04	-1E-04
Enrollment^2	0	0	0	0	0	0	0	0	0	0
Design center		0.2624		0.1873		0.3047		0.252		0.1779
Enhanced option		0.4718		0.4476		0.3418		0.2438		0.1773
Magnet		-0.047		-0.017		0.0061		0.0922		0.0798
Minority	0.0824		0.0677		0.1332		0.1053		0.1542	
Free lunch	0.0824		0.0677		0.125		0.0777		0.0695	
Interaction	-0.0428		-0.014		-0.09		-0.034		-0.032	
2000	0.0041	-0.017	0.0027	-0.019	0.0212	0.0051	0.0003	0.0406	0.0441	0.0287
2001	0.009	-0.001	0.0105	-0.002	0.0355	0.0159	0.0008	0.0696	0.074	0.0402
2002	0.0286	0.0153	0.0379	0.0278	0.0498	0.0294	0.0008	0.0683	0.0765	0.0277
2003	0.0285	0.0034	0.045	0.048	0.0789	0.078	0.0004	0.0901	0.0722	0.0475
2004	-0.1525	-0.149	-0.103	-0.038	-0.023	0.0141	0.0003	0.0068	0.1105	0.0332
Note: All estimates significant at p<.0001, except *-p<.05 and **-p>.05.										

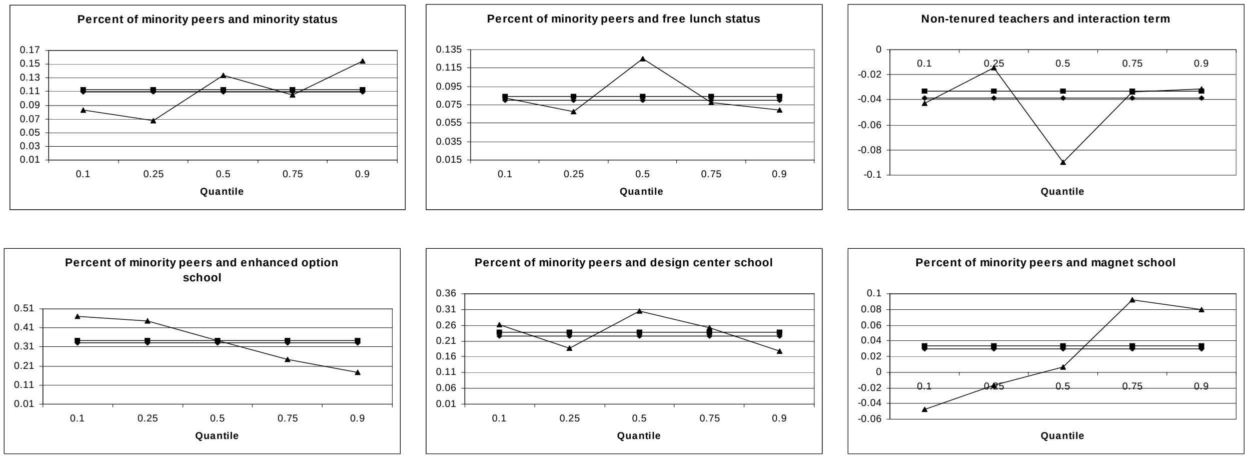

Figure 4.4 – Quantile estimates plotted against 95% confidence band for OLS estimates

Among school types, enhanced option schools have more of an impact among students who experience lower percentages of minority peers, and less of an impact among student who experience higher percentages of minority peers. The pattern for magnet schools is reverse – the impact of a magnet school is less among low-minority peer students and greater among high minority peer students. The pattern is mixed for design center schools, although the QR coefficients are outside of the OLS 95% confidence band.

School percent free lunch

Table 4.18 presents QR estimates for models run with the percentage of free lunch peers as a dependent variable. Additionally, figure 4.5 illustrates QR estimates along with a 95% confidence band for OLS estimated relationships. The relationship between free lunch students and minority peers is less than OLS estimates every quantile of the distribution of free lunch peers save for the .25 quantile, at which QR and OLS estimates are indistinguishable. Quantile regression estimates are lower than OLS estimates in describing the relationship between free lunch status and free lunch peers in every quantile save the .10 quantile, where the estimates relationship is greater than the OLS estimate.

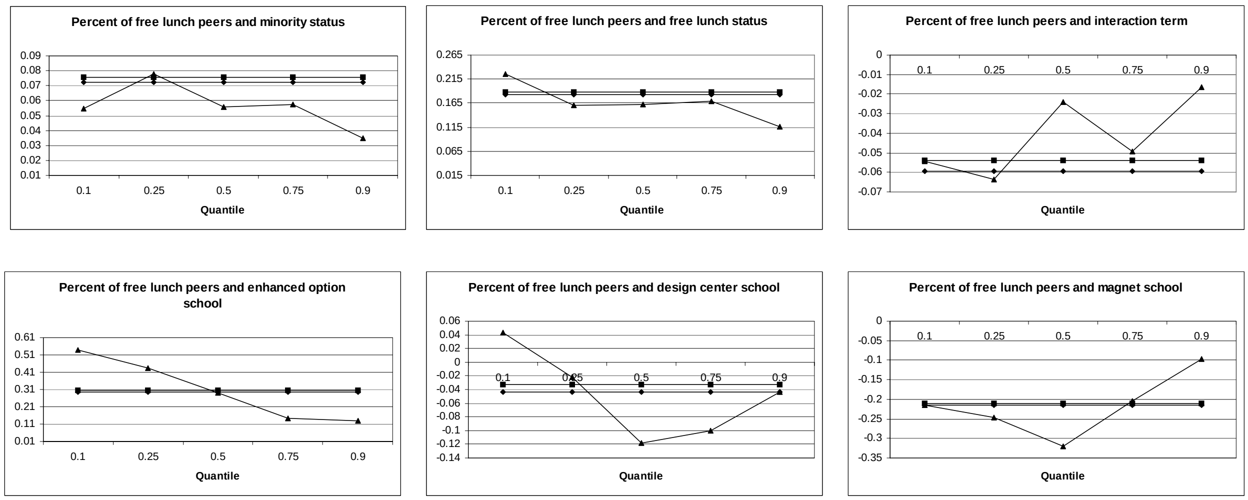

Figure 4.5 – Quantile estimates plotted against 95% confidence band for OLS estimates

The interaction of race and class is greater than OLS estimates in every quantile save the .10 and .25 quantiles. For school types, enhanced option schools have a greater impact than OLS estimates indicate at eh .10 and .25 quantiles the same relationship at the median and a smaller relationship than OLS coefficients indicate in quantile .75 and .90. Design center school effects on free lunch peers are larger than OLS estimates a quantile .10 and .25, smaller in quantiles .5 and .675 and the same at quantile .9. Magnet school effects are the same as OLS estimates at quantile .10 and .75, smaller at quantiles .25 and .5, and larger than OLS estimates and quantile .90.

Table 4.18 – Vertical equity quantile regression: percentage of free lunch peers										
	0.1		0.25		0.5		0.75		0.9	
	Student	School	Student	School	Student	School	Student	School	Student	School
Intercept	0.2567	0.3371	0.4073	0.5739	0.6272	0.7797	0.7718	0.929	0.9275	1.0272
Enrollment	-0.0003	-2E-04	-3E-04	-4E-04	-5E-04	-6E-04	-5E-04	-6E-04	-6E-04	-5E-04
Enrollment^2	0	0	0	0	0	0	0	0	0	0
Design center		0.0431		-0.022		-0.118		-0.1		-0.044
Enhanced option		0.5396		0.433		0.2907		0.1427		0.127
Magnet		-0.215		-0.246		-0.32		-0.205		-0.098
Minority	0.0546		0.0776		0.0559		0.0576		0.0351	
Free lunch	0.2254		0.1611		0.1619		0.1689		0.1165	
Interaction	-0.0546		-0.064		-0.024		-0.049		-0.016	
2000	-0.0014	-0.012	0.0085	0.0065	0.0094	0.0065	0.0235	0.0332	0.0307	-0.012
2001	-0.0129	-0.008	0.0132	-0.019	0.0088	0.0135	0.0303	0.0602	0.048	0.0017
2002	0.0072	0.0414	0.0362	0.0104	0.0306	0.0386	0.0599	0.0633	0.0565	0.037
2003	0.0178	0.088	0.056	0.0487	0.0608	0.0775	0.0742	0.0915	0.0761	0.062
2004	0.111	0.1813	0.1737	0.1472	0.2097	0.2141	0.2405	0.2417	0.2359	0.2458
Note: All estimates significant at p<.0001, except *-p<.05 and **-p>.05.										

Average teacher salaries

Table 4.19 presents school-based QR estimates of relationship between student characteristics, school types and five resource variables. Figure 4.6 presents these QR estimate plotted against the 95% confidence band of school-based OLS regressions. Among student types, QR relationships between teacher salaries and minority status are different only at the .10 and .75 quantiles. At these points in the distribution of teacher salary, the relationship with minority status is larger than OLS estimates. QR associations between free lunch students and teacher salary has a similar sloping pattern; QR estimates are greater than OLS estimates at the .10 and .25 quantiles, and lower at all of the others. Among school types, enhanced option schools have estimated impact on teacher salaries that are greater than OLS estimates across all quantile s save quantile .10. The sloping pattern reoccurs with design centers. Magnet schools have greater relationship greater than OLS estimates at quantiles .25, .5, and .9, less at quantile .10 and the same at quantile .75.

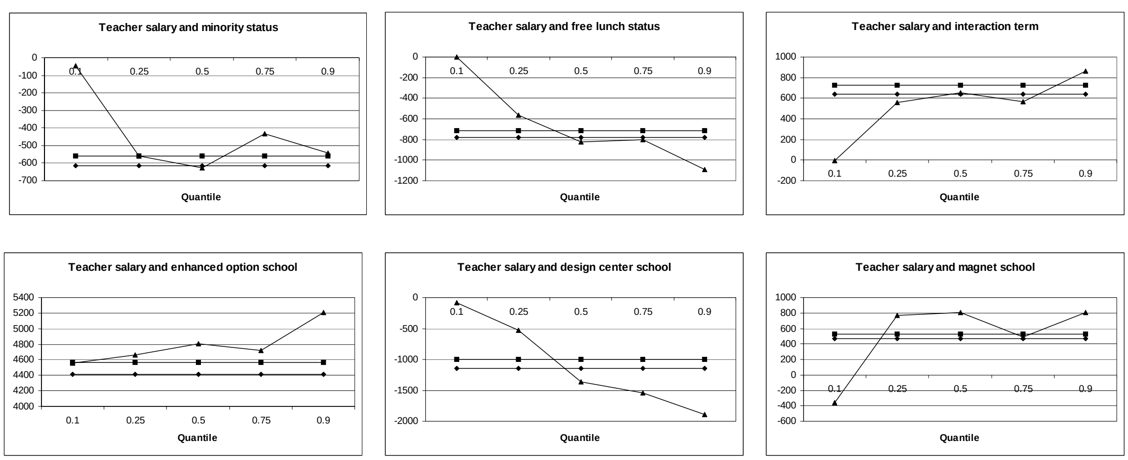

Figure 4.6 – Quantile estimates plotted against 95% confidence band for OLS estimate

Table 4.19 – Vertical equity quantile regression: average teacher salary

	0.1		0.25		0.5		0.75		0.9	
	Student	School	Student	School	Student	School	Student	School	Student	School
Intercept	37181.7	37181	38805	38105	40893	40102	43089	42371	45251	44996
Enrollment	5.0014	5.0014	4.9307	5.3273	4.9449	5.4593	4.8472	5.1843	3.186	2.8064
Enrollment^2	-0.0013	-0.001	-0.002	-0.002	-0.001	-0.001	-0.001	-0.001	-4E-04	0
Design center		-81.74		-529.5		-1363		-1538		-1886
Enhanced option		4554.8		4657.1		4808.2		4716.2		5209.3
Magnet		-358.4		764.59		806.86		486.52		805.97
Minority	-45.089		-561.8		-629.5		-433.8		-542.6	
Free lunch	-1.6251		-561.8		-823.1		-798.9		-1089	
Interaction	-2.3329		561.76		654		563.1		862.99	
2000	-453.09	-452.8	220.5	302.32	-86.96	22.511	-236.8	-430.7	1149	860.16
2001	-118.17	-118.2	556.1	485.69	-10.01**	-66.67	-635.8	-657.4	434.81	26.482
2002	1559.89	1564.4	2671.3	2680.3	2329.3	2118.2	1794.8	1745.2	1514.5	966.72
2003	923.404	879.61	1535.2	1528.7	913.92	696.08	672.54	744.69	615.23	114.63
2004	386.947	333.86	1016.8	992.83	693.75	635.96	31.768	-54.25	-317.5	-670.4

Note: All estimates significant at p<.0001, except *-p<.05 and **-p>.05.

Average other professional staff salaries

Table 4.20 shows school-based QR coefficients for models using staff salary as a dependent variable. In addition, figure 4.7 shows these QR coefficients plotted against the 95% confidence band of the OLS estimate. The patterns of QR plots relative to OLS plots are similar; reinforcing earlier observations that differences between teacher and other professional staff salaries are evident in amounts of funding, but those patterns of funding are essentially the same.

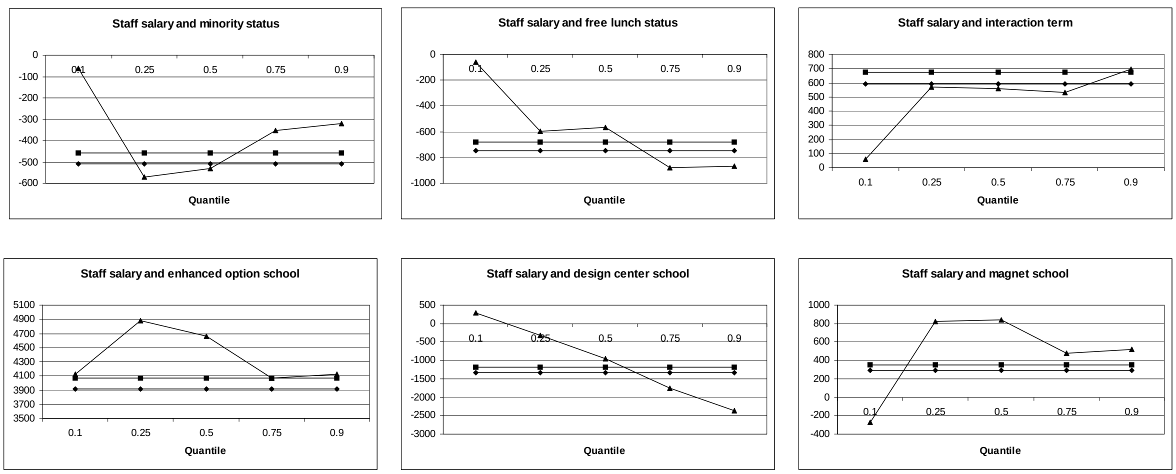

Figure 4.7 – Quantile estimates plotted against 95% confidence band for OLS estimates

Table 4.20 – Vertical equity quantile regression: average staff salary										
	0.1		0.25		0.5		0.75		0.9	
	Student	School	Student	School	Student	School	Student	School	Student	School
Intercept	38479.8	38262	40361	39780	42028	41035	44546	43949	47063	46385
Enrollment	5.5165	5.9443	5.7078	5.8756	4.8737	6.3741	4.2704	4.3677	2.4477	2.5632
Enrollment^2	-0.0016	-0.002	-0.002	-0.002	-0.001	-0.002	-9E-04	-8E-04	-2E-04	0
Design center		282.7		-320.8		-958.9		-1752		-2368
Enhanced option		4124.9		4882.3		4657.8		4065.9		4126.9
Magnet		-271.1		818.97		836.72		477.95		518.6
Minority	-61.899		-570.9		-530.8		-351.1		-319.4	
Free lunch	-61.899		-597.7		-563.9		-877.8		-867.8	
Interaction	61.8993		570.86		559.85		530.08		694.54	
2000	-11.274	19.001	-204.9	-279.3	70.234	-155.7	69.56*	-167.4	955.69	931.03
2001	406.597	404.67	296.44	287.6	266.24	22.68	-149.1	-342.8	555.31	393.04
2002	1622.06	1677.5	1902.8	1636.6	2023.2	2047.3	1517.5	1467.9	1025.8	1254.4
2003	964.273	925.43	812.36	568.52	1134.8	1008.6	514.99	539.73	-154.9	-460.5
2004	87.5817	-1.45**	448.59	290.98	674.64	751.84	207.14	73.589	-472.2	-331.8
Note: All estimates significant at p<.0001, except *-p<.05 and **-p>.05.										

Quantile regression relative to OLS

The above section reported on difference in QR coefficients relative to OLS coefficients in estimating vertical equity relationships using school-based data. Table 4.21 presents overall results of this analysis. Using five independent variables and five dependent variable over five quantiles yields a matrix of 125 cells. Of these cells, 110 (or 88%) of QR estimates were significantly different from OLS estimates. Only 15 cells, or 12%, exhibited no significant difference from OLS estimates. Of the 110 significantly different cells, 60 (or 55%) provided QR estimates greater than OLS estimates and 50 (45%) reported coefficients smaller than OLS estimates. All QR estimates were significant, indicating that vertical equity exists across GPS in terms of student characteristics and school types. The nature of the distribution of that inequity is more fully understood through use of quantile regression.

Table 4.21: QR and OLS differences

	Non-tenured					Percent minority					Percent free lunch					Teacher salary					Staff salary				
	.1	.25	.5	.75	.9	.1	.25	.5	.75	.9	.1	.25	.5	.75	.9	.1	.25	.5	.75	.9	.1	.25	.5	.75	.9
DC	+	+	-	-	-	+	-	+	+	-	+	+	-	-	-	+	+	-	-	-	+	+	+	-	-
EO	+	+	nc	-	-	+	+	nc	-	-	+	+	nc	-	-	nc	+	+	+	+	nc	+	+	nc	nc
Mag	-	+	+	+	+	-	-	-	+	+	nc	-	-	nc	+	-	+	+	nc	+	-	+	+	+	+
Minority	-	+	+	+	+	-	-	+	-	+	-	+	-	-	-	+	nc	nc	+	nc	+	-	-	+	+
Free lunch	-	+	+	+	nc	nc	-	+	-	-	+	-	-	-	-	+	+	-	-	-	+	+	+	-	-

Having established the manner in which school-based QR deviates from traditional OLS-based equity analysis, it its now appropriate to turn to an examination of sequence-based QR compared to school-based QR in order to answer a key research question : does a student's sequence of schools yield different vertical equity results than traditional, school-based analyses?

Modeling the impact of school sequences

In order to test the impact of school sequence based analysis on vertical equity, means across years for all dependent variables and relevant independent variables were constructed. That is, every student in the database was assigned the average value of each of the dependent variables weighted by the number of years that student participated in the district. Salary measures were expressed as average teacher and other professional staff salary; teacher experience was expressed as the average percentage of non-tenured teachers experienced, and peer characteristics were expressed as the average percentage of minority or free lunch peers in school. Independent variables were similarly transformed: enrollment is expressed as the average enrollment experienced by the pupil; minority as a marker remains a dummy variable with a value of "1" or "0";[22] the free lunch variable is expressed as the percent of years in the system that a student received free lunch; the interaction of minority and free lunch remains the multiplicative product of the two variables,; and school type variables, like the free lunch variable, are expressed in percentage terms, reflecting the number of years a student was enrolled within that school type as a ratio to the total number of years a student was enrolled in GPS. These percentage expressions for independent variables transform them from values of 0 or 1 to a categorical variable with 7 possible values – students could be free lunch status, in a design center, an enhanced option school or a magnet school for 0, 1, 2, 3, 4, 5, or 6 years, yielding percentage values for each of these variables as 0, .167, .333, .500, .667, .833, or 1.0 respectively. Year by year fixed effects were computed by creating a weighted variable for each year in the data sequence for each student creating similar categorical percentage variables.

[22] Students were checked across years to ensure that they were minority students consistently throughout the database.

These means represent the impact of multiple years of resource allocation across GPS schools. The amount of variation in resource allocation over time will vary by the number of years a student participated in the system, as well as if a student attended a magnet school or transferred out of the system. To capture this variation, while still providing a relevant comparison to the school-based vertical equity and quantile regression models described in the previous section, sequence based analysis proceeded in three steps.

The first step is to create a model to align closely with the models used in school-based OLS and QR regressions. Models used in sequence based quantile regression are:

$$\begin{aligned} Q\ (\tau \mid x) &= \beta_0 + \beta_1 MEANE + \beta_2 MEANE^2 + \beta_3 MIN + \beta_4 \%FRPL + \\ &\beta_5 (MIN \times \%FRPL) + \beta_6 2000w + \beta_7 2001w + \beta_8 2002w + \\ &\beta_9 2003w + \beta_{10} 2004w + \sigma(x) F^{-1} \tau \end{aligned} \tag{4.1}$$

and

$$\begin{aligned} Q\ (\tau \mid x) &= \beta_0 + \beta_1 MEANE + \beta_2 MEANE^2 + \beta_3 \%DC + \beta_4 \%EO + \\ &\beta_5 \%MAG + \beta_6 2000w + \beta_7 2001w + \beta_8 2002w + \beta_9 2003w + \\ &\beta_{10} 2004w + \sigma(x) F^{-1} \tau \end{aligned} \tag{4.2}$$

where Q is the specified quantile of the dependent variable, MEAN*E* is enrollment and *MIN* is the minority status of a student. Because this analysis occurs across sequences, the variable *%FRPL, %DC, %EO,* and *%MAG* indicate the percentage of years a student received free or reduced price lunch or was assigned to a design center, enhanced option, middle or magnet school. Year fixed effects are weighted as described above and noted as 2000w, 2001w, 2002w, 2003w, 2004w. These models provide the closest alignment with school level analysis. Each set of coefficients will be assed for difference using t-tests as well as the graphical analysis presented by Bassett, Tam and Knight and used to assess the differences between OLS and QR in the section above. Any differences can then be reported and examined to determine what those differences explain about the distribution of resources across GPS students.

Table 4.22 presents descriptive statistics for the .25, .50 and .75 quantile for each dependent and independent variable in the model.

Table 4.22 – Descriptive statistics for sequence-based quantile regression

Variable type	Variable	N	.25	.5	.75	Standard deviation
Dependent	Non-tenured teachers	69,274	.1725	.2283	.2817	.0776
	Percent minority	69,274	.4423	.5486	.6508	.1508
	Percent free lunch	69,274	.3213	.4688	.6352	.2085
	Mean teacher salary	69,246	42,371	43,626	45,309	2,716.9
	Mean staff salary	69,246	43,593	44,754	46,425	2,703.2
Independent	Enrollment	69,246	485.7	646	910.7	368.6
	Enrollment^2	69,246	235,872	417,316	829,314	745,951
	%Minority	69,246	0	1	1	0.4973
	%Free lunch	69,246	0	0.4	1	0.4355
	Interaction	69,246	0	0	0.8333	0.4303
	%Design center	69,246	0	0	0	0.0983
	%Enhanced option	69,246	0	0	0	0.1095
	%Magnet	69,246	0	0	0	0.2435
	2000w	69,246	0.1667	0.1667	0.2	0.0494
	2001w	69,246	0.1667	0.1667	0.25	0.0494
	2002w	69,246	0.1667	0.1667	0.25	0.0494
	2003w	69,246	0.1667	0.1667	0.2	0.0494
	2004w	69,246	0	0.1667	0.2	0.0494

Vertical equity – sequence-based quantile regression

Table 4.23 through 4.27 presents coefficient estimates from quantile regression conducted across sequence variables for each of five resource variables. These results will be briefly discussed before examining whether or not sequence-based analysis yielded different results from school-based analysis. Results from models with student characteristics and school characteristics are presented separately for each quantile examined: .1, .25, .5, .75 and .9. Results from complete models with both student and school type characteristics can be found in Appendix C.

Non-tenured teachers

Table 4.23 presents sequence based quantile regression estimates for the dependent variable of the percentage of non-tenured teachers. Some coefficients are not statistically significant: the square of enrollment at the .10 quantile for the school type model, the magnet school coefficient at the .50 and .75 quantiles, the year 2000 variables at the .25 and .90 quantiles in the school type model. Overall, the directionality for sequence-based results is the same as for school-based results.

Vertically inequitable relationships are apparent across all quantiles for student characteristics such as race and poverty, and for school types such as design center, enhanced option and magnet schools. Minority status and free lunch status increase a student's percentage of non-tenured teachers, enhanced option and design center schools increase a student's percentage of non-tenured teachers, and magnet school attendance decreases a student's percentage of non-tenured teachers in 3 out of 5 quantile. At the .75 and .9 quantile, among the most experienced teachers, magnet school attendance actually increases a student's percentage of non-tenured teachers.

Table 4.23 – Sequence-based quantile regression: percent non-tenured teachers										
	0.1		0.25		0.5		0.75		0.9	
	Student	School	Student	School	Student	School	Student	School	Student	School
Intercept	0.1511	0.1881	0.2268	0.2822	0.3468	0.3921	0.4313	0.4587	0.479	0.4784
Enrollment	-0.0001	0	-0.0001	-0.0001	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002
Enrollment^2	0*	0**	0	0	0	0	0	0	0	0
Design center		0.0937		0.0872		0.0582		0.0345		0.0064
Enhanced option		0.1137		0.1071		0.071		0.072		0.0379
Magnet		-0.0214		0.0078*		-0.002**		0.0008**		0.0111
Minority	0.0204		0.0369		0.0374		0.0202		0.0155	
Free lunch	0.0328		0.0452		0.0359		0.0199		0.0144	
Interaction	-.0052*		-0.0239		-0.0291		-0.014		-0.013	
2000	0.0459	0.0215*	0.0057**	-.004**		-0.0421	-0.03*	-0.0315	-0.079*	-0.065**
2001	-0.041	-0.0774	-0.0748	-0.0852	-0.0985	-0.1263	-0.081	-0.1079	-0.1047	-0.1424
2002	-0.0632	-0.0912	-0.1547	-0.1795	-0.1523	-0.1707	-0.140	-0.1491	-0.0699	-0.0583
2003	0.0178*	0.0123*	-0.0163*	-0.0532	-0.0902	-0.1071	-0.076	-0.0892	-0.0978	-0.1037
2004	-0.0264*	-0.0376	-0.028	-0.0271	-0.0682	-0.0653	-0.106	-0.1232		
Note: All estimates significant at p<.0001, except *-p<.05 and **-p>.05.										

School percent minority

Table 4.24 presents coefficients from sequence-based quantile regression using percentage of minority peers as a dependent variable. None of the student characteristics or school type variables are insignificant, although a number of the year-by-year control variable are insignificant, as is the coefficient for the square of enrollment variable at quantile .10.

Student type results again confirm vertically inequitable relationships. A minority student is associated with higher percentages of minority peers, as is a free lunch student. School type variables such as design center and enhanced option school attendance are associated with higher percentages of minority peers. This relationship is not necessarily inequitable; it is the intent of district policy that these school types serve neighborhoods with high concentrations of minority students. For three out of five quantiles, magnet school attendance is associated with decreased percentages of minority peers. At the .75 and .9 quantiles, however this relationship is reversed, and magnet school attendance is associated with increased minority peers. This reflects large minority population at magnet schools across GPS.

Table 4.24 – Sequence-based quantile regression: school percent minority										
	0.1		0.25		0.5		0.75		0.9	
	Student	School	Student	School	Student	School	Student	School	Student	School
Intercept	0.3327	0.3067	0.4255	0.5179	0.5764	0.7117	0.7229	0.8411	0.8266	0.9977
Enrollment	0.0001	0.0001	0	-0.0001	-0.0002	-0.0002	-0.0003	-0.0003	-0.0003	-0.0003
Enrollment^2	0**	0	0	0	0	0	0	0	0	0
Design center		0.518		0.4767		0.356		0.2746		0.2222
Enhanced option		0.2359		0.2288		0.2532		0.2791		0.223
Magnet		-0.007		-0.0173		-0.0282		0.0249		0.0699
Minority	0.0776		0.077		0.1107		0.0929		0.1305	
Free lunch	0.1001		0.1035		0.1242		0.0916		0.0645	
Interaction	-0.0205		-0.014		-0.0601		-0.0299		-0.0458	
2000	-.0764*	-.026*	-.0396*	-.0552	-.0544*	-0.0528*	-0.0407*	-0.0635	-0.020**	-0.1381
2001	-0.1469	-0.1124	-0.0909	-.1367	-0.0588	-0.0997	-0.002**	-0.0571	0.0476	-0.0463
2002	-0.1087	-0.1016	-0.0545	-.1046	-.012**	-0.097	0.0006**	-0.013*	0.0481	0.0118**
2003	-.028**	-.003**	0.0153**	-0.0437	0.001**	0.0361*	0.0259**	0.0221*	0.031*	-0.1213
2004	-0.04*	0.12	-0.009**	0.0561	-.0303*	0.0008**	-0.107	-0.1409	-0.1786	-0.2934
Note: All estimates significant at p<.0001, except *-p<.05 and **-p>.05.										

School percent free lunch

Table 4.25 presents sequence-based quantile regression estimates for school type and student characteristic models using free – lunch peers as a dependent variable. None of the student characteristics or school type variables are insignificant, although a number of the year fixed effect variables are.

Among student characteristics variables, student minority status has a vertically inequitable relationship with free lunch peers, whereby minority students are associated with increased percentages of free lunch peers. The same is true – and more greatly so – of free lunch students. Among school type variables, enhanced option schools are associated with decreases in free lunch peers for every quantile of the distribution except quantile .10. This pattern is the same for magnet school attendance: increased minority peers but decreases in free lunch peers.

Table 4.25 – Sequence-based quantile regression: percent free lunch peers										
	0.1		0.25		0.5		0.75		0.9	
	Student	School	Student	School	Student	School	Student	School	Student	School
Intercept	0.1826	0.3825	0.3279	0.6295	0.5717	0.7653	0.6751	0.8809	0.8373	1.0165
Enrollment	-0.0002	-.0002	-0.0003	-.0004	-0.0004	-.0005	-0.0005	-.0005	-0.0006	-0.0006
Enrollment^2	0	0	0	0	0	0	0	0	0	0
Design center		0.5487		0.4346		0.3005		0.1772		0.0967
Enhanced option		0.1248		-0.0002		-0.1333		-0.1135		-0.0781
Magnet		-0.1914		-0.2898		-0.35		-0.2885		-0.175
Minority	0.0725		0.05		0.0513		0.0462		0.0381	
Free lunch	0.2639		0.2275		0.2126		0.1847		0.1399	
Interaction	-0.074		-0.0464		-0.0393		-0.0479		-0.0413	
2000	0.0658*	-.004**	0.0872	-0.033*	0.0142**	-.002**	0.035*	-.003**	0.0407*	0.0093**
2001	0.0254**	-0.123	0.0383*	-0.1395	0.0186**	-0.0565	0.0775	0.028*	0.0893	0.0483
2002	-0.022**	-0.0883	0.0255*	-0.0961	-0.018**	-0.0183	0.077	0.0548	0.0791	0.0183*
2003	0.1047	0.0934	0.1441	0.0689	0.0912	0.089	0.1145	0.1389	0.1301	0.0543
2004	0.2898	0.1398	0.2793	0.1247	0.2472	0.2489	0.2989	0.2606	0.2788	0.2904
Note: All estimates significant at p<.0001, except *-p<.05 and **-p>.05.										

Average teacher and other professional staff salary

Table 4.26 presents estimates of sequence-based quantile regression using teacher salaries as a dependent variable.

All variables of immediate interest are statistically significant, although, again, many of the year fixed effect estimators are not. Among student characteristic variables, teacher salary relationships are inequitable. Both minority and free lunch status is associated with decreased teacher salaries. Among school type variables, students who attend design center schools and magnet schools are associated with increased teacher salaries, while students who attend enhanced option schools are associated with reduced teacher salaries. Table 4.27 demonstrates, as we have seen before, that results using staff salary as a dependent variable are similar to patterns and relationships found in an examination of teacher salaries.

Although more coefficients from sequence-based quantile regression are not statistically significant, the remaining coefficients are mostly the same direction and strength as school based quantile regression. The next section tests to see if sequence-based estimate are different from school-based estimates.

Table 4.26 – Sequence-based quantile regression: average teacher salary										
	0.1		0.25		0.5		0.75		0.9	
	Student	School	Student	School	Student	School	Student	School	Student	School
Intercept	37037	36765	37856.4	37157.5	40365.9	38991	42434.7	40671	43998.3	42325.7
Enrollment	8.2296	8.7337	8.1634	8.9405	6.6657	7.5143	6.569	6.7106	6.8235	8.236
Enrollment^2	-0.0031	-0.0033	-0.0033	-0.0036	-0.0022	-0.0025	-0.0018	-0.0017	-0.0019	-0.0024
Design center		5237.8		4400.17		4285.05		4678.45		4015.85
Enhanced option		217.5604*		-281.27		-920.42		-1981.2		-2035.8
Magnet		281.804		671.328		1027.46		1027.09		700.393
Minority	-114.48		-282.46		-732.294		-939.996		-577.426	
Free lunch	-117.1*		-354.644		-919.389		-1489.75		-1257.79	
Interaction	201.563		428.214		935.139		1245.25		929.753	
2000	-352**	-309.026*	133.4943**	-15.8**	-790.467*	-500.9*	-1393.7	-953.184*	-1558.08	-870.598
2001	891.032	803.143	1466.19	1707.64	482.4105*	843.387	-200.2**	739.837	354.1388**	288.918*
2002	2235.69	2282.19	3101.18	3095.57	3533.06	3988.39	4284.15	5073.27	2608.07	2619.07
2003	865.537	673.119	1493.23	1656.96	749.886	1379.62	-77.59**	253.8874**	-1739.81	-1122.99
2004	-1389.57	-1692.85	-807.497	-765.5	-1783.34	-1772.3	-3602.5	-2678	-3475.05	-2970.07
Note: All estimates significant at $p<.0001$, except *-$p<.05$ and **-$p>.05$.										

Table 4.27 – Sequence-based quantile regression: average staff salary										
	0.1		0.25		0.5		0.75		0.9	
	Student	School	Student	School	Student	School	Student	School	Student	School
Intercept	38727.2	91.8309	39541.7	38841.1	42134.4	40962	44447.5	42864.5	45312	44747
Enrollment	7.8031	0.0951	8.1522	8.8114	6.5246	7.1427	5.8915	6.1309	6.6992	7.9008
Enrollment^2	-0.0029	0	-0.0032	-0.0035	-0.002	-0.0022	-0.0015	-0.0015	-0.0019	-0.0023
Design center		4824.34		4329.66		4147.67		3978.12		3337.78
Enhanced option		-3.5757**		-479.09		-1097.96		-2039.33		-1989.43
Magnet		-74.5296**		553.632		885.871		842.391		172.502
Minority	-69.2011*		-216.613		-566.111		-831.985		-400.181	
Free lunch	-147.621		-259.832		-788.734		-1306.12		-1064.14	
Interaction	216.822		396.113		831.945		1148.03		812.588	
2000	-383.834**	-439.989*	-154.114**	-154.97**	-1233.43	-1013.2	-1734.07	-1355.51	-1394.08	-2300.95
2001	781.721	695.8	883.901	1326.15	174.6021**	677.484	-783.838*	183.0618**	251.5998**	-382.292**
2002	1966.29	1948.85	2541.79	2749.11	2564.44	2855.91	3389.09	4004.36	2139.72	2188.52
2003	1059.79	543.65	1158.28	1448.39	-151.643**	552.3984*	-1169.72	-619.282	-2334.53	-3286.73
2004	-2685.5	-2869.69	-2697.06	-2360.72	-3682.76	-3502.18	-5265.78	-4640.85	-4716.12	-5174.07
Note: All estimates significant at p<.0001, except *-p<.05 and **-p>.05.										

Comparing sequence-based and school-based results

A final piece of analysis is to determine whether sequence-based quantile regression estimates are different from school-based quantile regression estimates. This analysis will compare estimates graphically by using sequence-based estimates plotted against the 95% confidence band of school-based sequence estimates. This method will determine whether individual sequence-based estimates are different from their school-based counterparts.

95% confidence interval plots, such as those used by Basset, Tam, and Knight reveal that point estimates for each quantile in sequence-based regression are often outside of the 95% confidence band for school-based quantile regression. Figure 4.8 presents these plots for the dependent variable on non-tenured teachers.

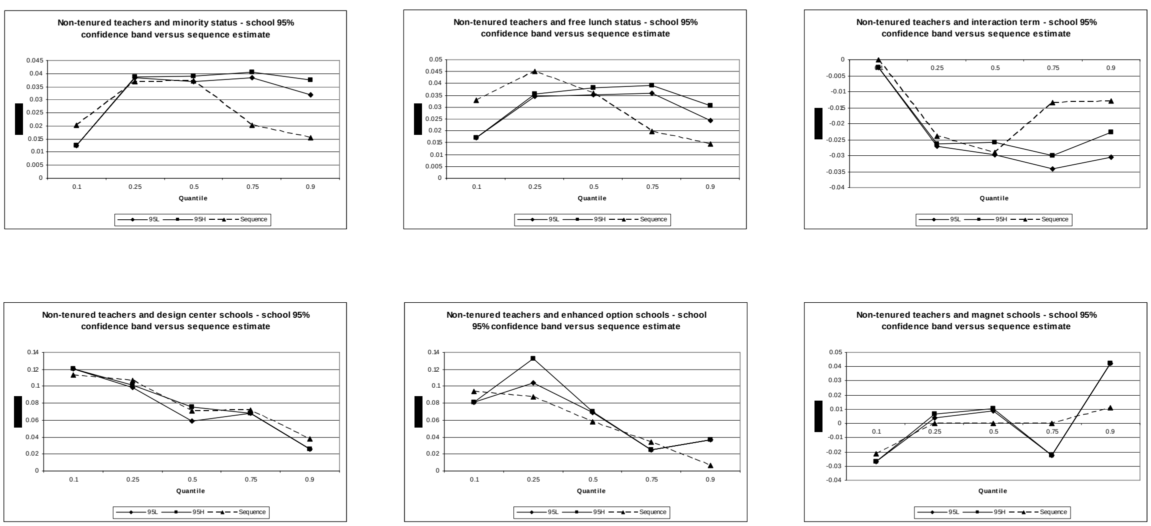

Figure 4.8: Sequence-based quantile estimates plotted against 95% confidence band for school-based quantile estimates

Among student characteristic variables, sequence-based estimates are generally higher at the lowest ends of the distribution (.10), and lower at the higher ends of the distribution (.9). This means that, even among the most advantaged students, free lunch students receive higher percentages of non-tenured teachers and among the least advantaged students lower percentages of non-tenured teachers relative to their more affluent peers. These findings can be interpreted in terms of stability: at the most privileged area in the distribution of non-tenured teachers, affluent students have consistently lower percentages of non-tenured teachers. Free lunch students, however, must have some periods of higher percentages of non-tenured teachers to “average up” from their affluent peers. At the worst end of the distribution of non-tenured teachers, the opposite is true; affluent students have more experience with higher percentages of non-tenured teachers. This means that poor students are less consistently in better school and affluent students are less consistently in worse schools, when considering the distribution of non-tenured teachers.

Among school types, sequence-based estimates are slightly less for design center school at the lowest percentiles of non-tenured teachers and very slightly more for design school students with the highest percentages for non-tenured teachers. Sequence-based estimates are slightly less for enhanced option schools at quantiles .25, .5, and .9 and very slightly greater at quantiles .10 and .75. For magnet schools, sequence-based analysis is similar for all quantiles of the distribution save the .75 and .9 quantiles. Sequence –based analysis reports greater effects at the .75 quantile and lesser effects at the .9 quantile.

Overall, the greatest observed differences between school-based and sequence-based estimates occurs at the highest ends of the distribution. In all cases but one, the sequence based variable presents a smaller and significant difference from school-based estimates.

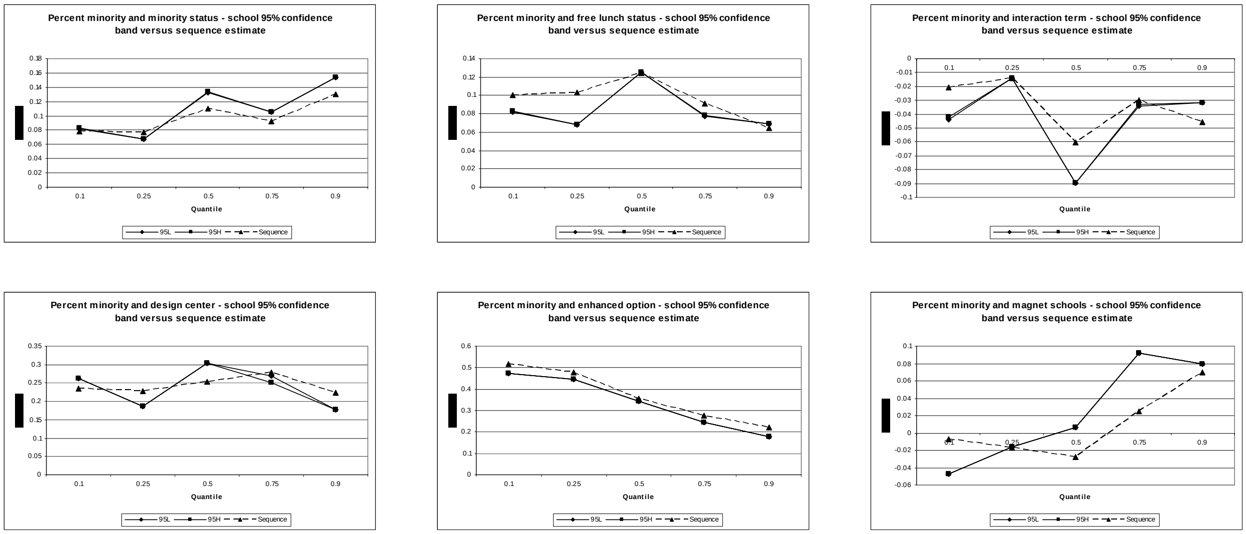

Figure 4.9: Sequence-based quantile estimates plotted against 95% confidence band for school-based quantile estimates

Figure 4.9 presents a comparison of sequence-based estimates along with the 95% confidence band for school-based estimates for the percent of minority peers dependent variable. Sequence-based analysis indicates no difference from school-based analysis when examining the impact of student minority status on that student's percentage of minority peers in schools at quantile .10 and .25. However, sequence based analysis seems to indicate less of an impact at the high percentile of the distribution of minority peers. That is, among students who encounter higher percentages of minority peers, sequence-based analyses reports a weaker positive influence than school-based analysis. Among free lunch students, sequence based analysis reports stronger associations at the lower end of the distribution of minority peers. That is, among students with lower percentages of minority peers, an individual student's free lunch status has a greater impact when examining through the lens of sequences than when examined through schools. This is true at the .75 quantile as well. Among school type variables, sequence-based results for the impact of design center school on percentages of minority peers presents a flatter, more consistent set of quantile estimates: less than school based estimates at quantile .10, greater at quantile .25, less at quantile .50, and greater at quantiles .75 and .9.

Sequence-based estimates for enhanced option school type are very slightly greater than school-based estimates across all quantiles. Finally, sequence based estimates for the relationship between magnet schools and minority peers are greater at quantile .10, the same at quantile .25 and less at quantiles .5, .75, and .9. At quantile .5, the sequence-based estimate is in the opposite direction as the school-based estimate. In most cases, the sequence estimate is closer to zero than school based estimates, meaning that sequence base estimates seem to yield more conservative relationships than school based estimates.

Figure 4.10 presents comparisons between sequence-base and school-based estimates using the percentages of free lunch peers.

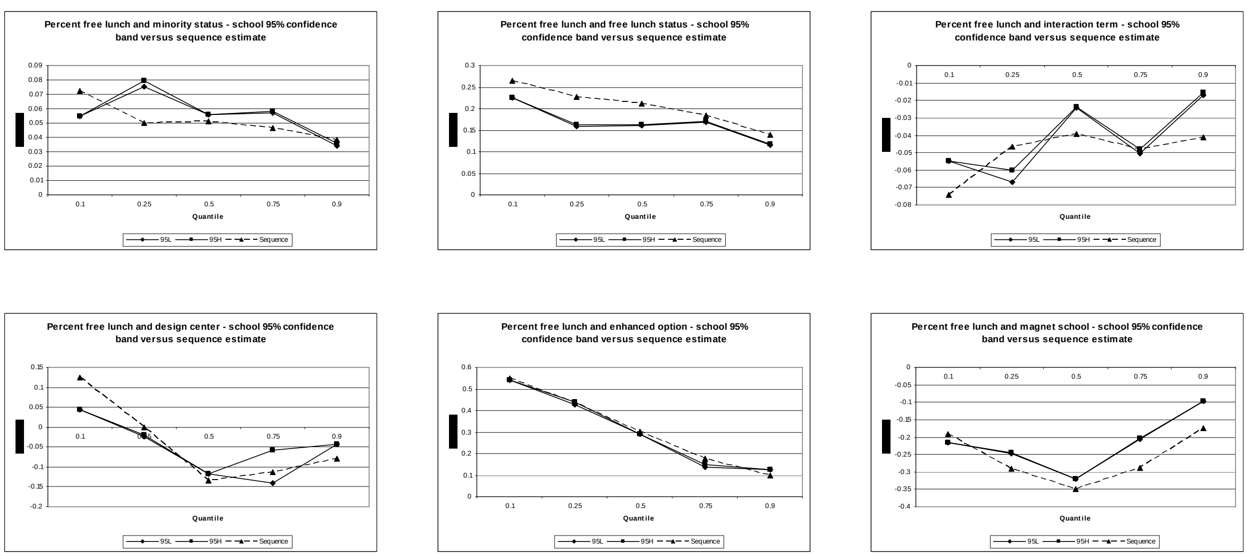

Figure 4.10: Sequence-based quantile estimates plotted against 95% confidence band for school-based quantile estimates

Sequence –based estimates are consistently less than school-based estimates for the minority status student variable (save for quantile .10), and consistently greater for the free lunch status variable. For the design center schools, sequence estimates are more strongly positive at quantile .10 and quantile .25, more strongly negative at quantile .50 and quantile .90 and the same at quantile .75. While sequence-based estimates are virtually the same as school-based estimates in reporting relationships between percent of free lunch peers and enhanced option schools, the sequence-bases results are consistently more negative than school based estimate when describing the relationship between free lunch peers and magnet schools. At the highest percentage of free lunch peers, the sequence-based gap between magnet schools and non magnet schools is almost double that of school-based estimates.

Figures 4.11 and 4.12 present sequence-based and school-based estimates of the relationships between student and school type variables conducted with teacher and staff salary as dependent variables. These two sets of graphics are virtually identical, meaning g that the vertical equity relationships are the same between student characteristics, school types and salary levels that exclude and include administrative pay.

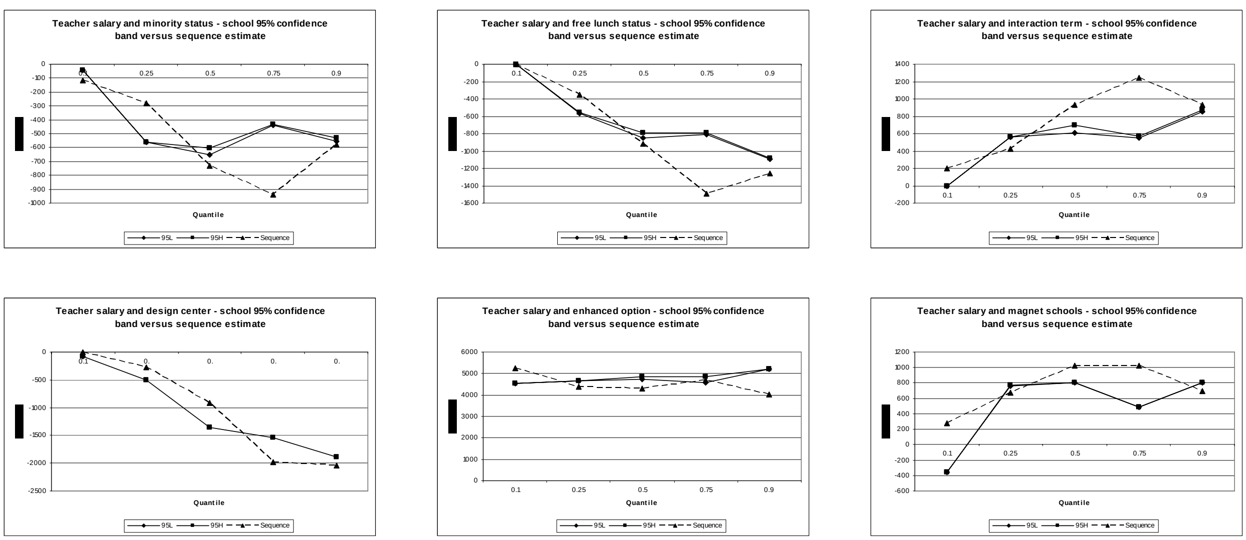

Figure 4.11: Sequence-based quantile estimates plotted against 95% confidence band for school-based quantile estimates

Among student characteristics, both sets of graphs demonstrate sequence-based results that are less negative than school-based estimates at quantiles .10 and .25, statistically similar at quantile .5, and more strongly negative at quantiles .75 and .90. Sequence-based and school-based estimates are similar in pattern and magnitude for enhanced option and design center schools.

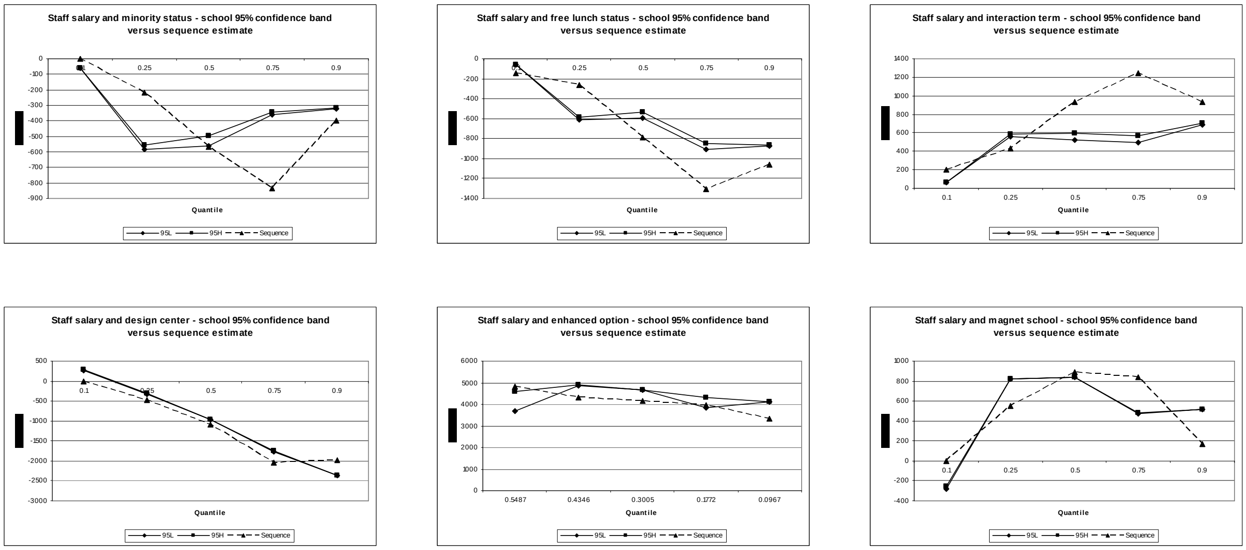

Figure 4.12: Sequence-based quantile estimates plotted against 95% confidence band for school-based quantile estimates

In each case, sequence-based estimates track the same patterns as school-based estimates when describing relationship with magnet schools. Sequence-based estimates, however are closer to zero at quantile .1, .25 and .9, but greater than school-based estimates at quantiles .5 and .75.

Plotting sequence-based results against 95% confidence bands of school-based quantile regression results demonstrates that, although sequences-based analysis provide different results than school-based quantile regression, there is no pattern to the differences. This is confirmed in table 4.28. This table presents a matrix of the differences between sequence-based quantile regression and school-based quantile regression estimates.

Table 4.28: Sequence based and school based quantile regression coefficient comparisons

	Non-tenured					Percent minority					Percent free lunch					Teacher salary					Staff salary				
Quantile	.1	.25	.5	.75	.9	.1	.25	.5	.75	.9	.1	.25	.5	.75	.9	.1	.25	.5	.75	.9	.1	.25	.5	.75	.9
D.Center	-	+	nc	+	+	-	+	-	+	+	+	+	-	nc	-	+	nc	+	-	-	-	-	-	-	+
E.Option	+	-	-	+	-	+	+	+	+	+	+	nc	+	+	-	+	-	-	-	-	+	-	-	nc	-
Magnet	+	-	-	+	-	+	nc	-	-	-	+	-	-	-	-	+	-	+	+	-	+	-	+	+	-
Minority	+	-	nc	-	-	-	+	-	-	-	+	-	-	-	+	+	+	+	-	+	+	+	nc	-	-
Free lunch	+	+	nc	-	-	+	+	nc	+	-	+	+	+	+	+	-	+	nc	-	nc	-	+	-	-	-

By using five independent variables and five dependent variable over five quantiles yields a matrix of 125 cells. Of these cells, 113 (or 90%) of sequence-based estimates were significantly different from school-based estimates. Only 12 cells, or 10%, exhibited no significant difference from school-based estimates. Of the 113 significantly different cells, 58 (or 46%) provided sequence-based estimates greater than school-based estimates and 55 (44%) reported coefficients smaller than school-based estimates. Although sequence-based estimates confirm the vertical equity found in school-based quantile regression estimates, there is little pattern in the direction of sequence-based versus school-based estimates.

Sequence effects on poor and minority students

Sequence-based estimates for minority students varied according to the resource in question. For non-tenured teachers, sequence-based analysis provided estimates that were smaller than school-based estimates for 3 quantiles out of five. Four out of five quantile estimates for the dependent variable percent of minority peers were smaller than sequence-based equity analysis. Three out of five sequence-based estimates were smaller than their school-based counteracts for the dependent variable describing the percentage of free lunch peers. The sequence-based estimates for teacher salary were greater than school-based estimates three times out of five, but greater only two times out of five when examining other professional staff salary levels as a dependent variable.

When examining free lunch students, difference between sequence based and school based estimates are “balanced” between positive and negative coefficients for the teacher salary and non-tenured teachers variable. For the percentage of minority peers, sequence-based analysis provided estimates greater than school-based estimates. This was overwhelmingly true for the dependent variable of percentage of free lunch peers. Staff salary estimates, however, were smaller using sequence based analysis when compared to school-based analysis.

At a general level, table 4.27 illustrates that sequence-based equity analysis provided estimates that show school-based estimates to be under-estimated for minority students and generally over-estimated for free lunch students.

Conclusion

Analysis conducted throughout this chapter has demonstrated that the distribution of teacher experience, student peer groups, teacher and other professional staff salaries are all inequitably distributed across GPS students with three or more years of experience in the school system. These findings have policy implications for student assignment policies, which will discussed in more detail below. Methodologically, this chapter has introduced the use of quantile regression in the vertical equity analysis and demonstrated the difference to be found between quantile regression and more traditional ordinary least squares regression analysis. Finally, this chapter has examined differences between vertical equity analysis based on school level models and school-sequence level models. The hypothesis motivating this part of the analysis asserted that resource distribution measured across the sequence of schools a student attended would be different from resource distribution examined across schools without consideration of the sequences of schools. Although sequence-based analysis did yield statistically different estimates than school-based analysis, those estimates were not different in a specific or systematic manner. Sequence–based analysis sometimes showed greater impact of independent variables (such as the overall effect for minority students) and sometimes less (such as with free lunch students). We are left with the idea that the unit of analysis in vertical equity studies should conform to that theory being used by the researcher and the specific research questions at are asked.

CHAPTER V

CONCLUSION

Review of findings

This dissertation research posed two research questions:

1. Are measures of intradistrict equity different when measured across school sequences than when measured across schools?
2. Do school sequences for poor and minority students differ from school sequences for other students? If so, do poor and minority students attend sequences with greater or fewer resources than their non-poor, non-minority peers?

Through an analysis of resource distribution, results indicate that there exist some small differences between equity analysis conducted across sequences and equity analysis conducted across schools. When examining resource with measures of horizontal equity, sequence-based analysis seems to produce estimates that are smaller than school-based estimates. When using measures of vertical equity, findings indicate that sequence-based estimates are almost equally greater than and less than school-based estimates.

For poor and minority students, levels of inequity across sequences mirror inequity across schools. That is, poor and minority students receive inequitable levels of key resources across sequences in much the same manner that they do when examined across schools. Viewed positively, poor and minority students are treated no worse over time than they are from year to year; viewed negatively, the resource distribution inequities faced by poor and minority students is not ameliorated over time.

The creation of student sequences yielded findings that GPS is a highly mobile district with relatively few students remaining in their district-assigned sequences and high transfer rates across all cohorts.

Examination of the data using three standard measures of horizontal equity: the coefficient of variation, the McLoone Index and the Gini coefficient – demonstrate that expenditures for salary are equitably distributed across GPS but that inexperienced teachers are inequitably distributed across GPS schools, as are poor and minority student peers. Inequity in the distribution of free lunch students is the most pronounced across student types. However, very few of the horizontal equity measures were statistically different from one another.

Traditional vertical equity analysis using ordinary least squares used a model that predicted anywhere from 8% to 24% of the variation in the dependent variables. Each independent variable was a statistically significant predictor of each of the five dependent variables. Analysis if these findings focused on relationships between poverty and minority status. Although there were moderate and significant effects for different school types, the small number of magnet, design center and enhanced option schools dictated that those coefficients be interpreted with care as high leverage point may bias estimates. School types were used as control variables in these models. These models indicate inequitable relationships between student status (poor, minority) and school type.

A first round of quantile regression (QR) models was used to approximate the equation used in OLS. These findings confirmed OLS findings of inequitable relationships between dependent variables and student and school characteristics. In addition, these QR models demonstrated that the inequity among teacher salary, other professional staff salary and teacher experience variables increased over quantiles; that is, the effect of poverty and minority students was greater at higher ends of the distribution of each of these variables. Relationships across quantile remained relatively stable for school-level percent minority and school-level percent free lunch variables.

Finally, QR models were used to determine the impact of school sequences. Although sequence-based QR provided different estimates from school-based QR analysis, these differences ere not systematic enough for an explanation of how sequence based analysis alters estimates from school-based analysis.

To return to the two research questions posed: school sequences matter in the measurement of vertical equity, less so in measures of horizontal equity, and the impact of student racial and economic characteristics is generally less in models that include student sequence types. The general conclusion, then, is that models that do not account for school sequence both overstate and understate by small to moderate amounts the inequitable relationship between race, poverty and school-level resources. This analysis has provided a number of findings about school system assignment policies, intradistrict resource allocation, and methods for assessing vertical equity in school finance studies. These research and policy implications are described in detail below.

Research implications

As conducted, this research has research implications on two fronts. First, the finding that school sequences matter has implications for the conduct of school finance research. Secondly, the use of quantile regression also has implications for equity analysis in school finance.

It seems apparent upon initial consideration that the use of longitudinal data will provide better estimates than cross sectional data. Heretofore, based on a model of examining intradistrict school finance equity; that is, equity across districts within states, the impact of local students' assignment and choice policies as been ignored. In the intradistrct context, local policies are viewed as simply part of a district effect on resource allocation. In making the transition to intradistrict study, researchers have continued to assume that district level policies are fixed across students. This is not a correct assumption. As has been demonstrated, some district policies – those that allocate students into sequences of schools over time – impact a different group of students than those policies that provide choice in schools. If data is available, constructing sequences for students provides not only an important independent variable with which to predict the distribution of resources across schools, but also a potential new level of analysis, as the creation and description of student sequence types can yield insights into the overall effect of policies on student mobility.

The use of quantile regression in estimating the effects of student racial and economic characteristics provide an additional methodological tool with which researchers can better understand the distribution of resources across students in an intradistrict context. Quantile regression estimates exhibit more robust characteristics in their imperviousness to outliers than their OLS counterparts. In addition, the ability to obtain estimates of relationships across the distribution of a dependent variable adds a level of insight into the nature of inequity. Although, as has been shown in this research, interpretation of quantile regression estimates can be a bit counter-intuitive (the effects of the independent variable are interpreted as associations with a specific quantile of the dependent variable, making the determination of inequity more difficult), the ability to track associations across a distribution is an important addition, especially to a field of research concerned with distribution of resources across a population.

Policy implications

Findings regarding school sequences have additional implications for policymakers. Specifically, the findings of few students in district assigned sequences presents administrators with a challenge. In addition, the finding that school sequences matter for resource equity concerns places an emphasis on thoughtful student assignment plans that provide resource equity across years of student attendance. Finally, the finding of salary stability simultaneous with variations in teacher experience indicates that teacher salary issues may mask teacher quality disparities across schools.

First, the finding that few students participated in the district assigned school sequence has policy implications for district administrators. Much has been made of the loosely coupled nature of school districts, and the manifold means in which participants in the system can game the system (Weick, 1976). District administrators may wish to pay attention to the manner in which policies are implemented and the degrees to which the system allows exceptions to the system, particularly if the policies involved have resource equity implications.

It is clear that student assignment matters at the aggregate student assignments matter as well. This resents a fine line for school system administrators to work vis-à-vis student assignment. On one hand, administrators must pay careful attention to the schools in which students are assigned. However, constant change in the pursuit of such balance may have deleterious consequences for public support.

Finally, findings from this research point subtly to problem within the single teacher salary schedule. Implications of some findings indicate that, while students may be receiving equitable teacher salary spending, they are not receiving equitable distributions of teacher experience. Better alignment between teacher qualifications and teacher compensation may allow for better tracking of teacher quality distributed across different student types.

Data limitations

First, the use of GPS data to test a theory of student assignment represents a data limitation of a sort. It is important to note that few districts would have been able to provide the richness of data such as that provided by GPS. Nevertheless, it is conceivable that data on student assignments could be pooled across districts to allow for a more powerful examination of these issues. In addition, limitations confronted by this study were encountered with each type of data available: student level, teacher level, school level and district level. An account of limitations follows.

Next, the student database provided limited information on student status. For example, special education status was not recorded on the student database. Another imitation was that student records were not linked to an address. Much of the sequence coding was based on comparisons of predicted attendance (via district assignment databases) to actual student school attendance. Determining if a student has moved houses within the district would have aided in better coding of transfer students, and allowed for a determination of the precise number of students who remained in their residence but did not attend schools in sequence.

Although teacher level data allowed for the construction of school-specific teacher salary variables, the teacher database itself was limited. There were no records of grades or subjects taught, only teacher certifications. In addition, literature on teacher qualifications indicates that some variable representing teacher academic performance – such as a college GPA or a standardized test score – would have allowed for better differentiation of teacher quality. An ideal situation would have been each teacher's value added ranking from the Tennessee Value Added Assessment System (TVAAS). This would have allowed for the construction of a school-specific teacher quality index separate from the school-specific teacher salary variable.

School-level data was incomplete for some schools for some years. Newer schools especially, were hampered by limited data available via the State of Tennessee's web reporting function. Such omission may have introduced bias into the findings, if all newer schools were underreported.

Finally, district student assignment files proved difficult to work with. A longitudinal examination of GPS student assignment databases reveals that GPS only assigns streets to schools when those streets are populated with school age children. As a result, the student assignment database is essentially reconfigured every academic year, and the street/address combinations do match up from year to year. Matching these records over time was a laborious task. As mentioned earlier in this dissertation, it need not be this way. The Wake County (NC) Public School System, for example, assigns every street into a permanent node. Nodes are then reassigned every academic year based on in- and out-migration of students, opening of new schools, growth another factors. Tracing the impact on neighborhoods over time would be a much easier task within that framework.

Next steps

A number of options present themselves for continued research in this area. First, continued work on the equity implications of the use of student sequences in a number of large urban districts would confirm or disconfirm a trend in the findings presented here. Second, continued work in the field of school finance using quantile regression as a methodological tool would improve researcher's understanding of the strengths and weaknesses of this application.

Finally, this research has focused solely on equity as a concept valued by policymakers. Another concept, one of adequacy, has also been popular with policymakers. Adequacy as a concept addresses the interrelationship between resources, students, and outcomes in a manner that hopes to clarify amounts of spending needed to bring all students in a jurisdiction up to appropriate levels of academic performance. It may be the case that school attendance sequences have implications for the academic attainment of students. It may also be the case that quantile regression as a methodological tool may be able to refine current applications in adequacy research by ensuring that students across a distribution of, say, academic outcomes, receive the resources necessary to meet those academic requirements.

Concluding thoughts

In some ways, the use of school attendance sequences as a unit of analysis may seem a futile hairsplitting of an already over-sown field in school finance. However, as recent legislation such as No *Child Left Behind* continues to focus researchers' attention o the interrelationships between resources and performance, the ability to accurately describe exactly those resources received by each student is an important part of the policy puzzle. School sequences help develop a better understanding of the manner in which students receive resources, and the distribution of those resources. These findings merit inclusion in the policy debates that continue to challenge the field of school finance in general and intradistrict school finance in particular.

Appendix A: Fully specified models for school based ordinary least squares (OLS) analysis

Table A-1: OLS models for each dependent variable					
Variable	Non-tenured teachers	Percent minority	Percent free lunch	Teacher salary	Staff salary
Intercept	0.25651	0.47062	0.57415	40832	42346
Enrollment	-0.00007229	-0.00008066	-0.00036873	5.31594	5.03928
Enrollment^2	2.32E-08	2.62E-08	7.30E-08	-0.00141	-0.00133
Minority	0.02623	0.10526	0.07903	-609.06565	-491.73113
Free lunch	0.02698	0.08642	0.16581	-727.6014	-709.27155
Interaction	-0.01621	-0.04156	-0.0602	573.01812	535.85322
Design Center	0.07468	0.21289	-0.04601	-997.33162	-1213.15823
Enhanced Option	0.05831	0.29153	0.2446	4694.28944	4164.4556
Magnet	0.01285	0.04289	-0.18666	425.25363	245.18932
2000	0.02031	0.0125	0.00735	26.36594	34.75731
2001	0.00673	0.02513	0.01339	85.1473	238.4959
2002	-0.04248	0.03421	0.03164	1966.02766	1732.53948
2003	-0.00697	0.04831	0.05927	862.2926	678.95502
2004	-0.06623	-0.04396	0.2024	181.46845	142.45768
F	3366.15	6859.01	22954.8	7577.19	6703.22
Adjusted R^2	0.1181	0.2315	0.4776	0.2318	0.2107
Note: All estimates significant at $p<.0001$.					

Appendix B: Fully specified models for school-based quantile regression

Table B-1: School-based quantile regression: percentage of non-tenured teachers					
	0.1	0.25	0.5	0.75	0.9
Intercept	0.0978	0.1685	0.2459	0.347	0.3917
Enrollment	0	-1E-04	-1E-04	-1E-04	-1E-04
Enrollment^2	0	0	0	0	0
Minority	0.115	0.0972	0.0669	0.0547	0.014
Free lunch	0.0712	0.106	0.061	0.0103	0.0304
Interaction	-0.015	0.0061	0.0101	-0.02	0.0315
Enhanced option	0.0138	0.0335	0.0377	0.0365	0.0327
Design center	0.0166	0.0335	0.04	0.0333	0.0268
Magnet	-0.007	-0.025	-0.029	-0.031	-0.027
2000	-6E-04	0.0138	0.0208	0.0532	0.0599
2001	0.0079	-1E-04**	0.0061	0.0163	0.0375
2002	-0.037	-0.049	-0.043	-0.029	-0.032
2003	-0.022	-0.012	-0.008	0.011	0.0147
2004	-0.042	-0.049	-0.069	-0.078	-0.08
Note: All estimates significant at p<.0001, except *-p<.05 and **-p>.05.					

Table B-2: School-based quantile regression: school percent minority					
	0.1	0.25	0.5	0.75	0.9
Intercept	0.1879	0.3244	0.4601	0.646	0.7305
Enrollment	0.0002	0	-1E-04	-2E-04	-2E-04
Enrollment^2	0	0	0	0	0
Minority	0.238	0.1636	0.27	0.2204	0.1301
Free lunch	0.4594	0.3751	0.3012	0.2154	0.1385
Interaction	-0.04	-0.012	0.045	0.0872	0.0781
Enhanced option	0.0729	0.0661	0.1314	0.0958	0.1397
Design center	0.0693	0.0661	0.1244	0.0759	0.0708
Magnet	-0.04	-0.019	-0.09	-0.038	-0.062
2000	0**	0.0022	0.0198	0.0146	0.0431
2001	0.0127	0.0139	0.0364	0.0469	0.0565
2002	0.0229	0.0353	0.0502	0.0555	0.0619
2003	0.0345	0.0427	0.0743	0.0694	0.0787
2004	-0.161	-0.094	-0.024	0.0443	0.1024
Note: All estimates significant at p<.0001, except *-p<.05 and **-p>.05.					

Table B-3: School-based quantile regression: school percent free lunch					
	0.1	0.25	0.5	0.75	0.9
Intercept		0.4773	0.619	0.77	0.9023
Enrollment	-2E-04	-4E-04	-5E-04	-5E-04	-5E-04
Enrollment^2	0	0	0	0	0
Minority	0.0019	-0.022	-0.084	-0.019	-0.069
Free lunch	0.4762	0.3616	0.2378	0.1412	0.0916
Interaction	-0.179	-0.229	-0.245	-0.165	-0.135
Enhanced option	0.059	0.0521	0.0867	0.0584	0.046
Design center	0.1295	0.1182	0.1574	0.159	0.1185
Magnet	-0.059	-0.033	-0.053	-0.05	-0.036
2000	-0.01	0.0068	0.013	0.0073	0.0242
2001	0.0096	0.0137	0.0249	0.0193	0.0342
2002	0.0254	0.03	0.0406	0.0365	0.043
2003	0.0648	0.0536	0.0713	0.0636	0.0666
2004	0.1464	0.1635	0.2152	0.2318	0.2456
Note: All estimates significant at p<.0001, except *-p<.05 and **-p>.05.					

Table B-4: School-based quantile regression: average teacher salary					
	0.1	0.25	0.5	0.75	0.9
Intercept	37090	38355	40689	43235	45157
Enrollment	5.2838	5.7571	5.3554	4.5226	3.6204
Enrollment^2	-0.001	-0.002	-0.001	-9E-04	-6E-04
Minority	-10.95	-818.4*	-1250	-1328	-1504
Free lunch	4611.7	5047.2	4899.7	5018.5	5485
Interaction	-356.7	578.49	908.14	420.93	433.57
Enhanced option	-75.12	-629	-743.9	-701.2	-569.2
Design center	-75.12	-654.1	-822	-858.2	-1083
Magnet	75.115	628.96	743.94	701.24	682.41
2000	-441.5	201.31	-197.6	-512	767.94
2001	-108	597.94	-92.05	-681.7	300.32
2002	1587.1	2751.1	2318.6	1657.6	1336.6
2003	910.27	1654	868.65	438.37	381.87
2004	314.48	1186.2	678.56	65.938	-478.6
Note: All estimates significant at p<.0001, except *-p<.05 and **-p>.05.					

Table B-5: School-based quantile regression: average staff salary					
	0.1	0.25	0.5	0.75	0.9
Intercept	38385	40032	41671	44559	46998
Enrollment	5.8841	6.4689	5.6669	4.03	2.8128
Enrollment^2	-0.002	-0.002	-0.002	-8E-04	-2E-04
Minority	330.81	-463	-1188	-1795	-2178
Free lunch	4110.1	5009	4679.8	4165.2	4127.6
Interaction	-359.6	776.45	896.63	314.53	403.76
Enhanced option	-100.8	-556.1	-626.5	-391	-334.1
Design center	-100.8	-556.1	-626.5	-860	-863.8
Magnet	100.78	556.07	605.55	477.06	446.46
2000	-77.33	-364.7	-50.67	-122.7	467.6
2001	352.38	214.82	314.58	-328.7	92.127
2002	1669.7	1589.9	2117.8	1497.8	864.75
2003	930.9	556.78	997.74	607.13	-392.9
2004	11.085	261.74	780.26	297.46	-612.8
Note: All estimates significant at p<.0001, except *-p<.05 and **-p>.05.					

Appendix C: Fully specified models for sequence-based quantile regression

Table C-1: Sequence-based quantile regression: percent non-tenured teachers					
	0.1	0.25	0.5	0.75	0.9
Intercept	0.2934	0.4136	0.5625	0.6928	0.8209
Enrollment	0.0001	0**	-0.0002	-0.0002	-0.0003
Enrollment^2	0*	0	0	0	0
Minority	0.0791	0.0729	0.1089	0.0942	0.12
Free lunch	0.1095	0.1024	0.1263	0.1038	0.0808
Interaction	-0.0302	-0.0174	-0.0654	-0.0518	-0.0614
Enhanced option	0.4328	0.3681	0.2932	0.2369	0.1931
Design center	0.2247	0.2056	0.2371	0.2628	0.2016
Magnet	0.0272	0.0116	0.0226	0.0443	0.0631
2000	-0.0477*	-0.0453*	-0.0644	-0.0607	-0.0963
2001	-0.1141	-0.0914	-0.0785	-0.0421	-0.0499
2002	-0.1016	-0.0619	-0.0322*	-0.0181**	0.0039**
2003	-0.0497*	-0.0086**	-0.0116**	-0.0155**	-0.0567
2004	0.0124**	-0.0133**	-0.0505	-0.1332	-0.2231
Note: All estimates significant at p<.0001, except *-p<.05 and **-p>.05.					

Table C-2: Sequence-based quantile regression: school percent minority					
	0.1	0.25	0.5	0.75	0.9
Intercept	0.2934	0.4136	0.5625	0.6928	0.8209
Enrollment	0.0001	0**	-0.0002	-0.0002	-0.0003
Enrollment^2	0*	0	0	0	0
Minority	0.0791	0.0729	0.1089	0.0942	0.12
Free lunch	0.1095	0.1024	0.1263	0.1038	0.0808
Interaction	-0.0302	-0.0174	-0.0654	-0.0518	-0.0614
Enhanced option	0.4328	0.3681	0.2932	0.2369	0.1931
Design center	0.2247	0.2056	0.2371	0.2628	0.2016
Magnet	0.0272	0.0116	0.0226	0.0443	0.0631
2000	-0.0477*	-0.0453*	-0.0644	-0.0607	-0.0963
2001	-0.1141	-0.0914	-0.0785	-0.0421	-0.0499
2002	-0.1016	-0.0619	-0.0322*	-0.0181**	0.0039**
2003	-0.0497*	-0.0086**	-0.0116**	-0.0155**	-0.0567
2004	0.0124**	-0.0133**	-0.0505	-0.1332	-0.2231
Note: All estimates significant at p<.0001, except *-p<.05 and **-p>.05.					

Table C-3: Sequence-based quantile regression: school percent free lunch					
	0.1	0.25	0.5	0.75	0.9
Intercept	0.2685	0.4811	0.6354	0.722	0.851
Enrollment	-0.0001	-0.0003	-0.0004	-0.0005	-0.0005
Enrollment^2	0**	0	0	0	0
Minority	0.0418	0.0499**	0.057	0.0561	0.0443
Free lunch	0.1874	0.1847	0.1779	0.1688	0.1413
Interaction	-0.0416	-0.0401	-0.0441	-0.0534	-0.0441
Enhanced option	0.4037	0.3409	0.2313	0.1315	0.0682
Design center	0.051	0.001	-0.0638	-0.1191	-0.097
Magnet	-0.1707	-0.2263	-0.2767	-0.2436	-0.1641
2000	0.0149**	-0.0091**	-0.0129**	0.0222*	-0.0048**
2001	-0.0506*	-0.0896	-0.0209*	0.0484	0.066
2002	-0.0441*	-0.0803	-0.0518	0.0648	0.042*
2003	0.1039	0.0682	0.063	0.1078	0.1012
2004	0.1158	0.1357	0.199	0.2528	0.2233
Note: All estimates significant at p<.0001, except *-p<.05 and **-p>.05.					

Table C-4: Sequence-based quantile regression: average teacher salary					
	0.1	0.25	0.5	0.75	0.9
Intercept	36829.9	37446.3	39846.8	42058.7	43815.5
Enrollment	8.7441	8.7633	7.0548	6.5234	7.581
Enrollment^2	-0.0033	-0.0035	-0.0023	-0.0017	-0.0022
Minority	-153.581	-294.184	-724.791	-925.706	-614.007
Free lunch	-96.9683*	-310.751	-829.626	-1341.32	-1256.35
Interaction	166.1863*	382.771	798.317	1040.45	729.111
Enhanced option	5298.55	4428.363	4584.97	5301.94	4637.16
Design center	245.025*	-269.749	-847.581	-1589.33	-1678.21
Magnet	322.7109*	685.571	1048.58	729.718	423.79
2000	-373.444**	64.1214**	-572.189*	-1284.91	-2049.88
2001	924.43	1536.75	794.474	105.1703**	-368.854*
2002	2134.89	3017.52	3537.74	4203.36	2462.25
2003	667.82	1529.2	1193.18	-110.319**	-2065.73
2004	-1571.26	-591.314	-1573.92	-2979.78	-3505.06
Note: All estimates significant at p<.0001, except *-p<.05 and **-p>.05.					

Table C-5: Sequence-based quantile regression: average staff salary					
	0.1	0.25	0.5	0.75	0.9
Intercept	38629.4	39122.4	41462.1	44066.1	45557.5
Enrollment	8.3133	8.6362	7.1295	6.061	7.2949
Enrollment^2	-0.0031	-0.0034	-0.0023	-0.0016	-0.0021
Minority	-70.9747*	-221.419	-550.462	-880.205	-385.624
Free lunch	-154.971	-263.291	-724.139	-1271.44	-1086.41
Interaction	165.0996*	340.26	702.15	1024.07	489.877
Enhanced option	4829.04	4351.88	4379.18	4479.82	3805.47
Design center	-37.2371**	-456.72	-1211.24	-1731.08	-1636.61
Magnet	-97.3441**	550.579	768.917	623.125	-115.198*
2000	-446.623**	-193.549**	-950.246	-1606.84	-2205.94
2001	681.1859*	1276.06	467.4167*	-620.624*	-665.25*
2002	1851.76	2520.28	2689.75	3753.89	1751.31
2003	618.3363*	1394.04	630.537	-1095.62	-2741.66
2004	-2820.13	-2427.61	-3391.64	-4867.86	-5224.13
Note: All estimates significant at p<.0001, except *-p<.05 and **-p>.05.					

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