The Superintendent’s Dilemma: Managing School District Capacity as Parents Vote with Their Feet*

Dennis Epple
Carnegie Mellon University

Akshaya Jha
Stanford University

Holger Sieg
University of Pennsylvania

February 19, 2013

*We would like to thank Lanier Benkard, Eric Bettinger, Flavio Cunha, John Engberg, Kirill Evdokimov, David Figlio, Eric Hanushek, Dave Marcotte, Francois Margot, Mark Rosenzweig, Petra Todd, Frank Wolak, and seminar participants at the APPAM conference in Washington D.C., Carnegie Mellon University, the 8th Meeting of German Economists Abroad in Berlin, a CESifo workshop on the Economics of Education, Stanford University and the University of Pennsylvania for comments. Financial support for
Abstract

Many urban districts confront the necessity of closing schools due to declining enrollments. To address this policy issue, we formulate a unified approach to estimation, computation of equilibrium, and optimal selection of schools to close. We develop a model of demand for public education that treats each district public school, as well as suburban and private options, as differentiated products. Using data for a mid-sized district with declining enrollments, we employ a two-step estimator that controls for unobserved heterogeneity among students as well unobserved school characteristics. This model is incorporated in a nonlinear integer programming framework to study optimal school closings. We show that consideration of student sorting is vital to assessment of any school closing policy. We find that the district can reduce excess school capacity without lowering parental perceptions of school quality. Our application also reveals that superintendents confront a difficult dilemma: pursuing an equity objective, such as limiting demographic stratification across schools, results in closure of high-achieving schools and the exit of many more students than are lost by an objective such as maximizing retention of students in the district or minimizing the number of students in schools chosen for closure.

This research is provided by the Institute of Education Sciences (IES R305A070117).
1 Introduction

Student retention has increasingly become an important issue for urban school districts, especially in the Midwest and East Coast. Districts such as Buffalo, Cincinnati, Cleveland, Detroit, Kansas City, Milwaukee, Pittsburgh, and Philadelphia have lost tens of thousands of students over the last two decades. When policies aimed at retaining students are not successful, urban school districts are forced to downsize. There are important research questions that arise in the context of downsizing a school district that have not been studied in the previous literature.\footnote{There is a small empirical literature that has focused on quantifying the impact of school closing on student achievement. See, for example, Engberg, Gill, Zamora, and Zimmer (2011).}

This paper attempts to fill this gap. We provide a retrospective analysis of the effects of downsizing on school choice which is based on one school district that was forced to close a significant number of schools. We also develop and implement a framework for prospective analysis which can be used to develop and evaluate alternative school closing scenarios.

The consideration of student sorting is vital to an assessment of any downsizing policy. Both retrospective and prospective analyses of the effects of school closings require us to characterize the demand for public schools. We, therefore, develop a demand model in which students can choose among a variety of schools, including public schools, charter schools, parochial schools, and other private schools. Each public school as well as each of the six outside options are treated as a differentiated product that can be characterized by a vector of observed and unobserved characteristics.\footnote{Our modeling approach is, therefore, rooted in the literature on characteristic models or differentiated products (Gorman (1980) and Lancaster (1966)).}

We observe school characteristics such as the composition of the peers. Unobserved characteristics – from the perspective of the econometrician –
are factors such as teacher or principal quality.

Our demand model also accounts for heterogeneity among students and parents. Since we have access to micro level data, we can control for a variety of observed student and parent characteristics. However, it is plausible that there are important unobserved differences among students. These differences are often insufficiently captured by additively separable error terms. We, therefore, use random coefficients in the specification of the utility function. This allows us to capture unobserved differences in preferences for school characteristics and is essential to generate realistic substitution patterns in demand. As we have panel data, we also adapt the standard static demand framework to model student choices over time.

We then analyze the planner’s problem of optimally closing schools. We consider three different objective functions for the central planner. Administrators clearly are concerned about minimizing the potential transition costs associated with school closings. In particular, they would like to keep the number of students that are in closed schools at a minimum. A second goal is to provide equal access to high quality schools, reducing the cream skimming that might otherwise occur across schools in the district. This objective entails limiting the extent of variation in peer characteristics across schools. A third goal is retention of students in the district. We also need to characterize the relevant constraints that are faced by the administrator. Some of the constraints such as capacity constraints are easy to

\[3\] There is a large literature on peer effects by social scientists. Methodological issues are discussed in Manski (1993), Moffitt (2001), and Brock and Durlauf (2001). Epple and Romano (2011) provide a review of models that incorporate peer effects and a review of the empirical literature on peer effects in education. Epple, Romano, and Sieg (2006) also find evidence that suggests that peer effects are important to explain admission and financial aid policies of colleges and universities in the U.S.
conceptualize. More challenging are the constraints that arise due to self-selection as parents make school choices for their children. This choice process is captured by our demand model.

The optimal school closing model cannot be cast as a simple assignment problem. The self-selection constraints depend on the control variables in a non-linear way, i.e.: closing a different set of schools will induce a resorting of students in the remaining schools. Our formulation of the optimal school closing problem gives rise to an integer programming problem with non-linear constraints. Despite the size of this problem – a large number of students and schools – we can compute exact solutions for reasonably size problems.

To implement both the retrospective and prospective analyses, we need to estimate the parameters of the demand model. We show that this can be done using a two step estimator that controls for unobserved heterogeneity among students as well as unobserved school characteristics.\footnote{Berry, Levinsohn, and Pakes (2004a) and Bayer, Ferreira, and McMillan (2007) also combine micro level data with aggregate to estimate a demand model for differentiated products.} In the first stage, we derive a maximum likelihood estimator that is based on the conditional choice probabilities generated by the random coefficient Logit model using school specific fixed effects to account for unobserved school characteristics. Then in the second stage, we decompose these school fixed effects into parts that can be explained by observed and unobserved school characteristics as suggested by Berry (1994). Most observed school characteristics are endogenous peer characteristics that are the outcome of the sorting process. We, therefore, need to use an instrumental variable approach to account for the endogeneity of school characteristics. We use administrative school assignment rules that are used by the school district to predict the composition of each school before and after the school closing. These predicted compositions of
schools are, therefore, not affected by sorting decisions of parents. This strategy was first used by Hoxby and Weingarth (2006) to instrument for peer effects in the estimation of a linear-in-means achievement function.

Our empirical analysis is based on administrative panel data from one urban district, which prefers to remain anonymous. We will, therefore, denote the district as Central City School District (CCSD). One key advantage of our data set is that the district provides transportation for all students in the district. As a consequence we also have data from students living in the CCSD that do not attend public schools. That allows us to model the extensive margin of the school choice problem. We use a short panel that includes observations from school years 2004-05 through 2007-08. Our findings provide strong evidence that parents and students care about peer characteristics, and that peer preferences vary depending on a student’s own demographic characteristics.

Our retrospective analysis of the effects of downsizing exploits the fact that the CCSD implemented a plan to close schools across the district during the time period. As a net result of the closures, the number of elementary and middle schools declined by approximately 25 percent following the 2005/06 school year. We find that closed schools had observed characteristics less desired by most parents than schools that remained open. We do not find evidence to suggest that the closed schools also had systematically lower unobserved characteristics that influenced parental choices.

Based on our estimated demand model for public schools, we then turn to our prospective analysis and implement our model of optimal school closing. Our computations suggest that the district can reduce excess capacity without lowering most parents’ perceptions of school quality. Retaining students nonetheless poses challenges because closing schools will inevitably cause some students to leave the

The rest of the paper is organized as follows. Section 2 develops our demand model for primary and secondary education and then formulates the optimal school closing problem. Section 3 introduces a parametrization of our model and derives an estimator for the parameters of the model. Section 4 discusses of the right-sizing plan in CCSD and the data used in the analysis. Section 5 provides
the empirical results. Section 6 discusses the findings of our analyses of optimal school closing. Section 7 offers some conclusions and discusses future research.

## 2 A Model

We first characterize the demand for public schools and then move to the problem of the planner that must reduce capacity in the public school system by closing a number of schools.

### 2.1 Demand for Public Schools

The first part of the analysis requires us to model demand for public education within one school district. Consider a student that lives in the district. Let $P_t$ denote the number of public schools that are available at time $t$.\(^5\)

The district operates an open enrollment policy at these schools, i.e. any student in the district can choose to enroll in one of these schools. In our application, almost all schools in the district had excess capacity. (See Figure 2).\(^6\)

In addition, there are a number of outside options denoted by $O_t$. Each student can also attend a (generic) charter school, three different parochial school types, or an independent private school within the district. We do not model heterogeneity

---

\(^5\)Technically speaking the number of school options available to a student depend on the grade. We control for this in the empirical analysis, but suppress this dependence for notational convenience here.

\(^6\)During the sample time period, there were a small number of selective magnet programs that were operating at capacity and used lotteries to determine admissions. In our empirical analysis we found that the findings do not depend on our treatment of these schools. The results are similar if we include or exclude students attending oversubscribed magnet programs.
in schools within these types. In addition, the student can leave the district to attend a (typically suburban) school outside the district. Thus the total number of elements of the choice set is given by \( J_t = P_t + O_t \).

A school \( j \) at time \( t \) has observed characteristics \( x_{jt} \) and unobserved characteristics \( \xi_{jt} \). In our application, \( x_{jt} \) includes measures of peer characteristics such as average achievement of students in the school, and measures of demographic variables such as proportion of students eligible for subsidized lunch, proportions in different racial/ethnic groups. Unobserved characteristics are, for example, the quality of the principal and the teachers.

Let \( z_{it} \) be the observed vector of characteristics of student \( i \) at time \( t \). Variables in \( z_{it} \) include the grade level, student’s ability, race, driving time to schools, free or reduced lunch status, as well as a measure of behavioral problems. Let \( d_{ijt-1} \) be an indicator variable which is equal to one if student \( i \) attended school \( j \) in period \( t - 1 \). Previous school choices matter in our model since transferring to a new school is costly.\(^7\) Let \( \epsilon_{it} \) denote a vector of idiosyncratic choice specific shocks. Finally, let \( \beta_i \) denote a vector of individual specific (random) coefficients that characterize unobserved heterogeneity among students.

A student is, therefore, completely characterized by a vector of characteristics \((z_{it}, d_{it-1}, \beta_i, \epsilon_{it})\). The key assumption is that only the last year matters and captures of the full history of past choices (a first-order Markov assumption). This allows us to estimate the model based on conditional choice probabilities as discussed in detail below.

We assume that the utility function of student \( i \) at time \( t \) is additively separable

\(^7\)Switching to a new school may be costly since it requires the student to new school rules and familiarize herself with new peers, facilities, and teachers.
in the idiosyncratic preference shocks and can thus be written:

\[ U_i(x_t, \xi_t, z_t, d_{t-1}, \beta_i, \epsilon_{it}) = \sum_{j \in D^o_{it}} d_{ijt} \left[ u(x_{jt}, \xi_{jt}, z_{it}, d_{it-1}, \beta_i) + \epsilon_{ijt} \right] \] (1)

Students maximize utility by choosing one of the discrete options in their choice set at each point of time. Integrating out the unobserved heterogeneity among students yields conditional choice probabilities for each school option. Let us denote the conditional choice probabilities by:

\[ Pr\{d_{jt} = 1 | x_t, \xi_t, J_t, z_t, d_{t-1}\} \] (2)

Aggregating choices among all students yields aggregate demand functions for each public school and each outside option. These aggregate demand functions play an important role in the analysis of school closing.

### 2.2 The Optimal School Closing Problem

Next we study the optimal school closing problem. A new school configuration is given by a set \( J^o_t \), that characterizes the schools that remain open in period \( t \). Each school that remains open is characterized by a vector \( x^o_t \), that captures peer characteristics, and a vector of unobserved characteristics, \( \xi^o_t \). Similarly, let \( J^c_t \) denote the set of schools that are closed.

Given a new school configuration \( (J^o_t, x^o_t, \xi^o_t) \), our demand model determines the probability that a student with observed characteristics \( (z_t, d_{t-1}) \) attends school \( j \). Let us denote the new conditional choice probabilities by:

\[ Pr\{d_{jt} = 1 | x^o_t, \xi^o_t, J^o_t, z_t, d_{t-1}\} \] (3)

We say that a new school configuration, \( (J^o_t, x^o_t, \xi^o_t) \), is feasible, if and only if the vector of school peer characteristics \( x^o_t \) are consistent with the implied student
sorting, i.e. if the vector $x_{jt}^o$ satisfy the following requirement:

$$x_{jk}^o = z_{jk}^o = \frac{\int z_k P_r\{d_{jt} = 1|x_{jt}^o, \xi_{jt}^o, z, d_{t-1}\} f(z, d_{t-1}) \, dz \, dd_{t-1}}{\int P_r\{d_{jt} = 1|x_{jt}^o, \xi_{jt}^o, z, d_{t-1}\} f(z, d_{t-1}) \, dz \, dd_{t-1}} \forall k, j \quad (4)$$

Feasibility thus implies that the system of equations given by (3) and (4) is internally consistent.

To apply our framework, we illustrate the implications of alternative district objectives: limiting demographic stratification across schools, retaining students in the districts, and minimizing the number of students attending schools chosen for closure.

To measure inequality in the provision of education, we can use the sum of the weighted squared deviation between school $j$’s and the district’s characteristics. Let $z^d$ denote the mean characteristics at the district level. Summing over all schools gives the total inequality index:

$$I = \sum_{j \in J} \sum_{k=1}^K \omega_k \left(z_{jk} - z_k^d\right)^2 \quad (5)$$

where $\omega_k$ is the weight assigned to school characteristic $k$. \(^8\)

The district wishes to attract and retain students in district schools. A measure of student retention is given by:

$$R = \sum_{j \in J^o} \int P_r\{d_{jt} = 1|x_{jt}^o, \xi_{jt}^o, J_t^o, z, d_{t-1}\} f(z, d_{t-1}) \, dz \, dd_{t-1} \quad (6)$$

Finally, the district wishes to limit the number of students that are attending schools that are closed. A measure of those students is given by:

$$D = \sum_{j \in J^c} \int P_r\{d_{jt} = 1|x_t, \xi_t, z, d_{t-1}\} f(z, d_{t-1}) \, dz \, dd_{t-1} \quad (7)$$

\(^8\)We determine the numerical values for the weights ($\omega_k$’s) in our computational analysis in order to scale the characteristics such that they have approximately equal weight in the objective function.
where \( p^*_b \) denote the baseline probabilities associated with the full choice set.

The district then maximizes \( I (R \text{ or } D) \) over the set of feasible new school configuration subject to the following constraints:

a) the school capacity constraints must be satisfied:
\[
\int Pr \{ d_{jt} = 1 \mid x_t, J^o, z, d_{t-1} \} f(z, d_{t-1}) \, dz \, dd_{t-1} \leq n_j \text{ for all } j \in J^o; \tag{8}
\]
b) total capacity is reduced by a predetermined amount, denoted by \( n_c \):
\[
\sum_{j \in J^c} n_j \geq n_c. \tag{9}
\]

Our approach to rationing is the following. Suppose public school \( j \) has admission price \( p_j \). For schools with excess capacity, we set \( p_j = 0 \). For schools with excess demand, demand must be rationed. Operationally, this probably occurs in a variety of ways. Parents who want to get their kids in the school may invest effort in making an early application to the school, in cultivating the principal, and in pursuing other activities to enhance the likelihood that their kids will get admitted. These activities are costly. Suppose we let \( p_j \) denote the shadow cost of effort for the marginal admit to the school. This is deducted from the utility that parents obtain from having their kid attend the school. The approach is the efficient rationing solution. It allocates the available capacity to those who value it most. As part of our algorithm, we need to compute the shadow prices for oversubscribed schools and impose the efficient rationing rule.\(^9\)

We can solve this problem for a reasonable number of schools and individual types. The algorithm consists of two loops. For a given set of schools that remain open, i.e. a given set \( J^o \), the inner loop determines a feasible school configuration. This part of the algorithm involves the following steps:

\(^9\)Alternatively, we could use a proportional rationing rule discussed in Epple, Geyer, and Sieg (2012).
1. Consider a possible combination of schools that remain open, $J^o$.

2. At the beginning of iteration $n$, we have a vector of school characteristics denoted by $\bar{z}_j^n$ and shadow prices $p_j$.

3. Given the school characteristics $\bar{z}_j^n$ we can compute the conditional choice probabilities using equation (3).

4. Update the school characteristics: $\bar{z}_j^{n+1}$ for each school $j \in J^o$.

5. Update conditional choice probabilities based on new set of school characteristics.

6. Iterate until convergence of school characteristics and conditional choice probabilities.

7. Check the school specific capacity constraints. If constraints are violated, update the shadow prices for oversubscribed schools and go back to step 1.

8. Evaluate the objective function $W$.

The inner loop of the algorithm is similar to the computation of equilibrium in a neighborhood sorting model with agglomeration or spillover effects as discussed in detail by Bayer and Timmins (2005), who provide a detailed discussion of existence and uniqueness of equilibrium. While existence of a pure sorting equilibrium follows from a straightforward fixed point argument, there is some scope for multiplicity of equilibria. However, we find in our computational analysis that equilibria are typically locally unique.\footnote{We conjecture that the strategy employed in Calabrese, Epple, Romer, and Sieg (2006) can be adopted to this class of sorting models to show the resulting equilibrium is unique conditional on the size distribution of schools, i.e. two different equilibria result in different market shares} The main difference between
our approach to calculating feasible allocation and the Bayer-Timmins sorting model is that we need to account for excess demand and sorting due to capacity constraints.

The outer loop of the algorithm then searches over all possible combinations of school closings and finds the one that minimizes the objective function.

3 Estimation

3.1 A Parametrization

To estimate the model, we need to introduce a parametrization of the demand model. Utility of individual $i$ in school $j$ in year $t$ is given by:

$$U_{ijt} = \sum_{k=1}^{K} x_{jkt} \beta_{ikt} + \xi_{jt} + \epsilon_{ijt}$$ (10)

where the $k$th characteristic of school $j$ is denoted by $x_{jkt}$ and

$$\beta_{ikt} = \alpha_{0k} + \sum_{m=1}^{M} \alpha_{kl} z_{imt} + \sigma_{k} u_{ik}$$ (11)

and the $z_{imt}$ is the $m$th component of individual $i$’s characteristics at time $t$. The random coefficient errors are time invariant and satisfy: $u_{ik} \sim N(0,1)$.\footnote{Alternatively, one could generate realistic substitution patterns in demand using a nested Logit model as shown by McFadden (1981) and Goldberg (1995).}

Define the fixed effect of school $j$ in year $t$ as:

$$\delta_{jt} = \sum_{k=1}^{K} \alpha_{0k} x_{jkt} + \xi_{jt}$$ (12)

for schools as well as different peer qualities. Conditioning on observed peer qualities and market shares then effectively conditions on the equilibrium under which the data were generated.

11
We assume this error terms are independent across time. We can then write the school specific utility of individual $i$ in year $t$ as:

$$ u_{ijt} = \delta_{jt} + \sum_{k=1}^{K} \sum_{m=1}^{M} \alpha_{1km} x_{jkt} z_{imt} + \sum_{k=1}^{K} \sigma_k x_{jkt} u_{ik} + \epsilon_{ijt} \quad (13) $$

For expositional simplicity, we have ignored travel times as a determinant of school specific utility above. We have also omitted the moving costs which are given by $mc_{it} = \gamma_{it} 1\{d_{jt} \neq d_{kt-1}\}$ where $\gamma_{it} = \gamma_0 + \sum_{m=1}^{M} \gamma_{1l} z_{imt} + \sigma_{k+1} u_{ik+1}$. We add these terms to the model specification when we estimate the model.

### 3.2 Conditional Choice Probabilities

We assume that the idiosyncratic shocks in the utility function follow a Type I extreme value distribution (McFadden, 1974). Conditional on the observed characteristics $(x_t, z_{it}, d_{it-1})$ and the unobserved shock $u_i$, the choice probabilities are then given by:

$$ Q_{ijt} = \Pr\{d_{ijt} = 1|x_t, z_{it}, u_i, d_{it-1}\} \quad (14) $$

$$ = \frac{e^{\exp(\delta_{jt} + \sum_{k=1}^{K} \sum_{l=1}^{L} \alpha_{1kl} x_{jkt} z_{ilt} + \sum_{k=1}^{K} \sigma_k x_{jkt} u_{ik})}}{\sum_{m} e^{\exp(\delta_{mt} + \sum_{k=1}^{K} \sum_{l=1}^{L} \alpha_{1kl} x_{mkt} z_{ilt} + \sum_{k=1}^{K} \sigma_k x_{mkt} u_{ik})}} $$

In our application, we model choices for four consecutive time periods ($T=4$):

$$ \Pr\{d_{ij1}, d_{ik2}, d_{il3}, d_{im4}|x_t, z_{it}, u_i, d_{in0}\} = Q_{ij1} Q_{ik2} Q_{il3} Q_{im4} \quad (15) $$

Given that we do not observe $u_i$, we need to integrate out the errors to obtain conditional choice probabilities that only depend on observables.

$$ \Pr\{d_{ij1}, d_{ik2}, d_{il3}, d_{im4}|x_t, z_{it}, d_{in0}\} = \int Q_{ij1} Q_{ik2} Q_{il3} Q_{im4} dF(u_i) \quad (16) $$

Recall that the random coefficients are time invariant and independently normally distributed. We can, therefore, approximate these distributions using quadrature methods (Skrainka and Judd 2011).
3.3 A Two Step Estimator

Estimation of the model proceeds in two stages. First, we estimate the discrete choice model with school-year level fixed effects. Second, we decompose these fixed effects into observed and unobserved components using an IV strategy. Note that the conditional choice probabilities in equation (7) depend on the parameters $\alpha_1$, $\sigma$, and the mean utilities $\delta = (\delta_{11}, \ldots, \delta_{JT})$. We can, therefore, estimate these parameters using a ML estimator. The likelihood function is given by

$$L = \Pi_{i=1}^N \int Q_{ij1} Q_{ik2} Q_{id3} Q_{im4} dF(u_i)$$

(17)

The first stage of our estimation algorithm yields an estimator of the school specific fixed effects. Before we proceed, we offer three observations. First, our likelihood function conditions on the observed average peer characteristics for each school. As we discussed in the modeling section, these peer characteristics are the result of student sorting based on unobservables, and are, therefore, potentially endogenous. Furthermore, there is scope for multiplicity of equilibria in these types of sorting games. By conditioning on the observed peer characteristics in schools, we are explicitly conditioning on the equilibrium under which the data were generated. Recall that we consider an economy with a continuum of individuals, each one of whom has a negligible impact on the peer characteristics of a school and the sorting equilibrium. The estimator only exploits that each individual behaves optimally given the observed collective choices made by other individuals, i.e. given the peer characteristics of each school. As a consequence, we can consistently estimate the parameters of the model.\footnote{Bayer and Timmins (2005) provide a comprehensive Monte Carlo study which shows that these types of estimators are well behaved in large samples.} Second, since we are conditioning on observed equilibrium outcomes, we can implement the estimator without having
to compute the equilibrium of the model. Finally, we can identify and estimate a subset of the parameters by appealing to large $N$ (number of students), finite $J$ (number of schools) asymptotics.

In the second stage, we regress the fixed effects on the observed characteristics.

$$\delta_{jt} = \alpha_0 x_{jt} + \xi_{jt}$$

Following Berry (1994), we assume that $E[\xi_{jt} | w_{jt}] = 0$ for some instruments $w_{jt}.^{13}$

As discussed in the detail above, most of the school characteristics that we observe are endogenous. We, therefore, need to use instrument variables for the endogenous school characteristics. The basic idea is to use school assignments made by the district to predict the composition of each school before and after the school closing. As discussed in detail in Hoxby and Weingarth (2006), who first suggested to use these instrument for peer effects in the estimation of a linear-in-means achievement function, the validity of the instruments relies on the assumption that administrative assignment rules are not based on unobserved school characteristics such as teacher or principal quality. However, they are clearly based on geography and thus correlated with peer effects that result in equilibrium.

Alternatively, we exploit the panel nature of the data set and use lagged school characteristics as instruments. These instruments are in the spirit of recent work in the estimation of dynamic panel data models which uses timing assumptions and lagged endogenous variables to generate instrumental variables (Arellano and Bond, 1991). Essentially, we are exploiting the assumption that the $\xi_{jt}$ are assumed to be independent across time. Thus the lagged endogenous characteristics

---

$^{13}$Berry, Linton, and Pakes (2004b) discuss the asymptotic properties of the second stage estimator. The basic requirement is that $N$ grows fast enough so that the ratio between $J \ln(J)/N$ goes to zero. In our application that ratio is approximately 0.069.
are predetermined. We can relax the independence assumption, but then have to use higher order lagged endogenous variables.

4 Data

4.1 Institutional Background

Similar to many school districts, CCSD has been facing declining enrollment, fiscal strain, low student achievement, and troubling achievement gaps by income and race. At the same time, state and federal accountability systems are demanding higher levels of student proficiency. The county in which CCSD is located contains more than 40 suburban school districts and is home to approximately sixty percent of the population of the metropolitan area. The county thus serves as a natural point of reference for summarizing the fortunes of CCSD relative to suburban school districts.

Figure 1 plots the student enrollment “market share” of the urban district considered in this paper relative to the broader educational market (measured by all districts in the county.) The district was maintaining its student share during the 1990’s when enrollment was rising in the market, but its enrollment and market share both dropped rapidly when metropolitan enrollment began to decline. Countywide births started to decline in the early 1990’s. Much of this decline in births was a result of the end of the ”Echo Boom.” Largely as a result of the decline in births beginning in the early 1990’s, countywide enrollment began to decline in 1998. The district not only shared in the countywide decline in the student population, but experienced a disproportionate decline as its share of county enrollment also fell. To explore this phenomenon, we ranked school
districts in the county by income and aggregated them into quartiles of roughly equal enrollment. We found that more affluent districts more than held their ground during the overall decline in enrollments. This finding is consistent with the notion that more affluent households exited the city and moved up the school district income hierarchy (“voting with their feet”). As a consequence, the district bore 75 percent of the countywide decline in public school enrollment. In 2005, CCSD launched a series of initiatives aimed at addressing these challenges. This led to closure at the end of the 2005-06 school year of 22 schools serving students in Kindergarten through eighth grade.14

4.2 The Sample

The empirical analysis of this paper focuses on the impact of school closing on parental choices in CCSD. Our sample consists of all K-8 students that are part of the CCSD database between 2004 and 2007 and attended public schools for at least one year. We thus exclude all private school students that never attended a public school. This is done for two reasons. First, our analysis of transitions between private and public schools shows that few students that attend private schools return to public schools. Second, we do not observe test scores for students outside public schools and, thus, must impute achievement for these students. We also eliminate high school students from our sample since high schools were not

---

14In addition, the district initiated a shift away from middle schools toward K-8 and 6-12 schools, and the reconstitution of other low-performing schools as “Accelerated Learning Academies” with extended school hours and a comprehensive reform model. CCSD also created a small number of new magnet schools with focused curricula, adopted new test instruments for admission to the district’s gifted programs and imposed greater uniformity in testing across applicants to the gifted programs. We do not study these changes in this paper.
affected by the school closing plan adopted in 2005.

Table 1: Summary Statistics of the PPS Sample K-8

<table>
<thead>
<tr>
<th></th>
<th>2004</th>
<th>2005</th>
<th>2006</th>
<th>2007</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample Size</td>
<td>24660</td>
<td>24876</td>
<td>24489</td>
<td>23735</td>
</tr>
<tr>
<td>Sample Size: Public + Private</td>
<td>22158</td>
<td>21189</td>
<td>20333</td>
<td>19045</td>
</tr>
<tr>
<td>Sample Size: Public</td>
<td>21239</td>
<td>20180</td>
<td>19189</td>
<td>17956</td>
</tr>
<tr>
<td>Free or Reduced Lunch</td>
<td>17438</td>
<td>17840</td>
<td>17446</td>
<td>16866</td>
</tr>
<tr>
<td>Race: Black</td>
<td>14256</td>
<td>14219</td>
<td>13866</td>
<td>13312</td>
</tr>
<tr>
<td>Race: White</td>
<td>8498</td>
<td>8545</td>
<td>8405</td>
<td>8164</td>
</tr>
<tr>
<td>Race: Other</td>
<td>1906</td>
<td>2112</td>
<td>2218</td>
<td>2259</td>
</tr>
<tr>
<td>Moving choices indicator</td>
<td>10938</td>
<td>9920</td>
<td>12255</td>
<td>8796</td>
</tr>
<tr>
<td>Driving times to school attended</td>
<td>3.086</td>
<td>3.130</td>
<td>3.273</td>
<td>3.362</td>
</tr>
<tr>
<td>Individual achievement measure</td>
<td>-0.042</td>
<td>-0.033</td>
<td>-0.031</td>
<td>-0.045</td>
</tr>
</tbody>
</table>

Table 1 provides summary statistics of student characteristics for our sample. The variables used in this study are defined as follows. For the moving indicator, we count as “moved” any student who attended a different school than in the previous year. This categorization includes students moving into the district, and students changing from elementary to middle school or middle school to high school. We do this, as students moving from elementary to middle school face similar sorts of moving costs as those switching schools in another grade, such as acclimation to new facilities, teachers, and peers. The driving times variable denotes the median driving time from home to school in minutes. Individual ability is measured as an average of all observed standardized test Z-scores.
4.3 School Capacity in the District

In order to measure capacity, we use the combination of two sources. First, the district gave us a time-invariant measure of capacity, which we call “stated capacity”. However, this stated capacity is sometimes lower than even actual enrollment in some years. For this reason, we find the maximum actual enrollment for each school over the years 2002-2007. Denote this magnitude as the “observed capacity.” Then, to create the capacity measure utilized in the optimal closing analysis, we simply take the maximum of stated capacity and the observed capacity.\(^{15}\) Using these capacity measures we find that the district had a capacity of 34,053 in 2005 before the school closing in all K-8 schools. The capacity was reduced to 24,588 after the school closing were implemented. For grades K-5 (6-8) the capacity was reduced from 13,192 (20,861) to 9,037 (15,550). Figure 2 plots the empirical distribution of capacity utilization – the fraction of enrollment over capacity – for the schools in the district. We find that only a few schools operated near capacity before the reforms. Even after the reforms, there was still a lot of excess-capacity left in the system.

\(^{15}\)It will sometimes be necessary to calculate the capacity available for middle school students (grades 6-8). For schools serving kindergarten through eighth grade (K-8 schools), the 6-8 capacity measure is calculated as the overall capacity multiplied by the proportion of students in grades 6-8 in that year.
5 Empirical Results

We estimate our demand models with and without fixed fixed effects. We also implement the fixed effect Logit model with random coefficients. For computational reasons, we only implement the random coefficient model for a 10 percent random subsample of the original sample. For comparison purposes we also estimate the fixed effect Logit model without random coefficients using the 10 percent sample. We start with a model specification that includes all possible interactions between school and individual characteristics. We then eliminate those interactions that are not significantly different from zero. Table 2 summarizes the point estimates and estimated standard errors for different specifications of our demand model.

Overall, we find that the fixed effects model fits the data much better than the model without fixed effects. The point estimates are similar using the full and the 10 percent sample. Adding random coefficients to our specification improves the fit of the model.

We then implement the second stage using three different techniques. The first estimator is just a simple OLS estimator. The second estimator uses lagged school characteristics as instruments. Our third estimator uses the Hoxby and Weingarth (2006) instruments. Table 4 reports the point estimates and estimated standard errors for the second stage estimator.

Given the large amount of heterogeneity in the sample and the multitude of interaction effects that are significantly different from zero, it is useful to plot the distributions of the key coefficients. Figure 3 shows that the vast majority of students in the sample value schools with higher ability kids. High achieving students have a higher valuation of mean achievement than low achieving students.
Table 2: First Stage Estimates

<table>
<thead>
<tr>
<th></th>
<th>No Fixed Effects</th>
<th>Fixed Effects</th>
<th>Fixed Effects</th>
<th>Fixed Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No Random Coef</td>
<td>No Random Coef</td>
<td>No Random Coef</td>
<td>Random Coef</td>
</tr>
<tr>
<td></td>
<td>Full Sample</td>
<td>Full Sample</td>
<td>10 % Sample</td>
<td>10 % Sample</td>
</tr>
<tr>
<td>School Ability × ability</td>
<td>1.3433, 0.0374</td>
<td>1.3715, 0.039</td>
<td>1.4848, 0.1240</td>
<td>1.8723, 0.1609</td>
</tr>
<tr>
<td>School Ability × black</td>
<td>-0.1861, 0.0647</td>
<td>-0.2908, 0.073</td>
<td>-0.1671, 0.2475</td>
<td>-0.6472, 0.2781</td>
</tr>
<tr>
<td>School Ability × FRL</td>
<td>0.5255, 0.0651</td>
<td>0.6083, 0.072</td>
<td>0.5990, 0.2445</td>
<td>0.3268, 0.2768</td>
</tr>
<tr>
<td>School Black × ability</td>
<td>0.7657, 0.0368</td>
<td>0.6855, 0.0428</td>
<td>0.7710, 0.1423</td>
<td>0.8278, 0.1598</td>
</tr>
<tr>
<td>School Black × black</td>
<td>0.7657, 0.0368</td>
<td>3.0924, 0.0850</td>
<td>3.1558, 0.2876</td>
<td>3.6778, 0.3044</td>
</tr>
<tr>
<td>School Black × FRL</td>
<td>-0.6481, 0.0660</td>
<td>-0.6243, 0.0825</td>
<td>-0.8110, 0.2794</td>
<td>-0.7934, 0.2906</td>
</tr>
<tr>
<td>School FRL × ability</td>
<td>0.4941, 0.0391</td>
<td>0.3075, 0.0486</td>
<td>0.4559, 0.1639</td>
<td>0.4105, 0.1838</td>
</tr>
<tr>
<td>School FRL × black</td>
<td>-1.8534, 0.0716</td>
<td>-0.8734, 0.0839</td>
<td>-1.3920, 0.2844</td>
<td>-1.0795, 0.3212</td>
</tr>
<tr>
<td>School FRL × FRL</td>
<td>2.4717, 0.0777</td>
<td>3.9485, 0.0860</td>
<td>4.2640, 0.2875</td>
<td>5.031, 0.3502</td>
</tr>
<tr>
<td>School FRL × suspensions</td>
<td>0.1143, 0.0064</td>
<td>0.1359, 0.0095</td>
<td>0.1409, 0.0282</td>
<td>0.1659, 0.0373</td>
</tr>
<tr>
<td>School suspensions × ability</td>
<td>0.0150, 0.0065</td>
<td>0.0293, 0.0101</td>
<td>0.0423, 0.0298</td>
<td>0.0244, 0.0406</td>
</tr>
<tr>
<td>School suspensions × black</td>
<td>-0.1282, 0.0136</td>
<td>-0.0615, 0.0203</td>
<td>-0.0620, 0.0622</td>
<td>-0.1145, 0.0788</td>
</tr>
<tr>
<td>School suspensions × FRL</td>
<td>0.0809, 0.0144</td>
<td>0.0613, 0.0204</td>
<td>0.0830, 0.0615</td>
<td>0.1179, 0.0824</td>
</tr>
<tr>
<td>School suspensions × suspensions</td>
<td>0.0154, 0.0010</td>
<td>0.0320, 0.0012</td>
<td>0.0334, 0.0035</td>
<td>0.0452, 0.0053</td>
</tr>
</tbody>
</table>
Table 3: First Stage Estimates (cont)

<table>
<thead>
<tr>
<th>No Fixed Effects</th>
<th>Fixed Effects</th>
<th>Fixed Effects</th>
<th>Fixed Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Random Coef</td>
<td>No Random Coef</td>
<td>No Random Coef</td>
<td>Random Coef</td>
</tr>
<tr>
<td>Full Sample</td>
<td>Full Sample</td>
<td>10 % Sample</td>
<td>10 % Sample</td>
</tr>
<tr>
<td></td>
<td>Estimate</td>
<td>Std. Error</td>
<td>Estimate</td>
</tr>
<tr>
<td>Moving costs</td>
<td>-4.4206</td>
<td>0.0296</td>
<td>-4.3259</td>
</tr>
<tr>
<td>Moving costs × ability</td>
<td>-0.2953</td>
<td>0.0186</td>
<td>-0.2766</td>
</tr>
<tr>
<td>Moving costs × black</td>
<td>-0.0736</td>
<td>0.0327</td>
<td>-0.1650</td>
</tr>
<tr>
<td>Moving costs × FRL</td>
<td>0.1992</td>
<td>0.0333</td>
<td>0.1882</td>
</tr>
<tr>
<td>Moving costs × suspensions</td>
<td>0.0421</td>
<td>0.0039</td>
<td>0.0500</td>
</tr>
<tr>
<td>Travel costs</td>
<td>-0.3716</td>
<td>0.0041</td>
<td>-0.4223</td>
</tr>
<tr>
<td>Travel costs × ability</td>
<td>-0.0017</td>
<td>0.0029</td>
<td>0.0003</td>
</tr>
<tr>
<td>Travel costs × black</td>
<td>0.1118</td>
<td>0.0046</td>
<td>0.1092</td>
</tr>
<tr>
<td>Travel costs × FRL</td>
<td>-0.1226</td>
<td>0.0047</td>
<td>-0.1217</td>
</tr>
<tr>
<td>School Ability × Standard Normal</td>
<td>2.411</td>
<td>0.1762</td>
<td>2.4307</td>
</tr>
<tr>
<td>School FRL × Standard Normal</td>
<td>160,902</td>
<td></td>
<td>136,777</td>
</tr>
<tr>
<td>School Black × Standard Normal</td>
<td>0.4159</td>
<td></td>
<td>0.4159</td>
</tr>
<tr>
<td>School Susp × Standard Normal</td>
<td>0.4159</td>
<td></td>
<td>0.4159</td>
</tr>
</tbody>
</table>
Table 4: Second Stage Estimates

<table>
<thead>
<tr>
<th></th>
<th>No Random Coefficients</th>
<th></th>
<th>Random Coefficients</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Lagged</td>
<td>Hoxby &amp; Weingarth</td>
<td>Lagged</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
</tr>
<tr>
<td>OLS</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.457)</td>
<td>(.507)</td>
<td>(.459)</td>
<td>(.700)</td>
</tr>
<tr>
<td>School Black</td>
<td>-1.713</td>
<td>-1.707</td>
<td>-1.446</td>
<td>-2.283</td>
</tr>
<tr>
<td></td>
<td>(.163)</td>
<td>(.168)</td>
<td>(.216)</td>
<td>(.229)</td>
</tr>
<tr>
<td>School Ability</td>
<td>-.441</td>
<td>.061</td>
<td>.150</td>
<td>.631</td>
</tr>
<tr>
<td></td>
<td>(.279)</td>
<td>(.292)</td>
<td>(.347)</td>
<td>(.454)</td>
</tr>
<tr>
<td>School Suspensions</td>
<td>-.171</td>
<td>-.145</td>
<td>.015</td>
<td>-.215</td>
</tr>
<tr>
<td></td>
<td>(.031)</td>
<td>(.032)</td>
<td>(.056)</td>
<td>(.057)</td>
</tr>
</tbody>
</table>

All estimators control for elementary school and middle school fixed effects.

Figures 4 and 5 show that the valuation of the peer effects measured by mean school black and FRL differs significantly by individual characteristics. Both distributions are bimodal. Students on FRL tend to prefer school with high FRL means and vice versa. Similar results hold for race. Our findings, therefore, support the similarity hypothesis which states that individuals prefer environments that allow them to interact with individuals that are similar in observed characteristics.

Figure 6 shows that the impact of mean suspensions is ambiguous. High suspensions in a school may be an indictor of a school with troubled students, which
is an undesirable school characteristic. On the other hand, it may indicate that a no-excuses approach to disruptive behavior is enforced by the administration, which could be positively valued by some parents.

Finally, we find that parents are reluctant to change schools once they have made their initial choices. This is reflected in our estimates of the moving costs, which are identified by the lagged observed choices made by students. Similarly students also face significant travel costs. School choices that force students to commute long distances are not popular.

Next we quantify the impact of the right-sizing plan. We would like to determine whether closed schools were perceived by parents to be less desirable than schools that remained open. We can perform an unconditional test based on the difference of the fixed effects among the two type of schools. Implementing this test we find that the mean fixed effect of closed schools is significantly lower than the mean fixed effect of schools that remained open.

Of course, these differences may reflect differences in peer characteristics across schools. We, therefore, perform a second test that conditions on observed peer quality measures and allows for potential time trends. To implement this approach we adopt a difference-in-difference strategy in the second stage of the estimation procedure. We implement this test by adding the following variables to our second stage: a) a post reform time dummy; b) an indicator for a school that was closed.

Overall, we do not find much evidence that the downsizing of the district affected parents’ perceptions of the distribution of school qualities. Closed schools were not viewed as systematically worse than schools that remained open once we condition on observed school characteristics, i.e. we do not find any significant differences in unobserved school characteristics that influenced parental choices.
This finding confirms our initial results that parental perceptions of differences in school quality are largely driven by sorting of students among schools and the resulting differences in peer effects.

6 Optimal School Closing

We consider the problem of optimally closing schools. We focus on middle schools and consider students in grades 6-8. We consider two scenarios in which the district plans to close three out of 31 of the existing schools. In one scenario, capacity must be reduced by at least 10 percent. The computations are based on our estimated demand model without random coefficients. We solve for the pre-closing and post-closing equilibrium allocations, imposing the consistency restriction on the conditional choice probabilities and school peer effects. The counterfactual (post closing) scenarios refer to solutions of the optimal closing problem using three different objective functions: a) minimizing differences in peer characteristics across schools, b) minimizing number of students leaving the district, i.e maximizing retention; c) minimizing the number of students who relocate as a result of the school closings, i.e. minimizing dislocation. As a shorthand, we refer to these objectives as Similarity, Retention, and Dislocation objectives. We solve the model with and without imposing the capacity constraints at the school level.

\footnote{In principle, it is not difficult to allow for random coefficients. In practice, it significantly increases the computational burden of the analysis.}

\footnote{We find that simulated pre-closing school enrollments fit well except for private school enrollments. Recall that we imputed achievement in private schools. The imputation my understate actual private school achievement. For our counterfactual analysis we adjust private school fixed effects to bring simulated enrollments into close correspondence to actual enrollments.}
Table 5: Optimal School Closing Analysis

<table>
<thead>
<tr>
<th>District</th>
<th>Similarity</th>
<th>Retention</th>
<th>Dislocation</th>
<th>Similarity</th>
<th>Retention</th>
<th>Dislocation</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>Baseline Enrollment in Closed Schools</td>
<td>981</td>
<td>982</td>
<td>904</td>
<td>991</td>
<td>1069</td>
<td>904</td>
</tr>
<tr>
<td>b</td>
<td>Mean FRL</td>
<td>0.64</td>
<td>0.78</td>
<td>0.64</td>
<td>0.64</td>
<td>0.77</td>
<td>0.67</td>
</tr>
<tr>
<td>c</td>
<td>Mean Black</td>
<td>0.65</td>
<td>0.60</td>
<td>0.45</td>
<td>0.65</td>
<td>0.62</td>
<td>0.55</td>
</tr>
<tr>
<td>d</td>
<td>Mean Achievement</td>
<td>0.12</td>
<td>-0.15</td>
<td>0.17</td>
<td>0.11</td>
<td>-0.21</td>
<td>0.15</td>
</tr>
<tr>
<td>e</td>
<td># Students Leaving Public Schools</td>
<td>357</td>
<td>158</td>
<td>270</td>
<td>575</td>
<td>307</td>
<td>587</td>
</tr>
<tr>
<td>f</td>
<td>Mean FRL</td>
<td>0.60</td>
<td>0.67</td>
<td>0.72</td>
<td>0.66</td>
<td>0.68</td>
<td>0.75</td>
</tr>
<tr>
<td>g</td>
<td>Mean Black</td>
<td>0.57</td>
<td>0.08</td>
<td>0.49</td>
<td>0.62</td>
<td>0.37</td>
<td>0.64</td>
</tr>
<tr>
<td>h</td>
<td>Mean Achievement</td>
<td>0.18</td>
<td>0.14</td>
<td>0.01</td>
<td>0.06</td>
<td>0.20</td>
<td>-0.14</td>
</tr>
</tbody>
</table>
While our model assumes a continuum of students, it is useful to translate the results in number of students affected by the policies. To accomplish this task, recall that there were 8,245 students in middle schools in the district in 2005. We, therefore, use this number to translate changes in market shares into “number of students.” Table 8 summarizes the key findings that we obtain from our counterfactual policy analysis. We begin with the case in which the closings must eliminate at least 10% of excess capacity and ignore the school level capacity constraints. For ease of reference, we will refer to elements of Table 8 by column number and row letter.

All results are predictions of the model, so we simplify by dropping ”predicted” as a modifier in the following summary. The results in (1a) show, for the Similarity objective, that the enrollment in schools selected for closure is 981 students. Schools chosen for closure under this objective have peer characteristics (1b to 1d) that differ substantially from the district averages (7b to 7d).

Relative to the district averages, the schools chosen for closure have higher achievement, fewer low-income students, and fewer black students. We also see from (1e) that these closings induce net departure from district schools of 357 students. Relative to the district schools and the schools that are closed, these ”leavers” have high achievement, and are disproportionately non-poor students (1f to 1h). These results illustrate the challenge that the district faces in attempting to achieve a peer-equalization objective when closing schools. Pursuit of this objective induces flight of high SES students from the district.

Column (2) reports results with the Retention objective. This objective results in closing of schools attended by a similar number of students (982) than the Similarity objective. Relative to the district averages (7b to 7d), these schools have low achievement (2d) and are attended disproportionately by low-income...
(2b) black (2c) students. Interestingly, these closures result in departure of only 158 students. Hence, the district schools available to most students impacted by these closures were as attractive as their outside options. More generally, the contrast of outcomes under the Similarity and Retention objectives illustrates that decisions about school closures can have a large impact on incentives of different groups of students to leave the district.

Minimizing dislocation (column 3) leads to closure of schools attended by 904 students. Characteristics of students in those schools (3b to 3d) are very similar to the district averages in column (7). Relative to district averages, leavers (3f to 3h) are similar in achievement and in FRL status but disproportionately white. While this objective minimizes the number of students who relocate as a result of the closures, the relocations result in considerably more departures (270 students) than for the retention objective (158 students).

Columns (4) through (6) report the results for the exercise when we also impose the school level capacity constraints. Comparing these results to the ones reported in column (1) through (3), we find that the results are qualitatively similar. However, there are some important quantitative differences. First note, that imposing the school level capacity constraints implies that the number of students that are affected by the school closings increases in all scenarios. Moreover, the fraction of students leaving the district increases by 55 to 117 percent. This is not surprising. The more popular schools are operating much closer to the capacity constraints than the less popular schools. Imposing the school level constraints then implies that some of the most popular schools will be oversubscribed and hit the capacity constraints. Not having access to their preferred school, a greater number of students decided to leave the district. As a consequence, retaining students is even more problematic one we take school level capacity constraints
into consideration.

Summarizing the discussion, we find that the choice of the objective function is important. The objective of creating more similar peer characteristics across schools is potentially very costly for the district. The "superintendent’s dilemma" is that focus on this objective results in departure of a large number of disproportionately high SES students. Minimizing dislocation also proves to be relatively costly from the perspective of loss of students. For a district struggling with declining enrollments, focusing on student retention is likely to be the most appealing objective. Our computational results show that such a focus can, in fact, result in substantially lower student departures than under the other objectives. More generally, our results show the feasibility and value of bringing a model of school choice to bear in informing school closing decisions.

7 Conclusions

The downsizing challenges confronted by CCSD in 2005 and 2006 are now being confronted by many districts across the country. For example, the Philadelphia school district recently announced the intention to close 37 schools. We have shown how to formulate the planer’s problem of optimally downsizing a school district as an integer programming problem with non-linear constraints. For reasonable problems, an exact solution can be determined by simply evaluating all possible combinations of school closings. The problem increases exponentially in complexity with the number of schools to be closed, making enumeration of all alternatives an infeasible approach for large problems. Future applications of our framework may be able to draw on recent computational advances in operations research. Current operations research methods permit computing an approximate
solution that is reasonably close to the optimum (Belotti, Lee, Liberti, Margot, and Waechter, 2009). Moreover, these approaches permit a determination of the extent by which the approximate solution falls short of the full optimum, and research is presently focussed on enhancing the speed and accuracy of these approximation methods.

Another interesting extension is to include teacher reassignments into the optimal school closing analysis. Downsizing not only implies that students have less options in the public school system. It also implies that teachers that were employed in closed schools need to be reassigned to new schools. As a consequence, school quality in the remaining schools will change for two reasons, a change of student peer effects and a change in teacher quality. We do not have access to reliable measures of teacher quality in our analysis. Differences in teacher and principal quality are captured in our estimation by school specific fixed effects which are allowed to change over time. Solving the optimal school closing allowing for endogenous teacher reassignment is exceedingly difficult. The optimal school closing analysis problem can, however, be solved with an exogenous policy rule for reassigning teachers. Such an exogenous rule might capture the seniority-driven nature of teacher reassignments. It is then not difficult to extend our framework to incorporate teacher reassignments. These are important avenues for ongoing research to provide districts with more sophisticated tools for addressing problems of declining enrollments that can be expected to stretch well into the future for many urban school districts. Such tools also have the potential to be extended to help districts with growing enrollments select among potential locations for opening new public schools.
References


Figure 1: Market Share of the Urban District
Figure 2: Capacity the Urban District

Enrollment/Capacity By School: 2004

Enrollment/Capacity By School: 2005

Enrollment/Capacity By School: 2006

Enrollment/Capacity By School: 2007
Figure 3: The Distribution of the School Ability Coefficient

![Ability Coef Dist Middle 90, All Years](image)

- Frequency
- Ability Coefficient
- 0
- 2000
- 4000
- 6000
- 8000
- 10000
- -2
- -1
- 0
- 1
- 2
- 3
Figure 4: Distribution of School Black Coefficient

Black Coef Dist Middle 90, All Years

Black Coefficient
Frequency
0 2000 4000 6000
Figure 5: Distribution of School FRL Coefficient
Figure 6: The Distribution of the School Suspensions Coefficient

`susp_days Coef Dist Middle 90, All Years`