Charter School Entry and School Choice: The Case of Washington, D.C.

Maria Marta Ferreyra Grigory Kosenok
Carnegie Mellon University New Economic School

March 8, 2013
Preliminary and Incomplete
Please do not cite without permission

Abstract

We develop and estimate a structural equilibrium model of charter school entry and competition. In the model, households choose among charter, public and private schools. Faced with uncertainty about demand shocks and competitors’ actions, charter schools choose whether to enter, exit or relocate based on their expected equilibrium demand. We estimate the model using school-level panel data for Washington, D.C. We use our parameter estimates to investigate the potential effects of changes in the institutional and demographic environment on charter entry, student sorting across schools, and the distribution of student achievement.
1 Introduction

The dismal academic performance of public schools in urban school districts has been a growing concern in recent decades. Charter schools provide families with additional school choices and are seen by many as a possible solution. Unlike traditional public schools, charter schools are run independently of school districts by private individuals and associations, and are formed from a successful combination of private initiative and the institutional regulations of the policymaker.

Charter schools receive public funding in the form of a per-student stipend. They do not have residence requirements and if oversubscribed they determine admission by lottery. Charters are free from many regulations that apply to public schools, but are subject to the same accountability requirements as traditional public schools and are regulated by state laws. Minnesota passed the first law in 1991, which has been followed by laws in 40 states and the District of Columbia, all of which differ widely in their permissiveness towards charters. The nation’s 5,400 charters currently serve 1.7 million students, or about 3 percent of the primary and secondary market.\footnote{See http://www.edreform.com/Fast_Facts/K12_Facts/}

While seemingly small, this market share conceals large variation across states and districts.

A prospective charter entrant must formulate and present a proposal to the chartering entity. The proposal, akin to a business proposal, must specify the school’s mission, curricular focus (such as arts or language), grades served, teaching methods, anticipated enrollment, intended physical facilities, and a financial plan. In other words, the decision to open a charter school is similar to that of opening a firm. Like firms, entering charters seek to exploit a perceived opportunity. For example, in a residence-based system, a low-income neighborhood with low-achieving public schools may create an opportunity for a charter entrant to serve households not satisfied with their local public schools. Other example opportunities are middle-class families reasonably well served by the local public schools but who are interested in a different type of academic program, or by families who send their children to private schools but are willing to experiment with a charter school so as to not pay tuition.

In this paper we investigate charter school entry and household choice of school, and study the case of Washington, D.C. We document the pattern of charter school entry in the city by geographic area, thematic focus and grade level in order to gain insights about the opportunities exploited by charters. Building on these insights we explore how households sort among public, private and charter schools. We also study the effects that the entry, exit or relocation of a school has on others. Finally, we explore how the educational landscape would change in response to changes in the regulatory framework for charter, public and private schools. This question seems particularly relevant given the current focus of federal education policy on charter expansion.\footnote{The federal ”Race to the Top” program favors states with permissive charter legislation. See http://www2.ed.gov/news/pressreleases/2009/06/06082009a.html for further details.}

Addressing these research questions poses several challenges. Consider, for instance, the case of a new charter entrant. Some families will switch from their current school into the charter, in a process that will shape the peer characteristics of the new school as well as affect the peer characteristics of the schools previously attended by those children. Since parents care about their children’s peers, this will further affect their choices. In other words, charter school entry triggers equilibrium effects because it leads to a re-sorting of students across schools. Even though the charter entrant can specify a number of aspects about the new school, such as its thematic focus and educational philosophy, an important characteristic – the composition of the student body – is beyond its control. In this sense charter schools are at a disadvantage with respect to public schools, which typically have residence requirements and can restrict admission in that way, and with respect to private schools that can apply their own admission criteria. The second complicating
factor in our research questions is the uncertainty faced by schools when making their decisions, both about their own demand and the actions of other schools. This uncertainty is more severe for new entrants, who may not know their ability to conduct the new enterprise.

Thus, we develop and estimate an equilibrium model of household school choice, charter school entry and school competition in a large urban school district. In the model, we view a charter entry point as a combination of location (neighborhood), thematic focus and grade level. Since charter funding is connected with enrollment, prospective entrants must be able to forecast the demand for their services in order to assess their financial viability. Hence, we model how prospective entrants predict enrollment and peer characteristics of their student body as a function of their geographic location, grades served and thematic focus. The prospective entrant enters or not depending on the expected success of its entry and subsequent viability. We model the entrant as being uncertain about its own quality at the entry stage.

We estimate the model using a unique and detailed data set from Washington D.C. from 2003 to 2007. The main data set consists of information for all public, private and charter schools in Washington, D.C. including enrollment by grade, school demographics, focus and proficiency rates in standardized tests. We supplement this data set with neighborhood-level information on the fraction of children who attend charter schools, and average distance traveled to public and charter schools. Lacking student-level data, we further augment the school-level data with the empirical distribution of child age, race, poverty status and family income at the block group level, and draw from this distribution in order to calculate the model’s predictions. Since market shares for public, private and charter schools vary widely across grades, our market consists of a grade-year combination. We estimate the model in three stages corresponding to demand, supply and proficiency rates.

We model schools as differentiated products and estimate the demand side of the model using an approach similar to Berry et al (1995), henceforth BLP. In particular, we allow for the existence of an unobserved school-grade-year quality component (such as teacher quality) that households observe when making choices but the researcher does not. This creates correlation between the resulting school peer characteristics and the unobserved quality component, similar to the correlation between unobserved quality and price in BLP. Unlike price, which is determined by the firm under consideration, peer characteristics are determined by aggregate household choices and are similar to the local spillovers in Bayer and Timmins (2007). Following Nevo (2000, 2001), we exploit the panel structure of our data and include school, grade and year fixed effects to capture some of the variation in the unobserved quality component.

We have chosen to focus on a single, large urban district in order to study the decisions of prospective entrants that confront the same institutional structure. We study Washington, D.C. for several reasons. The city has a relatively old charter law (passed in 1996) that is highly permissive towards charters. For instance, charter funding in D.C. is more generous than in most other areas, as the per-student charter stipend is equal to the full per-student spending in traditional public schools, and charters receive a facilities allowance. Moreover, the charter sector has grown rapidly in D.C., reaching 40 percent of total public school enrollment in 2011. The fact that D.C. contains a single public school district facilitates research design and data collection. Finally, the city is

---


4 As of 2010, the districts where this share surpassed 30 percent were New Orleans, Louisiana (61 percent); Washington, D.C. (38 percent); Detroit, Michigan (36 percent); and Kansas City, Missouri (32 percent). Source: http://www.charterschoolcenter.org.
relatively large and contains substantial variation in household demographics, thus providing scope for charter entry.

Currently we have estimated the demand and achievement sides of the model. Our estimates reveal large heterogeneity in preferences over school types on the part of households as well in school quality. In addition, they reveal substantial differences is achievement depending on school type and level, and large variation in school value added to achievement. Such heterogeneity in household preferences and in the access to desirable schools on the part of households creates rich opportunities for charter entry.

Throughout we make several contributions. First, we contribute to the study of charter school entry. While most of the literature on charters studies their achievement effects, relatively little research has focused on charter entry. The first study was conducted by Glohm et al (2005) for Michigan in a reduced form fashion. Rincke (2007) estimates a model of charter school diffusion in California. In a recent study, Bifulco and Buerger (2012) have studied charter entry in the state of New York. A theoretical model of charter school entry is developed by Cardon (2003), who studies strategic quality choice of a charter entrant facing an existing public school. We build on the foundation established in these papers by modeling intra-district charter school entry decisions, parental choice, and the impact of entrants on public and private school incumbents. Perhaps closest to our approach is the work of Imberman (2009), who studies entry into a single large urban district in a reduced-form fashion, and Mehta (2012) who studies charter entry in North Carolina in a structural fashion. The most salient differences between our work and Mehta’s are that: a) we endogenize school peer characteristics as equilibrium outcomes determined by household choices; b) while we model charters as being responsive to public schools, we do not model the strategic behavior of public schools given the lack of evidence for such behavior - as explained below; c) in our model, all charter schools in the economy are available to a given household regardless of its location, in accordance with the absence of residence requirements for charter schools.

Second, we contribute to the literature on school choice by studying household choice among all public, private and charter schools in D.C. while modeling school peer characteristics as the outcome of household choices. While others have studied school choice with endogenous peer characteristics (Ferreyra 2007, Altonji et al 2011), they have not relied on the full choice set available to households and have not modeled school unobserved quality.

Third, in addition to market shares we match additional features of the data, namely school peer characteristics, neighborhood fraction of children enrolled in charter schools and neighborhood average travel distance to public and charter schools. This exercise, in the spirit of Petrin (2002), provides a natural set of overidentifying restrictions that increase the efficiency of our estimates.

Fourth, we contribute to the computational literature on the estimation of BLP models. We recast our demand-side estimation as a mathematical programming with equilibrium constraints (MPEC) problem following Dube et al (2011), Su and Judd (2011) and Skrainka (2011). We solve the problem by combining two large-scale contrained optimization solvers, SNOPT and MINOS in order to minimize computational time and attain the highest possible accuracy in the solution. While Dube et al (2011) and Skrainka (2011) rely on analytical gradients and Hessians in order to achieve these goals, we rely on an efficient combination of solvers and do not require analytical first- or second-order derivatives, whose derivation is involved and prone to errors. Thus, our research lies at the frontier of computational methods and estimation.

Finally, we contribute to the entry literature on firm entry in industrial organization. A

---

review of this literature is provided in Draganska et al (2008). Whereas most of this literature assumes a reduced-form function for demand, we specify a structural model of household choice of school and allow for unobserved school quality. In addition, a major focus of the entry literature is the strategic interaction between entrants and/or incumbents. While we model the strategic interaction among charter schools, we do not model public or private school decision making. The reason is that during our sample period public and private schools displayed very little entry or exit, a feature that would prevent the identification of a model of strategic decision making for them. Moreover, between 1998 and 2007 the District of Columbia Public Schools (DCPS) had six superintendents. This high turnover, coupled with financial instability, suggests that DCPS may not have reacted strategically to charters during our sample period. Since charters experienced more entry, exit and relocation than public or private schools we model them as being strategic with respect to each other while taking the actions of public and private schools as given. A final difference with respect to the entry literature is that we rely on panel data, which is quite rare in entry studies. Our panel provides us with variation over time in entry patterns. Perhaps more importantly, by providing us with post-entry outcomes, the panel allows us to learn about the quality of both entrants and incumbents.

We use our parameter estimates to study the effect of changes in the regulatory, institutional and demographic environment on charter entry, household sorting across schools and student achievement. For instance, we explore whether greater availability of building sites for charters would spur the creation of more charter schools, where these would locate, which students they would attract, and how achievement would change among the pre-existing schools. Since the authorizer plays a critical role in this environment, we examine changes in the authorizer’s preferences with regards to focus and school level.

The rest of the paper proceeds as follows. Section 2 describes our data sources and basic patterns in the data. Section 3 presents our theoretical model. Section 4 describes our estimation strategy, and Section 5 describes our estimation results. In Section 6 we provide some discussion and describe our intended counterfactuals. Section 7 concludes.

2 Data

Our dataset covers the 2003-2007 period. It includes annual school-level information on every public, charter and private school in Washington, D.C. for each year, and annual neighborhood-level information on school choice and distance traveled to school for 2003-2006. We have focused on the 2003-2007 time period to maximize the quality and comparability of the data over time and across schools. In addition, 2007 marked the beginning of some important changes in DCPS and hence constitutes a good endpoint for our study. Appendix I provides interested readers with further details on our data.

We begin by describing our school-level data. While public and private schools have one campus each, many charters have multiple campuses. Hence, our unit of observation is a campus-year, where a "campus" is the same as a school in the case of schools that have one campus each. We have 700, 228 and 341 observations for public, charter and private schools respectively. Our

---


7 In 2007, Michelle Rhee began her tenure as chancellor of DCPS. She implemented a number of reforms, such as closing and merging schools, offering special programs and changing grade configurations in some schools, etc. The first such reforms took effect in Fall 2008.

8 A campus is identified by its name and not its geographic location. For instance, a campus that moves but retains its name is still considered the same campus.
The dataset includes regular schools and specifically excludes special education and alternative schools, schools with residential programs and early childhood centers. For each observation we have campus address, enrollment by grade for grades K through 12,\(^9\) percent of students of each ethnicity (black, white and hispanic),\(^10\) and percent of low-income students (who qualify for free or reduced lunch). We also have the school’s thematic focus, which we have classified into core curriculum, language (usually Spanish), arts, vocational and others (math and science, civics and law, etc.).

For public and charter schools we have reading and math proficiency rates, which is the fraction of students who are proficient in each subject based on D.C.’s own standards and assessments. For private schools we have school type (Catholic, other religious and non-sectarian) and tuition.

In Washington, D.C. traditional public schools fall under the supervision of DCPS. Although there is only one school district in the city, there are many attendance zones. As for charters, until 2007 there were two authorizers: the Board of Education (BOE) and the Public Charter School Board (PCSB). Since 2007, the PCSB has been the only authorizing (and supervising) entity. The overarching institution for public and charter schools at the "state" level is the Office of State Superintendent of Education (OSSE).

Data on enrollment and proficiency for public and charter schools comes from OSSE. For public schools, the source of school addresses and student demographics are the Common Core of Data (CCD) from the National Center for Education Statistics (NCES) and OSSE. Curricular focus for public schools comes from Filardo et al (2008). For PCSB-authorized charters, ethnic composition and low-income status come from the School Performance Reports (SPRs). For BOE-authorized charters, the pre-2007 information comes from OSSE, and the 2007 information from the SPRs. CCD provided supplementary data for some charters. For charters, focus comes from the schools’ statements on the web, SPRs and Filardo et al (2008).

The collection of public school data was complicated by poor reporting of public schools to the Common Core of Data during the sample period. Nonetheless, much more challenging was to re-construct the history of location, enrollment and achievement for charter schools, particularly in the case of multi-campus organizations. The reason is that no single data source contains the full history of charters for our sample period. Thus, we drew on OSSE audited enrollments, SPR’s for PCSB-authorized charters, web searches of current websites and past Internet archives, charter school lists from Friends of Choice in Urban Schools (FOCUS) and phone calls to charters that are still open. The resulting data reflect our efforts to draw together campus-level information from these different sources, with the greatest weight given to OSSE audited enrollments and achievement data, and the SPRs.

With the exception of tuition, our private school data come from the Private School Survey (PSS) from NCES. The PSS is a biennial survey of private schools. We used the 2003, 2005 and 2007 waves. We imputed 2004 data by linear interpolation of 2003 and 2005, and similarly for 2006. Tuition comes from Salisbury (2003) and is average tuition per school; only for a few schools that cover both elementary and middle/high school grades do we observe separate tuitions by grade level. We express tuition in dollars of the year 2000. Note that our tuition data does not vary over time.

According to grades covered, we have classified schools into the following grade levels: elementary (if grades covered fall within the K-6 range, since most primary schools covered up to 6th grade in D.C. during our sample period), middle (if grades covered are 7th and/or 8th, high

\(^9\)We do not include adult or ungraded students, who account for less than 0.6% of total enrollment. We do not include students in preschool or prekindergarten because these data are not available for private schools.

\(^10\)Since students of other races (mostly Asian) constitute only 2.26 percent of the total K-12 enrollment, for computational reasons we added them to the white category.
(if grades covered fall within the 9th - 12th grade range), elementary/middle (if grades span both the elementary and middle level), middle/high, and elementary/middle/high. This classification follows DCPS’s criteria and incorporates mixed-level categories (such as middle/high), which are quite common among charters. When convenient, we employ an alternative classification with three categories: elementary (including all categories that encompass elementary grades: elementary, elementary/middle, elementary/middle/high), middle and high (defined similarly). Note that a grade level is a set of grades and not a single grade.

The data appendixes in Filardo et al (2008) are the source of our neighborhood-level data. D.C. planning agencies often use the concept of "neighborhood cluster" to proxy for a neighborhood. A cluster is a collection of Census tracts, and there are 39 clusters in DC (and 188 Census tracts). In what follows we use the word "neighborhood" to refer to a neighborhood cluster. For the children who reside in each neighborhood, we observe the fraction who attend charter schools relative to the total number of children enrolled in the public system, and the average distance traveled to public or charter schools.

2.1 Descriptive Statistics

The population in Washington, D.C. peaked in the 1950s at about 802,000, declined steadily to 572,000 in 2000, and bounced back to 602,000 in 2010. It is estimated that the population grew from 577,000 in 2003 up to 586,000 in 2007, although the school-age population declined from 82,000 to 76,000. The racial breakdown of the city has changed as well over the last two decades, going from 28, 65 and 5 percent white, black and hispanic in 1990 to 32, 55 and 8 percent respectively in 2007. Despite these changes, the city remains geographically segregated by race and income. Whereas in 2006 median household income was $92,000 for whites, it was only $34,500 for blacks (Filardo et al, 2008).

2.1.1 Basic trends in school choice

In 2007, 56 percent of students attended public schools, 22 percent charter schools and 22 percent private schools. In what follows, "total enrollment" refers to the aggregate over public, private and charter schools, and "total public" refers to enrollment in the public system (adding over public and charter schools).

In national assessments, DC public schools have ranked consistently at the bottom of the nation in recent years. For instance, in the 2011 National Assessment of Educational Progress, D.C.’s proportion of students in the below-basic proficiency category was higher than in all 50 states. This might be one of the reasons why charter schools have grown rapidly in DC since their inception in 1996. During our sample period alone, the number of charter school campuses more than doubled, from 27 to 60, whereas the number of public and private school campuses declined slightly as a result of a few closings and mergers (see Figure 1 and Table 2). Over the sample period, 43 percent of private schools were Catholic, 24 percent belonged to the Other Religious category and 32 percent were nonsectarian.

Even though total enrollment declined during our sample period by about 6,000 students, enrollment in charter schools grew approximately by the same amount (see Figure 2). As a result, the market share of charter schools grew from 13 to 22 percent (see Figure 3) and charter share relative to total public enrollment rose from 16 to 28 percent.

11 Source: Population Division, U.S. Census Bureau. School-age population includes children between 5 and 17 years old. An alternative measure of the size of school-age population is total K-12 enrollment, which also declined from 81,500 to 75,000 students (see Figure 2).
As Table 1a shows, student demographics in public and charter schools are quite similar – more than 90 percent black or hispanic and about two thirds low-income. In contrast, in private schools about 60 percent of students are white and less than a quarter low-income. As Figures 4a-c show, charters are spread throughout the city except in the northwestern sector, where private schools have a strong presence. Even though private schools tend to be located in higher-income neighborhoods than public or charter schools, they are quite heterogeneous (see Table 1b). Catholic schools enroll higher fractions of black and hispanic students than other private schools. On average, they also charge lower tuition and are located in less affluent neighborhoods.

Table 1c depicts the variation in school choices by student race and poverty status. Over the sample period, 62 percent of children are enrolled in public schools, 17 percent in charter schools and 21 percent in private schools. While approximately 70 percent of black and hispanic children attend public schools, only 28 percent of whites do. Charters capture between 15 and 20 percent of black and hispanic students, yet only 3 percent of white students. Almost three quarters of white students attend private schools, vis-a-vis less than 15 percent of black and hispanic students.

2.1.2 Variation by grade level

As Table 3 shows, most public schools are elementary. Public schools rarely mix levels, but about a third and three quarters of charter and private schools do, respectively. For instance, half of Catholic schools’ students are enrolled in elementary/middle schools and about 60 percent of the students in other private schools are enrolled in elementary/middle/high schools. At every level, private schools tend to be smaller than charter schools, which are in turn smaller than public schools. High schools are the exception, because the average private (in particular, Catholic) high school is almost as large as the average public high school. Market share for each school type differs across grade levels: most public school enrollment corresponds to elementary school students, yet most of charter and private school enrollment corresponds to higher grades.

Figure 5 offers more detailed evidence on this point. Public school shares peak for elementary grades; charter school shares peak for middle grades and private school shares peak for high school grades. This is consistent with a popular narrative in D.C. that claims that middle- and high-income parents "try out" their neighborhood public school for elementary grades but leave the public sector afterwards.\footnote{Some might claim that white parents leave the District altogether once their children finish elementary school. As a simple test of this conjecture we calculated the fraction of white children at each age. This fraction declines steadily between ages 0 and 4, from 19 to 13 percent, but stabilizes around 10 or 11 percent between ages 5 and 18. Thus, white parents appear to leave the District before their children start school, not after elementary school.}

While market shares at the high school level changed little over the sample period, they experienced greater changes for elementary and middle school grades. Public schools lost elementary school students to private and charter schools, yet more striking was their loss of middle school students to charter schools. This may be explained in part by the fact that at the end of 6th grade public school students must switch schools, making 7th grade a natural entry point into a new school. But, as Figure 6 indicates, it may also be explained by the fact that the supply of charter relative to public schools is much greater for middle than elementary school grades. While charters are severely outnumbered by public schools for elementary grades, the difference is much smaller for middle grades because charter school supply grew the most for these grades over the sample period. Moreover, charter middle schools have fewer students per grade than public schools (see Figure 7), a feature that many students may find attractive.\footnote{This does not necessarily mean that charter schools have smaller class sizes, as charters may have the same (or bigger) class size yet fewer classrooms per grade.} Note in passing that the number of public and private high schools is about the same, yet private schools are much smaller.
The popular narrative described above finds support in Table 4, which shows a decline in the fraction of white students in middle and high school relative to elementary school while the reverse happens in private schools.\textsuperscript{14} Note, also, that private high schools are located in higher income neighborhoods than private elementary or middle schools. Whites are a very small fraction of charter school enrollment in elementary and middle school yet they are an even smaller fraction for high school. Perhaps as a result of the differences in the student body across grade levels, proficiency rates in public schools are higher for elementary than middle or high school grades. In contrast, charter proficiency peaks for middle schools. It then falls for high schools, which enroll a particularly disadvantaged student population and are located in low-income neighborhoods.

2.1.3 Variation by focus

More than half of charters offer a specialized curriculum (see Table 5a). Among public and private schools, only public high schools engage substantially in this practice. Across all types of schools, language and arts are popular focuses for elementary schools and vocational is popular for high schools (see Table 5b). Most elementary schools focused on arts are charters that attract very disadvantaged students and are located in low-income neighborhoods (see Table 6a). Language schools attract high fractions of Hispanic students and vocational schools attract very disadvantaged students. Although whites attend charter schools at lower rates than public or private schools, charters that offer other focuses (such as math and science, special educational philosophies, classics, etc.) attract relatively large fractions of whites. Perhaps for this reason, these schools also tend to have relatively high achievement.

As Table 6b shows, during our sample period 80 percent of students attend a core-curriculum school, with "other focus" being the second most popular focus. There is little variation in focus choice across races and poverty status, with the exception of language, which is chosen by 19 percent of Hispanic students.

2.1.4 Relocations, closings and multiple-campus charters

Relative to charter schools, public and private schools experienced few openings, closings or relocations during the sample period (see Table 2), particularly when measured against the number of schools of each type that existed by the end of 2002.\textsuperscript{15} In contrast, openings and relocations were quite frequent among charters. It is fairly common for charter schools to add grades over time until completing the grade coverage stated in the charter. Hence, many charters first open in a temporary location that is large enough to hold the initial grades, but then move to their permanent facilities once they reach their full grade coverage.

Our sample includes 63 campuses and 45 schools, of which 35 contain only one campus. The 10 multi-campus schools account for 53 percent of all charter enrollment over the sample period. Multi-campus organizations typically run multiple campuses in order to serve different grade levels.\textsuperscript{16} Relative to single-campus charters, multi-campus charters are more likely to focus

\textsuperscript{14}The relatively low percent of white students in middle schools is explained by Catholic schools dominating this grade level and enrolling a majority of Black students.

\textsuperscript{15}Since 2000, DCPS has engaged in efforts to “rightsize” the public school system. These efforts have included school renovations, openings, mergers and closings, with closings due to declining student population and enrollment (Filardo et al 2008). Most of the public school relocations were associated with renovations – while a particular building was being renovated, students would occupy “swing space” in another building and move to the renovated building at the end of the renovations. As for private school closings, most of them affected small schools, with an enrollment between 15 and 30 students.

\textsuperscript{16}For instance, Friendship has two elementary school campuses (Southeast Academy and Chamberlain), one elementary/middle school campus (Woodridge), one middle school campus (Blow-Pierce), and one high school campus.
on a core curriculum. They also attract slightly higher fractions of black students and achieve greater proficiency rates.

2.1.5 Early v. recent entrants

Given our focus on charter entry, an important question is whether the 27 campuses that entered before our sample period ("early entrants") are different from the 36 campuses that entered during our sample period ("recent entrants"). As Table 7 shows, recent entrants tend to be smaller and are more likely to serve elementary or middle school. They are also more likely to belong to a multi-campus organization. They enroll greater fractions of white students and are more likely to have a specialized curriculum. They are located in slightly higher income neighborhoods and enroll lower fractions of low-income students. In other words, it seems as though the charter movement has been including less disadvantaged students over time. Since these students are likely to enjoy access to good public (and perhaps private) schools, in order to reach them charters seem to be offering increasingly more curriculum specialization.

2.1.6 Variation across neighborhoods

Given the geographic distribution of income and race across neighborhoods in Washington, D.C., one would expect variation in charter school attendance among neighborhoods. As Figure 8 shows, children who live in the eastern portion of the city are more likely to attend charter schools. Regardless of their neighborhood of residence, children travel longer to charter than to public schools (compare Figures 9 and 10). Median distance traveled to public schools is equal to 0.33, 0.64 and 1.47 miles for elementary, middle and high school respectively, whereas median distance traveled to charter schools is equal to 1.42, 1.66 and 2.37 miles for the corresponding school levels.

To summarize, our data set is unique and draws from a variety of sources. It has not been compiled or used by any other researcher before. Moreover, its rich variation over over time, and across schools and neighborhoods will help us identify the parameters of our model.

3 Model

In this section we develop our model of charter schools, household school choice and equilibrium. In the model, the economy is Washington, D.C. There are public, private and charter schools in the economy. Each school serves a different grade level, where a grade level is a collection of grades, and there is a finite set of grade levels (for instance, elementary, middle and high). The economy is populated by households that live in different locations within the city and have children who are eligible for different grades. For a given household, the school choice set consists of all public, private and charter schools that offer the required grade and may be attended by the child.

At each point in time, every neighborhood has a prospective entrant for each grade level and focus. We use the term “entry point” to refer to a combination of location, grade level and focus. A prospective charter entrant chooses whether to enter or not, whereas an incumbent charter decides whether to remain open and relocate, remain open in the same location, or exit. We assume that charters take the locations, grades served, and focus of public and private schools as given. They also take private school tuitions as given.

To make their decisions, both incumbents and potential entrants forecast enrollment given the competition they face from other schools. To develop this forecast they anticipate households’
choices. At the beginning of any given period schools are uncertain about their demand shock yet
potential entrants face even greater uncertainty because they do not know their aptitude at running
a school.

The model thus has multiple stages: several stages of charter action, and a household choice
stage. Since the latter is used in the former, we begin by presenting the model of household choice

3.1 Household Choice of School

The economy includes $J$ schools, each one offering at least one grade. The economy is populated
by households that have one child each. In what follows, we use “household”, “parent”, “child”
and “student” interchangeably. Student $i$ is described by $(g, D, \ell, I, \varepsilon)$, where:

- $g$ is the grade of the student. Our data covers 13 grades: kindergarten, and grades 1st through
  12th.
- $D$ is a vector describing student demographics. This vector contains $D$ elements. In our
  empirical application $D$ has $D = 3$ rows, each one storing a 0 or 1 depending on whether the
  household is white, hispanic (default race is black), and non-poor (this indicator equals 1 if
  the student does not qualify for free- or reduced lunch, and 0 otherwise).
- $\ell \in \{1, \ldots, L\}$ is the location of the household in one of the $L$ possible neighborhoods of the
  school district. A student’s location determines her geographic distance with respect to each
  school.\(^{17}\)
- $I$ is the income of the student’s family.
- $\varepsilon$ is a vector that describes the student’s idiosyncratic preference for each school.

We use $j$ and $t$ subscripts to denote respectively a school and year. Throughout, if a school
has only one campus, $j$ refers to the school; otherwise it refers to the campus. We do not equate
a campus with a physical location; if a campus relocates we still treat it as the same campus. We
treat multiple campus of the same organization as separate entities because in many cases they are
run as such. In what follows, we use "school" and "campus" interchangeably. Our data includes
$J = 281$ schools and $T = 5$ years (between 2003 and 2007). A household’s choice depends on
several variables that characterize a particular school and that are observed by the household at
the time of making its choice:

- $\kappa_{jt}$ is the set of grades served by the school, often referred to as "grade level." A household
  chooses among the set of schools that offer the grade needed by its child. This set changes
  over time, as a school can add or remove grades.
- $x_{ijt}$ is the geographic distance from the household’s residence to the school. Since schools can
  relocate, distance can vary over time.
- $y_j$ denotes time-invariant school characteristics such as type (public, charter, Catholic, other
  religious, nonsectarian) and focus (core, language, arts, vocational, other). For presentational
  clarity we will refer to $y_j$ as “focus.”

\(^{17}\)We assume that a student’s location is given and does not depend on her choice of school. For models of joint
residential and school choice, see Nechyba (1999, 2000) and Ferreyra (2007, 2009). In our empirical application,
distance is measured as network distance and is expressed in miles.
• $p_{jgt}$ is tuition. Public and charter schools cannot charge tuition, but private schools can. Private school tuition can vary by grade.

• $D_{jt}$ represents peer characteristics of the student body at the school. Unlike school characteristics $y_j$ and $p_{jgt}$, $D_{jt}$ is the outcome of household choices. It is the average over the vectors $D$ of the students who attend the school and hence has $D$ elements as well. In our empirical application, $D_{jt}$ stores percent of white, hispanic and non-poor students. These characteristics may change over time, as household choices change.\footnote{We incur in an abuse of notation here. Strictly speaking, $D_{jt}$ represent households’ beliefs about the demographic composition of school $j$ at time $t$. In equilibrium, those beliefs are consistent with the aggregate choices made by households. In estimation we impose equilibrium and quantify these beliefs through observed school demographic composition, which is equal to equilibrium aggregate choices up to sampling error.}

• $\xi_{jgt}$ is an unobserved (to us) characteristic of the school and grade. This includes characteristics of the teacher such as her responsiveness to parents and her enthusiasm in the classroom; physical characteristics of the classroom, etc.

• $\xi_a^g$ is an unobserved (to us) characteristic of the school and grade that affects children’s achievement (in contrast, $\xi_p^g$ affects household satisfaction with the school and grade for reasons other than achievement). Thus, $\xi_a^g$ captures elements such as teacher effectiveness at raising achievement, the usefulness of the grade curricula to enhance learning, etc.

We define a market as a (grade, year) combination. The size of the market for grade $g$ in year $t$ is $M_{gt}$, equal to the number of students who are eligible to enroll in grade $g$ at time $t$.

The household indirect utility function is:

$$U_{ijgt} = \delta_{jgt}^p + \mu_{ijgt}^p + \varepsilon_{ijgt}$$

where $\delta_{jgt}^p$ is the baseline utility enjoyed by all the grade $g$ children who enroll in school $j$ at time $t$, $\mu_{ijgt}^p$ is a student-specific deviation from the common school-grade utility, and $\varepsilon_{ijgt}$ is an individual idiosyncratic preference for $(j,g)$ at $t$. The baseline utility depends on school and peer characteristics as follows:

$$\delta_{jgt}^p = y_j \beta^p + D_{jt} \alpha^p + \xi_{jgt}^p$$

Here, $\alpha^p$ and $\beta^p$ are vectors of parameters. In what follows, we refer to $\xi_{jgt}^p$ as a preference shock for school $j$ and grade $g$ at time $t$. A remark on notation is in order at this point. We use a $p$ superindex to denote some elements of the utility function above, and an $a$ superindex to denote elements of achievement, to economize on notation when we combine utility and achievement below.

The household-specific component of utility is given by:

$$\mu_{ijgt}^p = E(A_{ijgt})\phi + D_i y_j \beta^p + D_i D_{jt} \alpha + x_{ijt} \gamma + \varphi \log(I_i - p_{jgt})$$

This component of utility depends on the expected achievement of the student, $E(A_{ijgt})$, which is explained below. It also depends on the interaction of $y_j$ and $D_i$, which captures the variation in attractiveness of the thematic focus across students of different demographic groups, and the interaction of $D_i$ and $D_{jt}$, which captures the potential variation in preferences for school peer characteristics across different demographic groups. In addition, it depends on the distance between the household’s residence and the school and on school tuition.

Student achievement $A_{ijgt}$ depends on a school-grade factor common to all students, $Q_{jgt}$, a student’s demographic characteristics, the fit of the thematic focus to the student (captured by the
interaction of student demographics and focus below), and a zero-mean idiosyncratic achievement shock $\nu_{ijgt}$, which parents do not observe at the time of choosing a school:

$$A_{ijgt} = Q_{jgt} + D_i\omega^o + y_j D_i\tilde{\beta}^o + \nu_{ijgt} \tag{4}$$

As is common in empirical studies of achievement, we include student demographics in this equation because factors such as parental education, wealth and income (for which we do not have detailed measures and which are likely to affect achievement) vary across racial and ethnic groups. As detailed below, the school-grade factor, $Q_{jgt}$, depends on the thematic focus of the school, peer characteristics of the student population, and a productivity shock $\xi_{jgt}$ for school $j$ and grade $g$ at time $t$. Since peer characteristic measures are available at the school but not the grade level, we do not place the subscript $g$ on $D_i$ below:

$$Q_{jgt} = y_j \beta^o + D_jt\alpha^o + \xi_{jgt} \tag{5}$$

Substituting (5) into (4), we obtain

$$A_{ijgt} = y_j \beta^o + D_jt\alpha^o + D_i\omega^o + y_j D_i\tilde{\beta}^o + \xi_{jgt} + \nu_{ijgt} \tag{6}$$

Since parents observe $\xi_{jgt}$ but $\nu_{ijgt}$ has not been realized yet at time they choose a school, their expectation of (4) is:

$$E[A_{ijgt}] = y_j \beta^o + D_jt\alpha^o + D_i\omega^o + y_j D_i\tilde{\beta}^o + \xi_{jgt} \tag{7}$$

Note that when a parent forms the expectation of her child’s achievement at a particular school, she conditions on the same student-level information that we use - namely, demographic characteristics. In particular, the parent does not condition on the child’s ability (which we do not observe). This modeling choice is driven by the fact that we cannot model unobserved student characteristics in the absence of student-level data.

Substituting (7) into (3), we obtain:

$$\mu_{ijgt}^p = y_j \beta^o \phi + D_jt\alpha^o \phi + D_i\omega + y_j D_i\tilde{\beta} + D_jt\tilde{\alpha} + x_{ijt}\gamma + \varphi \log(I_i - p_{jgt}) + \phi\xi_{jgt} \tag{8}$$

where $\omega = \omega^o \phi$. The coefficient of the interaction of $y_j$ and $D_i$ is $\tilde{\beta} = \tilde{\beta}^p + \phi\tilde{\beta}^o$. This interaction captures both the variation in attractiveness of a school’s focus across students of different demographic groups ( $\tilde{\beta}^p$ ) and the fit between focus and student type in the achievement function ( $\phi\tilde{\beta}^o$ ).

Substitute (2) and (8) into (1) and regroup terms to obtain:

$$U_{ijgt} = \delta_{jgt} + \mu_{ijgt} + \xi_{ijgt} \tag{9}$$

where $\delta_{jgt}$ and $\mu_{ijgt}$ are defined below in (10) and (12). We now turn to a discussion of these terms, beginning with the baseline utility component $\delta_{jgt}$:

$$\delta_{jgt} = y_j \beta + D_jt\alpha + \xi_{jgt} \tag{10}$$

In this expression, the coefficient of $y_j$ captures both household preference for school focus and impact of focus on achievement: $\beta = \beta^p + \phi\beta^o$. Thus, the model captures an interesting potential tension between school characteristics that enhance productivity and school characteristics that attract students. For example, a long school day may enhance achievement, but parents and students may not like the longer day. Similarly, the coefficient of $D_jt$ captures both household
preference for peer characteristics and the impact of peer characteristics on student achievement: \( \alpha = \alpha^p + \phi \alpha^a \). The error term in (10) impounds both a preference and a productivity shock: \( \xi_{jgt} = \xi_{jgt}^p + \phi \xi_{jgt}^a \). We will refer to this composite shock as a demand shock or unobserved quality. Since the demand shock captures elements that affect both utility and achievement, it reflects the same kind of tension described above. For instance, parents may like the atmosphere created by a teacher in her classroom and the enthusiasm she instills in the students even if these are not reflected in higher achievement. Following Nevo (2000, 2001), we decompose the demand shock as follows:

\[
\xi_{jgt} = \xi_j + \xi_g + \xi_t + \Delta \xi_{jgt}
\]  

(11)

In this decomposition, the school-specific component \( \xi_j \) captures elements that are common to all grades in the school and constant over time, such as the school’s culture and average teacher quality. We refer to \( \xi_j \) as the permanent quality of the school, or simply school quality. The grade-specific component \( \xi_g \) captures elements that are common to a given grade across schools and over time. For instance, grade retention rates are highest in 9th grade, and dropout rates are highest in 12th grade. The time-specific component \( \xi_t \) captures shocks that are common to all schools and grades and vary over time, such as city-wide income shocks. We apply the following normalization: \( E(\Delta \xi_{jgt}) = 0 \). Hence, \( \xi_j + \xi_g + \xi_t \) is the mean school-year-grade demand shock, and \( \Delta \xi_{jgt} \) is a deviation from this mean – due, for instance, to the presence of a teacher whose quality is higher than the school average.

The household-specific component of (9) is:

\[
\mu_{ijgt} = D_i \omega + y_j D_i \tilde{\beta} + D_i \tilde{D}_{jt} \tilde{a} + x_{ijt} \gamma + \varphi \log(I_i - p_{jgt})
\]  

(12)

Since the household may choose not to send its child to any school, we introduce an outside good \((j = 0)\). This may represent home schooling, dropping out of school, etc. The indirect utility from this outside option is:

\[
U_{i0gt} = \varphi \log(I_i) + \xi_{0gt} + D_i \omega_0 + \varepsilon_{i0gt}
\]  

(13)

Since we cannot identify \( \xi_{0gt} \) and \( \omega_0 \) separately from the \( \xi_{jgt} \) terms of the “inside” goods or from \( \omega \), we apply the following normalizations: \( \xi_{0gt} = 0 \) and \( \omega_0 = 0 \).

Let \( J_{gt}^i \) denote the choice set of schools available to household \( i \) for grade \( g \) at time \( t \). This choice set varies over time because of entry and exit of schools that serve that grade, and because some schools add or remove grades. Let \( X_{ijt} \) denote the observable variables that are either specific to the household or to the match between the household and the school: \( D_i, I_i, \) and \( x_{ijt} \). The household chooses a school from the set \( J_{gt}^i \) in order to maximize its utility (it may also choose the outside good). Assuming that the idiosyncratic error terms in (9) and (13) are i.i.d. type I extreme value, we can express the probability that household \( i \) chooses school \( j \) in grade \( g \) at date \( t \) as follows:

\[
P_{jgt}\left(y_j, y_{j-1}, \tilde{D}_{jt}, \tilde{D}_{j-1}, \xi_{jgt}, \xi_{j-gt}, p_{jgt}, p_{j-gt}, X_{ijt}; \theta^d\right) = \frac{\exp(\delta_{jgt} + \mu_{ijgt})}{\exp(\varphi \log(I_i)) + \sum_{k=1}^{J_{gt}^i} \exp(\delta_{kgt} + \mu_{ikgt})}
\]  

(14)

where \( \theta^d \) refers to the collection of demand-side parameters to be estimated.

Let \( h(D, I, \ell, g) \) be the joint distribution of students over demographics, income, locations and grades in the economy, and let \( h(D, I, \ell | g) \) be the joint distribution of demographics, income and location conditional on a particular grade. Recall that each location \( \ell \) is associated with a
distance to each school. Given (14), the number of students choosing school $j$ and grade $g$ at time $t$ is equal to:

$$
\hat{N}_{jgt} = \int \int \int p_{jgt}(\cdot) dh(D, I, \ell | g)
$$

(15)

Thus, the market share attained by school $j$ in grade $g$ at time $t$ is equal to:

$$
\hat{S}_{jgt}(y_j, y_{-j}, \hat{D}_{jt}, \hat{D}_{-jt}, \xi_{jgt}, \xi_{-jgt}, p_{jgt}, p_{-jgt}; \theta^d) = \frac{\hat{N}_{jgt}}{M_{gt}}
$$

(16)

The total number of students in school $j$ at time $t$ is hence equal to $\hat{N}_{jt} = \sum_{g \in \kappa_{jt}} \hat{N}_{jgt}$. The resulting demographic composition for the schools is thus equal to

$$
\hat{D}_{jt}(y_j, y_{-j}, \hat{D}_{jt}, \hat{D}_{-jt}, \xi_{jt}, \xi_{-jt}, p_{jt}, p_{-jt}; \theta^d) = \frac{\sum_{g \in \kappa_{jt}} \hat{N}_{jgt} \int \int D p_{jgt}(\cdot) dh(D, I, \ell | g)}{\hat{N}_{jt}}
$$

(17)

where the dot in $\xi$ and $p$ indicates the set of all grades in the corresponding school. In equilibrium, the school peer characteristics taken as given by households when making their school choices, $\bar{D}$, are consistent with the peer characteristics determined by those choices, $\hat{D}$.

Since we do not have individual-level achievement data, we cannot identify the parameters of the achievement function (4). However, we can derive the following equation for a school’s expected proficiency rate (see Appendix II for details):

$$
q_{jt} = y_j \alpha^q + \hat{D}_{jt} \theta^q + y_j \hat{D}_{jt} \omega^q + \xi_j^q + \xi_t^q + \Delta \xi_{jt}^q
$$

(18)

where the parameters are non-linear functions of the parameters in (4). In this equation, the school fixed effect is a function of the school’s productivity shock and the mean grade productivity shock. The time fixed effect captures changes that affect proficiency rates in all schools and grades, such as modifications to the assessment instrument. The error term is a function of school idiosyncratic productivity shocks and the mean of the idiosyncratic components of performance of the school’s students.

### 3.2 School Supply

Having studied household choice of school, we now turn to the supply of schools. Although the model includes public, private and charter schools, we only model the behavior of charter schools. As Table 2 shows, episodes of entry, exit and relocation are much less common among public and private schools than charters, particularly when measured against their stock at the end of 2002. Such little variation in the data precludes the identification of a model of strategic decisions on the part of public or private schools. Hence, we assume that in any given time period these schools make decisions before charters do, and charters take them as given. Of course, it is possible that at some point public and private schools would react to changes in the environment, particularly those created by charter competition. To accommodate for this possibility, in our counterfactuals we implement simple policy rules for public and private schools, such as closing if enrollment falls below a specific threshold and remaining open otherwise.

Among charters, we distinguish between potential entrant and incumbent charter schools. Both prospective entrants and incumbent charters seek to maximize expected net revenue, equal
to expected enrollment times reimbursement per student minus the corresponding costs.\textsuperscript{19} In particular, charters must forecast their equilibrium demand, namely the demand they will face after households re-sort across schools in response to charter actions.

To predict its equilibrium demand, a charter needs to know the actions of its competitors and its competitors’ characteristics, particularly their demand shocks. With regards to the actions of the competitors, we specify an entry-exit-relocation game that explains charters’ beliefs about those actions. The game is inspired in the actual institutional process of entry, exit and relocation, which is described below. The game has two main features: a) it allows each charter to know the action of its competitors with probability one, thus simplifying the structure of charter beliefs; b) it delivers a unique equilibrium, thus enabling likelihood-based estimation of supply-side parameters.\textsuperscript{20} Although we do not estimate this model directly, the game structure facilitates the estimation of an approximation of the game. As for the characteristics of a charter’s competitors, below we describe the information structure facing charters.

3.2.1 Charter entry: institutional details

If a charter wishes to open in the Fall of year X, it must submit its application by February of (X-1). The Washington, D.C. charter law specifies that the school’s application must include a description of the school’s focus and philosophy, targeted student population (if any), educational methods, intended location, recruiting methods for students, and an enrollment projection. The applicant must also file letters of support from the community and specify two potential parents who will be on the school’s board. In addition, the application must contain a plan for growth – what grades will be added, at what pace, etc.

At the time of submitting its application, the school must provide reasonable evidence of its ability to secure a facility. The authorizer evaluates the enrollment projection by considering the enrollment in nearby public schools, similar incumbent charters, the size of the school’s intended building, and how many students will guarantee financial viability for the school given the expected fixed costs.

The charter learns the outcome of the application process in April or May of (X-1). If authorized, the charter starts negotiating with the authorizer on a number of issues, including facilities. At the time of receiving the approval notice, the school should have secured a building, or else the negotiations will break down. Provided the school secures a building, it then uses the following twelve months to hire and train its prospective leaders, renovate the building (if needed), recruit students and teachers, and get ready to start operating.

Charters are very aggressive in their efforts to recruit students. They do neighborhood searches, advertise in churches, contact parents directly, post flyers at public transportation stops and local shops, advertise in local newspapers and in schools that are being closed down or reconstituted, and host open houses. PCSB conducts a “recruitment expo” in January and charters participate in it. Word of mouth among parents also plays an important role. This is aided by the fact that a charter’s board must include two parents with children in the school.

Based on its projected enrollment, a charter opening in Fall of X receives its first installment in July of X. This means that any previous down payment on the facilities must be funded through a loan. An enrollment audit is conducted in October of X and installments are adjusted accordingly.

Charters can run surpluses – this is the case, for instance, of charters that are planning to expand in the future. They can also run deficits, as is the case with schools whose actual

\textsuperscript{19}"Reimbursement" is the per-student stipend that charters receive in lieu of funding.
\textsuperscript{20}Multiple equilibria is a pervasive and problematic feature of entry models, as discussed in Berry and Reiss (2006). Timing assumptions, such as those we impose in our model, are often used to attain unique equilibrium and enable likelihood-based estimation.
enrolment is too low relative to their fixed costs. However, PCSB only tolerates temporary deficits, and only in the case in which the school is meeting its academic targets. Thus, attracting and retaining students is of utmost importance to charters. Between 2004 and 2010 PCSB received 89 applications, of which only 29 were approved.

This long, well-specified entry process takes approximately a year from beginning (charter application) to end (household enrollment). Thus, a "period" in our model below is approximately equal to an actual year. To mirror the fact that some entry attempts succeed while others do not, the entry-exit-relocation game we describe below includes a process of action initiation and withdrawal on the part of charters. This process gradually releases information on schools' actions to all market participants.

3.2.2 Information structure

Recall that we have decomposed the demand shock as \( \xi_{jt} = \xi_j + \xi_g + \xi_t + \Delta \xi_{jt} \). We assume that when charters make their decisions at the beginning of the period, they do not observe demand shocks \( \xi_{jt} \) either for themselves or their competitors, although they observe them at the end of the period. We assume that at the beginning of \( t \) prospective entrants and incumbents observe \( \xi_g \) because it is time-invariant and common to all schools that offer \( g \). We also assume that \( \xi_t \) becomes public knowledge at the beginning of \( t \) and is thus observed by prospective entrants and incumbents. While incumbents observe their permanent quality \( \xi_j \), prospective entrants do not. This captures the notion that a prospective entrant does not know how good she will be at the enterprise of starting and running a school. We assume that if she does enter, she conducts activities that enable her and others to learn her permanent quality - she advertises the new school, hosts open houses, hires a principal and teachers, participates in charter fairs, engages in fundraising, renovates a building, builds ties with the community, etc. Importantly, parents observe \( \xi_{jt} \) when choosing schools.

We assume that at the beginning of \( t \) no school observes school-grade-year deviations \( \Delta \xi_{jt} \), but it does observe them at the end of \( t \). For instance, a school’s principal may not know a year ahead of time whether a particular teacher will be available to teach in a certain grade, but she will know a year later. We assume that \( \xi_j \) and \( \Delta \xi_{jt} \) are independent, and that the \( \Delta \xi_{jt} \)'s are independent across grades for a given school-year. Further, we assume that the distributions of \( \xi_j \) and \( \Delta \xi_{jt} \) are common knowledge, equal to \( N(0, \sigma^2_g) \) and \( N(0, \sigma^2_{\Delta \xi}) \) respectively. For convenience we sometimes refer to these distributions as \( N_{\xi_j} \) and \( N_{\Delta \xi_{jt}} \) respectively. Thus, \( \xi_{jt} \) is distributed \( N(\xi_j + \xi_g + \xi_t, \sigma^2_g + \sigma^2_{\Delta \xi}) \) for all incumbent public, private and charter schools, and \( N(\mu_{\xi} + \xi_g + \xi_t, \sigma^2_g + \sigma^2_{\Delta \xi}) \) for potential charter entrants.

3.2.3 Charter entrants

Recall that we have defined an entry point for charters as a combination of location \( \ell \), focus \( y \) and grade level \( \kappa \), and have assumed one prospective entrant per entry point per period. Consider a prospective entrant for entry point \( (\ell, y, \kappa) \). She forms beliefs about the expected demographic composition at her school as a solution of the following system of equations

\[
\tilde{D}_{jt} = \int_{\xi_j,t} \tilde{D}_{jt}(y, y_{-j}, \tilde{D}_{jt}, \tilde{D}_{jt}, \xi_j, \xi_{-j}, \theta^d) dN_{\xi_j}(\mu_{\xi}, \sigma^2_{\xi}) \prod_{g \in \mathcal{N}_{jt}} dN_{\Delta \xi_{jt}}(0, \sigma^2_{\Delta \xi})
\]

(19)

where \( \tilde{D}_{jt} \) are the beliefs of other schools about their peer characteristics, formed similarly to \( \tilde{D}_{jt} \). Note that \( \tilde{D}_{jt} \) is expected equilibrium demographics.
Given these beliefs, the prospective entrant’s predicted market share for grade \( g \) in case of entering is

\[
E \left[ \hat{S}_{jgt} \mid (\ell, y, \kappa) \right] = \int \hat{S}_{jgt}(y, y_{-j}, \tilde{D}_{j}, \tilde{D}_{-j}, \xi_{jt}, \xi_{-jt}, P_{-jg}; \theta^{d}) dN(\mu_{\xi} + \xi_{t} + \xi_{s}^{2} + \xi_{s2}) \quad (20)
\]

where \( \hat{S}_{jgt}(.) \) is given by (16) and \( \xi_{-jt} \) is evaluated at its mean as described above.

Let \( R_{gt} \) denote the reimbursement per student in grade \( g \) that a charter school obtains.\(^{21}\) Let \( V \) denote variable costs per student; these may differ by grade level, \( \kappa \). Let \( \zeta \) be an entry fee that is only paid when entering. Let \( F \) denote fixed costs which must be paid every year that the school is open. These may vary by location and grade level to capture variation in the main component of fixed costs, which is the cost of facilities, and to reflect the greater fixed cost of high school.

The expected revenue net of costs for the prospective entrant \( j \) in entry point \((\ell, y, \kappa)\) is

\[
\pi_{\ell\kappa}^{e} (\theta^{s}) = \sum_{g \in \kappa} M_{gt} E \left[ \hat{S}_{jgt} \mid (\ell, y, \kappa) \right] (R_{gt} - V) - \zeta - F + \nu_{\ell\kappa}^{e}
\quad (21)
\]

where \( \theta^{s} = \{ \mu_{\xi}, \sigma_{\xi}, \sigma_{\Delta_{\xi}}, \zeta, V, F, w \} \) refers to the collection of supply-side parameters to be estimated, and \( \nu_{\ell\kappa}^{e} \) is measurement error in the charter school’s profits that is unobserved by the econometrician. The prospective entrant enters if its expected revenue from entering is higher than the utility of not entering, equal to \( \nu_{\ell\kappa}^{e} \).\(^{22}\) In the \( \theta^{s} \) vector, parameter \( w \) denotes relocation costs and is used below in our model of incumbents. We assume that the error terms \( \nu_{\ell\kappa}^{e} \) and \( \nu_{\ell\kappa}^{e} \) are i.i.d. type I extreme value.

The objective function in (21) reflects several modeling choices we have made for simplicity. First, our model is static, which means that charters choose actions based on the current period’s expected profit. Second, a charter school in practice may serve only a few grades in the first year and add grades over time until reaching its full grade coverage. Our characterization in (21) assumes that the school decides on entry as it were serving its full set of grades from the beginning of its operations, and we take the pace of grade addition as given from the data.\(^{23}\) Third, we do not model capacity choice (i.e., how many students the school aims to have). Fourth, we treat the campuses of multi-campus organizations as independent schools. Alternative modeling choices are precluded either by lack of data (for instance, we do not observe charter capacity or intended grade coverage) or by computational complexity (for instance, dynamic models of entry are highly complex, particularly when involving as many players as in our case).

Modeling charters as profit-maximizers may not seem appropriate. However, charters cannot run permanent deficits and hence must worry about financial matters. Moreover, presumably they must keep their students satisfied in order to retain them – which suggests that the interests of the school and the students may be aligned. The concern remains that charters might keep students satisfied without raising their performance. Thus, in future versions we will explore alternative charter objective functions. Among these, an appealing alternative is a linear combination of (21) and the school’s contribution to expected student achievement.

\(^{21}\)For a given year, this reimbursement varies across grades. For 2007, the base reimbursement (“foundation”) is equal to $8002.06, and is adjusted by a grade-specific factor which is highest for high school and preschool. The foundation is adjusted by inflation every year. In addition, charters in D.C. receive a facility allowance per child, equal to $2,809.59 in 2007.

\(^{22}\)A potential extension is to have a charter school authorizer that imposes a minimum threshold for net revenue to internalize the externalities that a failing school imposes on its students.

\(^{23}\)On demand-side estimation we assume that the school is only available for the grades that are actually offered in a given year.
3.2.4 Charter incumbents

An incumbent charter school decides whether it will continue operations, and if so, whether to stay in the current location or move to another one. Moving imposes cost \( w \). Incumbent charter \( j \) located in \( \ell \), with focus \( y \) and grade level \( \kappa \) makes the decision that solves the following problem:

\[
\pi_{jt}^i (\theta^*) = \max \left\{ \begin{array}{ll}
\pi_{jt,\text{stay}}^i = \sum_{g \in \kappa} M_{gt} E \left[ \tilde{S}_{jgt} \mid (\ell, y, \kappa) \right] (R_{gt} - V) - F + \nu_{jt\ell}^i & \text{if stays in location } \ell \\
\pi_{jt,\text{move}}^i = \sum_{g \in \kappa} M_{gt} E \left[ \tilde{S}_{jgt} \mid (\ell', y, \kappa) \right] (R_{gt} - V) - F - w + \nu_{jt\ell'}^i & \text{if moves to location } \ell' \\
\pi_{jt,\text{exit}}^i = \nu_{jt0}^i & \text{if exits}
\end{array} \right.
\]

where \( \nu_{jt\ell}^i \) is idiosyncratic shock in the incumbent’s profits that is unobserved by the econometrician but observable by the incumbent, and the expectations are taken over the distribution of \( \Delta \xi_{jgt} \).

We assume that \( \nu_{jt\ell}^i \) and \( \nu_{jt0}^i \) follow an i.i.d. type I extreme value distribution.

3.2.5 Timing of entry-exit-relocation events, and equilibrium

Consider time period \( t \). At the beginning of \( t \) there are \( J_t \) charter incumbents from the previous period. Their permanent quality \( \xi_j \) is common knowledge as is the set of grade-specific demand shocks \( \xi_g \). The entry-exit-relocation game evolves as follows:

**Step 1 (Public and Private Schools).** At the beginning of \( t \) public and private schools make their decisions on entry, exit and relocation. These actions become public knowledge. The time-specific demand shock \( \xi_t \) becomes public knowledge as well.

**Step 2 (Expected Profits for Charter Schools).** All incumbent charter and potential entrants calculate the expected profit from each possible action and choose the action that maximizes their profit. In so doing they take as given the set of public and private schools in the market from Step 1, and the set of incumbents from the previous period. They assume that incumbents stay at their previous period location, and that no other charter enters. Charter expected profits are given by (21) and (22).

**Step 3 (Action Initiation).** The potential entrants that have decided to enter and the incumbents that have decided to relocate or exit in Step 2 initiate the corresponding actions. Their initiated (i.e., intended) actions become public knowledge. This captures the idea that a charter that has gained approval from PCSB needs to finalize the lease of its building, hire teachers, etc. As the charter undertakes these activities, others learn about the charter’s intention to enter.

**Step 4 (Action Revision).** The actions initiated in Step 3 yield a new market structure, as charters in the market now include those that initiated entry in Step 3, the incumbents that initiated relocation or exit in Step 3, and the incumbents that did not initiate any action in Step 3 (and thus remain in the same location). The charters that initiated actions in Step 3 recalculate their expected profit in light of the new market structure. If the re-calculated profit from this step is lower than the profit from the status quo (equal to not entering for intending entrants and not moving for incumbents), then the charter school revises its decision and withdraws from the initiated action. All withdrawals become public knowledge. The withdrawals capture the reality that for some charters the opening process fails at some point.

**Step 5 (Iteration):** Step 4 is repeated until no charter that initiated actions in Step 3 chooses to withdraw from the initiation process.\(^{24}\)

\(^{24}\)Step 4 can only be repeated a finite number of times.
Step 6: **(Households’ school choice)** At the end of \( t \), households observe the demand shocks \( \xi_{igt} \) of all the schools operating in the market, including new entrants and incumbents. Households choose schools based on this information.

As explained above, we do not estimate this model directly. However, the unique equilibrium of this model enables the likelihood-based estimation that we carry out. Uniqueness is a consequence of the assumptions on timing, action initiation (allowed only in Step 3) and action revision (when charters revise their actions, they do not take into account that other charters are revising actions at the same time). These timing assumptions produce a slow release of information among charters, such that at the end of Step 5 every charter believes that with probability one its competitors will undertake the actions that they actually undertake. Hence, timing gives a special structure to the beliefs of charters about their competitors’ actions. Our assumptions are thus equivalent to adopting an equilibrium selection rule to choose among the multiple equilibria that a simultaneous-move game would otherwise have.

To summarize, we model the market as the interaction of schools and households, and describe this interaction by the multistage game specified above. In the final stage of the game, households choose schools given the supply of schools and their (common) expectations about schools’ demographic composition. Schools form expectations about schools’ demographic compositions in the same way as parents, and predict expected enrollment based on those expectations. The other stages of the game represent the strategic interaction of the schools. In particular, we assume that schools play Perfect Bayesian Equilibrium. In equilibrium, given public information on schools’ intended actions every school forms consistent beliefs about the equilibrium market structure, households’ choices and the resulting peer compositions. Every charter school chooses the strategy that maximizes its expected payoff conditional on these beliefs, intended market structure and allowed set of choices.

Note that the sorting of households across schools can in principle exhibit multiple equilibria due to multiple consistent beliefs about the demographic composition of schools. For instance, white households may choose school A if they believe that other white households will attend A, yet they may choose school B if they believe other white households will attend B. The disutility of traveling should in principle mitigate this issue: in our example, white households may not care about school B if it is located far enough from their residences. Nonetheless, we cannot completely rule out the possibility of multiple equilibria. This issue does not affect the estimation of our demand-side parameters because we impose equilibrium and use observed student demographics, \( D \), to calculate the predicted market shares in \( (16) \). The counterfactuals, however, might be affected. Hence, we will examine the local uniqueness of the sorting equilibrium at the estimated parameter values (as in Ferreyra 2007). In addition, the use of a *tâtonnement*-type of algorithm to compute our equilibrium will alleviate some of the concerns related to multiple equilibria, as this type of algorithm naturally describes the path that moves the economy from one equilibrium to another.

### 4 Data and Estimation

To estimate the model, we proceed in three stages. First, we estimate demand-side parameters \( \theta^d \). Second, we estimate supply-side parameters \( \theta^s \). Third, we estimate proficiency rate parameters \( \theta^q \). Below we describe the data used to estimate the model, and the three estimation stages.

#### 4.1 Data

The data required to estimate the model consists of enrollment shares for schools in each market; school characteristics; neighborhood percent of children enrolled in charter schools and average
distance traveled by students enrolled in public or charter schools; information on the joint distribution of household residential location, income and demographic characteristics for each market; and number and characteristics of the schools that enter, exit and relocate each year during the sample period.

Our data includes 65 markets (13 grades times 5 years) and $J = 281$ campuses, for a total of $J^D = 1,269$ school-year observations and $J^X = 8,112$ school-grade-year observations. It also includes $J^C = 153$ neighborhood-year observations. Since we do not have direct information on the number of children eligible for each grade in each year, Appendix III describes how we estimate market size. Based on school-grade-year enrollment and grade-year market sizes we then calculate the vector $S$ with 8,112 school-grade-year enrollment shares.

Recall that we have observe the following school characteristics: governance (public, charter, Catholic, other religious, private non-sectarian), location, grade span, focus, peer characteristics (percent of students of each ethnicity and low-income status), and tuition for private schools. Some school characteristics change over time while others remain constant. Location varies for schools that move during the sample period. Grade span varies for a number of schools that either add or drop grades over the period. Entry and exit of schools offering a given grade as well as changes in grade span of the existing schools affects the composition of households’ choice sets. Thematic focus is constant over time and across grades within a school. Given the lack of time (and grade, for the most part) variation of tuition among private schools, tuition can also be viewed as a time-invariant school characteristic. For a given school, peer characteristics change over time. Proficiency rates vary over time.

In the model, the economy is a collection of locations. For the sake of our demand estimation, a location $\ell$ consists of a Census block group (there are 433 block groups in D.C.), and each location is populated by households characterized by the grade that their child must attend (K, 1, ..., 12), race (black, white or hispanic), income, and poverty status (whether they qualify for free- or reduced-lunch or not). Ideally, we would observe the joint distribution of child grade requirement, race, parental income and child poverty status at the block group level, and we would observe it for each year between 2003 and 2007. Since this is not the case, Appendix IV describes how we use 2000 Census data to non-parametrically estimate this joint distribution for year 2000 first and then for every year in our sample period.\(^{25}\)

Once we obtain this joint distribution, we randomly draw $ns = 100$ households for each market.\(^{26}\) In the absence of data on the distribution of child age by grade, we assume two ages per grade (ages 5 and 6 in kindergarten, 6 and 7 in first grade, etc.), and we draw an equal number of children of each age per grade.

At first we attempted to construct school choice sets for households in every location and grade that included all the charter and private schools offering that grade but only the public schools assigned to that location given attendance zone boundaries. Attendance zones are larger for middle and high schools than for elementary schools, and boundaries changed once during our sample period (in 2005). Appendix IV describes how we assigned each block group to an elementary, middle and high school attendance zone in each year. However, based on our resulting assignment

\(^{25}\)Our estimation combines school-level data with Census aggregate household data. These two sources are generally consistent except in one aspect, namely the percent of low-income students. Schools report that approximately 60 percent of their students receive free- or reduced- lunch, yet only 46 or 47 percent of school-age children qualify for it according to the Census. The discrepancy is worse for elementary schools than high schools. In future versions we will explore either dropping poverty status information altogether, or inflating the model’s predicted percent low income students by a grade-level multiplier in order to match the data.

\(^{26}\)Note that $ns = 100$ implies 6,500 household draws in total since we have 65 markets. When we began the project, RAM limitations prevented us from using larger values of $ns$. We have overcome some of those limitations now and will explore sensitivity of our results to greater values of $ns$. 

21
and other sources (Filardo et al 2008, and phone conversations with DCPS staff), we concluded that the actual assignment mechanism in D.C. was based on residential location only to a limited extent and was not systematic across the District. For instance, Filardo et al (2008) document that approximately half of the children enrolled in public schools attend an out-of-boundary school. Thus, we opted for modeling the choice set available to a household interested in a given grade as the full set of schools offering that grade - namely, as though there were open enrollment in public schools. In future versions we will explore intermediate solutions between a pure residence-based assignment and a pure open-enrollment system.

4.2 Demand Estimation

In the first stage of estimation we estimate the utility function parameters that explain the observed market shares and the school choices made by households. We formulate household choice of school as a discrete choice problem and estimate preference parameters using an approach based on BLP. An important point of departure relative to BLP is our inclusion of school endogenous peer characteristics in household utility. BLP allows for endogeneity in prices, yet prices are determined by producers. Our endogenous characteristics, in contrast, are the outcome of aggregate household choices. They are similar to the local spillovers in Bayer and Timmins’ (2007) sorting model.

To estimate the demand parameters \( \theta^d \), we proceed in two stages. First we use Generalized Method of Moments (GMM) to match market shares at the school-grade-year level, student demographic composition at the school-year level, and neighborhood average fraction of students attending charter schools, and distance traveled to public and charter schools. Among the demand-side parameters estimated via GMM is a set of campus fixed effects. Thus, in the second stage we regress these campus fixed effects via Minimum Distance Estimation (MDE) on time-invariant school characteristics. The residuals from these regressions are our estimates of school quality \( \xi_j \).

In what follows we lay out the details of our demand estimation.

We begin by calculating the predicted school-grade-year market shares, school-year demographic compositions and neighborhood-year percent of children in charter schools and average distance traveled to public and charter schools. Consider the \( ns \) children eligible to attend grade \( g \) in year \( t \) in our . The predicted enrollment in school \( j \), grade \( g \) at time \( t \) is

\[
\hat{N}_{jgt} = \frac{M_{gt}}{ns} \sum_{i=1}^{ns} \hat{P}_{jgt} \left( y_{j,y-j,\bar{D}_{jt},\bar{\bar{D}}_{jt},\xi_{jgt},\xi_{j-gt},\pi_{jgt},\pi_{j-gt},X_{ijt}}; \theta^d \right) \tag{23}
\]

Denote by \( X_t \) the union of the \( X_{ijt} \) sets. Based on the above, the predicted enrollment share for \( (j, g) \) at \( t \) is equal to \( \hat{S}_{jgt} = \frac{\hat{N}_{jgt}}{M_{gt}} \). Thus, the school’s predicted enrollment is equal to \( \hat{N}_{jt} = \sum_{g \in \mathcal{K}_{jt}} \hat{N}_{jgt} \), and predicted school peer characteristics are as follows:

\[
\hat{D}_{jt} = \frac{\sum_{g \in \mathcal{K}_{jt}} \left( \frac{M_{gt}}{ns} \right) \sum_{i=1}^{ns} D_i \hat{P}_{jgt}(\cdot)}{N_{jt}} \tag{24}
\]

where \( D_i \) are household \( i \)’s demographic characteristics. In the expressions above, the scaling factor \( \frac{M_{gt}}{ns} \) adjusts for differences in actual size across markets even though we randomly draw the same \( (ns) \) number of children for each market. Similarly, denote by \( \bar{\bar{C}}_{kt} \) the \( \bar{\bar{C}} \times 1 \) vector of predicted average values for neighborhood \( k \) in year \( t \) (we use \( C \) to denote neighborhood cluster). In our application, this vector contains the following \( \bar{\bar{C}} = 3 \) elements: percent of children enrolled in charter schools (relative to the total enrolled in public and charter schools), average travel distance
for children enrolled in public schools, average travel distance for children enrolled in charter schools. Use \( \tilde{C}_{kt} \) to denote the observed counterpart of this vector.

We assume that \( E(\tilde{D}_{jt} | X_t) = \hat{D}_{jt} \). Thus, observed peer characteristics \( \tilde{D}_{jt} \) are different from their expected value due to sampling (and perhaps measurement) error:

\[
\tilde{D}_{jt} = \hat{D}_{jt} + u^D_{jt} \tag{25}
\]

Similarly, we assume that \( E(\tilde{C}_{kt} | X_t) = \hat{C}_{kt} \), and that observed neighborhood cluster data are different from their expected value due to sampling or measurement error:

\[
\tilde{C}_{kt} = \hat{C}_{kt} + u^C_{kt} \tag{26}
\]

Since parents observe the unobserved (to us) school characteristics \( \Delta \xi_{jgt} \) when choosing schools, the school demographic composition \( \tilde{D}_{jt} \) that results from household choices is correlated with \( \Delta \xi_{jgt} \). Let \( Z^X_{jgt} \) be a row vector of \( L^X \) instruments, \( Z^D_{jt} \) be a row vector of \( L^D \) instruments and \( Z^C_{kt} \) be a row vector of \( L^C \) instruments. In our preferred specification, \( L^X = 330 \), \( L^D = 230 \), \( L^C = 18 \). Vertically stacking all observations yields matrices \( Z^X \) (dimension \( J^X \) by \( L^X \)), \( Z^D \) (dimension \( J^D \) by \( L^D \)) and \( Z^C \) (dimension \( J^C \) by \( L^C \)).

Following BLP and Nevo (2000, 2001), we assume that the school-grade-year deviation from a school’s unobserved mean quality is mean independent of the corresponding instruments:

\[
E[\Delta \xi_{jgt} | Z^X_{jgt}] = 0 \tag{27}
\]

In addition, we assume that the sampling error in student demographics and in neighborhood data is mean independent of the corresponding instruments:

\[
E[u^D_{jt} | Z^D_{jt}] = 0 \tag{28}
\]

\[
E[u^C_{kt} | Z^C_{kt}] = 0 \tag{29}
\]

Recall that vector \( u^D_{jt} \) has \( \tilde{D} \) elements, and \( u^C_{kt} \) has \( \tilde{C} \) elements. Hence, these conditional moments yield the following \( (L^X + L^D + \tilde{D} + L^C + \tilde{C}) \) moment conditions:

\[
E \left[ (Z^X_{jgt})' \Delta \xi_{jgt} \right] = 0 \tag{30}
\]

\[
E \left[ (Z^D_{jt})' u^D_{jt} \right] = 0 \tag{31}
\]

\[
E \left[ (Z^C_{kt})' u^C_{kt} \right] = 0 \tag{32}
\]

where \( u^d_{jt} \) and \( u^c_{jt} \) indicate the sampling error in a specific demographic characteristic \( d \) (for instance, in percent white students) or neighborhood-level variable \( c \) (for instance, percent of children in charter schools). Vertically stacking all observations yields vectors and rearranging elements yields vectors \( \Delta \xi, u^D \) and \( u^C \) with \( J^X, (J^D + \tilde{D}) \) and \( (J^C + \tilde{C}) \) rows respectively. The first set of \( J^D \) rows in vector \( u^D \) correspond to the first demographic characteristic; the second set set to the second demographic characteristic, and so forth for the \( \tilde{D} \) demographics. Vector \( u^C \) has a similar structure for neighborhood-level variables.
In order to interact the sampling error for each demographic characteristic with every instrument in $Z^D$, we introduce matrix $\tilde{Z}^D$, which is block diagonal and repeats $Z^D$ along the diagonal for a total of $\tilde{D}$ times. Similarly, block-diagonal matrix $\tilde{Z}^C$ repeats $Z^C$ along the diagonal for a total of $\tilde{C}$ times. We use the term "share moments" for (30), "demographic moments" for (31), and "neighborhood moments" for (32).

The sample analogs of (30), (31) and (32) are the following vectors:

$$
\begin{align*}
\lambda_X(\Delta \xi) &= \frac{1}{J^X} Z^X' \Delta \xi
\\
\lambda_D(\Delta \xi, \theta^d) &= \frac{1}{J^D} \tilde{Z}^D' \cdot u^D
\\
\lambda_C(\Delta \xi, \theta^d) &= \frac{1}{J^C} \tilde{Z}^C' \cdot u^C
\end{align*}
$$

with $L^X$, $(L^D \cdot \tilde{D})$ and $(L^C \cdot \tilde{C})$ elements respectively.

We estimate the model using Generalized Method of Moments (GMM). To estimate the BLP model, researchers typically rely on a nested-fixed point algorithm. This solves for the vector of common utilities $\delta$ that equates predicted and observed market shares each time that a value of $\theta^d$ is evaluated. As explained by Dube et al (2011), the algorithm is slow and potentially inaccurate. Thus, building on Su and Judd (2011), Dube et al (2011) recast the BLP demand estimation as a mathematical programming with equilibrium constraints (MPEC) problem that simultaneously calculates common utilities and estimates preference parameters. While the typical demand-side BLP approach would consist only of the share moments, we augment our MPEC objective function with the demographic and neighborhood moments.

We assume that sampling errors $u^D_{jt}$ and $u^C_{kt}$ are independent. Further, they are independent of the elements upon which households base their choices, including $\Delta \xi_{jgt}$. Thus, we write our MPEC problem as follows:

$$
\begin{align*}
\min_{\Delta \xi, \theta^d} \begin{bmatrix}
\lambda_X(\Delta \xi) \\
\lambda_D(\Delta \xi, \theta^d) \\
\lambda_C(\Delta \xi, \theta^d)
\end{bmatrix}' \begin{bmatrix}
V_X \\
V_D \\
V_C
\end{bmatrix}
\times
\begin{bmatrix}
\lambda_X(\Delta \xi) \\
\lambda_D(\Delta \xi, \theta^d) \\
\lambda_C(\Delta \xi, \theta^d)
\end{bmatrix}
\end{align*}
$$

where the sample moments are defined as in (33) for some positive definite matrices $V_X$, $V_D$ and $V_C$.$^{27}$ The MPEC algorithm simultaneously searches over values for $\Delta \xi$ and $\theta^d$; given values for these, it calculates the predicted market shares, peer characteristics and neighborhood-level variables. The constraints of the MPEC problem ensure that the observed enrollment shares $S$ match the predicted enrollment shares $\hat{S}$ given values for the preference parameters, demand shocks and observed peer characteristics. Our standard errors are robust to arbitrary within-school correlation of $\Delta \xi$ (across grades and over time), arbitrary correlation of sampling errors $u^c$ within a school-year, and arbitrary correlation of sampling errors $u^c$ within a neighborhood-year.

Finally, the decomposition of the demand shock in (11) suggests the inclusion of school-, grade- and time-fixed effects in the utility function. Since the school-specific dummy variables capture both the value of school characteristics that do not vary over time, $y_j \beta$, and the school-specific mean of unobserved quality, $\xi_j$ in (10), we apply a minimum-distance procedure as in Nevo

\footnote{We use $V_X = (Z^{X'X})^{-1}, V_D = (\tilde{Z}^{D'\tilde{D}})^{-1}$ and $V_C = (\tilde{Z}^{C'\tilde{C}})^{-1}$.}
In the second stage of estimation we match the entry, exit and relocation decisions of charters in order to estimate the supply parameters \( \theta^s = \{ \mu_\xi, \sigma_\xi, \sigma_{\Delta \xi}, \zeta, V, F, w \} \). In our empirical application we consider \( L = 39 \) locations (neighborhood clusters), \( Y = 5 \) focuses and \( K = 3 \) grade levels for a total of approximately 600 entry points. Over our sample period, these amount to 3,000 instances of possible charter entry, exit or relocation.\(^ {28} \) Yet as Table 2 illustrates there are only 36 entries, 3 exits and 20 relocations over our sample period. Such low number of episodes would not enable us to calculate the distribution of outcomes from the entry-exit-relocation game. Hence, we approximate this distribution by calculating the logit probability of these outcomes conditional on the observed market structure.

Some parameters in \( \theta^s \) can be estimated based on demand-side estimates. For instance, we can estimate the mean and variance of permanent quality for entrants, \( \mu_\xi \) and \( \sigma_\xi \), based on our demand-side estimates of \( \xi_j \)'s for charters. Similarly, we can estimate \( \sigma_{\Delta \xi} \) as the variance of the distribution of the \( \Delta \xi \) residuals recovered in the demand-side estimation.

To estimate the remaining parameters in \( \theta^s \) we use Maximum Likelihood Estimation (MLE). Denote by \( \hat{I}_t \) the information available to the econometrician on market structure for period \( t \). The likelihood function is then

\[
\hat{L} (\theta^s) = \prod_{t=1}^{T} \left\{ \prod_{j=1}^{C_t} \Pr \left( d_{jt} = \hat{d}_{jt} \mid \hat{I}_t \right) \right\} \left\{ \prod_{\ell=1}^{L} \prod_{y=1}^{Y} \prod_{\kappa=1}^{K} \Pr \left( d_{\ell y k} = \hat{d}_{\ell y k} \mid \hat{I}_t \right) \right\}
\]

(36)

where \( T \) is the number of periods in the data and \( C_t \) is the number of charter incumbents at the beginning of period \( t \). As for the probabilities inside \( \hat{L} (\theta^s) \), \( \Pr \left( d_{jt} = \hat{d}_{jt} \mid \hat{I}_t \right) \) is the conditional probability that incumbent \( j \) chooses action \( \hat{d}_{jt} \) given the observed market structure. We can condition on the observed market structure (as opposed to the incumbent’s beliefs about others’ actions) because our entry-exit-relocation game implies that market structure is known to charters with probability one when making their final decisions, at the end of Step 5 of the game.

Recall that the number of possible actions for the incumbent is equal to \( L + 1 \), as the incumbent can operate in any of the \( L \) locations or exit. We assign \( \ell = 0 \) to the option of exiting. Thus, the probability that the incumbent chooses location \( \hat{d}_{jt}, \hat{d}_{jt} \in \{0, 1, 2, ..., L\} \) is given by

\[
\Pr \left( d_{jt} = \hat{d}_{jt} \mid \hat{I}_t \right) = \frac{\exp \left( \pi^i_{j \ell \hat{d}_{jt}} \left( \hat{I}_t \right) \right)}{\sum_{\ell=0}^{L} \exp \left( \pi^i_{j \ell \ell} \left( \hat{I}_t \right) \right)}
\]

(37)

\(^ {28} \)In our data there is at most one entry per entry point and year.
where $\bar{\pi}_{jt}^i(\bar{I}_t)$ is the mean profit of incumbent $j$ at time $t$ if it locates in $\ell$. The profit is given by (22). The other set of probabilities in $\bar{I}(\theta^q)$, $Pr\left(d_{t+}\mid\bar{I}_t\right)$, describes entry behavior in each entry point $(\ell, y, \kappa)$. The probability of entering is given by

$$Pr\left(d_{t+}\mid enter\mid\bar{I}_t\right) = \frac{\exp\left(\bar{\pi}_{\ell y}^i(\bar{I}_t)\right)}{1 + \exp\left(\bar{\pi}_{\ell y}^i(\bar{I}_t)\right)}$$

(38)

where $\bar{\pi}_{\ell y}^i(\bar{I}_t)$ is the mean profit from (21). Since the probabilities in (38) and (37) also depend on the demand side parameters $\theta^d$, we use our estimates of these parameters when conducting MLE.

In order to calculate the likelihood function for a given parameter value we need to calculate the expected profits for entrants and incumbents, given by (21) and (22) respectively. This calculation poses several computational challenges. First, expected profits are a function of expected equilibrium demand. This means that the charters (and the econometricians) must solve for the equilibrium that would ensue if the charter were to take the action under consideration. Given that there are more than 600 potential entrants and incumbents per period, the equilibrium must be computed at least 600 times for each period and parameter point. Second, when charters choose actions they do not observe $\xi$’s for themselves or their competitors. Moreover, no charter observes $\xi_j$ for potential entrants - not even the entrant herself. Thus, when computing the equilibrium to calculated expected demand, each charter must integrate over the distribution of $\xi_i$ for each of its grades and for each grade covered by its competitors, and over the distribution of $\xi_j$ for each potential entrant. Third, the possibility of multiple equilibria in household sorting complicates the calculation of equilibrium demand.

To overcome these computational challenges we will proceed as follows. First, since charters tend to be small none of them in isolation may induce significant resorting. Thus, we will compute (21) and (22) assuming that the demographic compositions of other schools is not affected by the actions of individuals charters, which allows us to avoid re-calculating the equilibrium. While this assumption may not be appropriate for some counterfactuals, we believe it is acceptable for estimation. Second, we assume that the first-order uncertainty faced by a charter school is about its own $\Delta \xi$ and $\xi$. Hence, a charter will integrate over the distribution of its own demand shocks but will set demand shock for other charters equal to their mean when evaluating expected profits. We will check the validity of this assumption at the parameter estimates. Third, avoiding equilibrium calculations will allow us to bypass the issue of multiple equilibria in household sorting.

### 4.4 Proficiency Rate Estimation, and Summary

Although we cannot identify the parameters of the achievement function in (4), we can identify the parameters of the expected proficiency rate in (18), which is related to the observed proficiency rate $\bar{q}_{jt}$ as follows:

$$\bar{q}_{jt} = y_j \phi^q + \bar{D}_{jt} \omega^q + y_j \bar{D}_{jt} \omega^q + \xi_j^q + \xi^q + \Delta \xi_{jt} + \nu_{jt}^q \tag{39}$$

Here, the error term is the addition of the a school-year unobserved shock on proficiency $\Delta \xi_{jt}$ and school-year sampling or measurement error in proficiency rates $\nu_{jt}^q$. Since $\Delta \xi_{jt}$ may be correlated with the demand shocks $\Delta \xi_{jt}$ observed by parents when choosing schools, $\bar{D}_{jt}$ is likely

---

29 Aggregate achievement data, such as average test scores, would allow us to identify a subset of parameters of the achievement function. Detailed notes are available from the authors.
to be correlated with $\xi_{jg}^q$, thus requiring the use of instrumental variables. Denote by $Z^Q$ the set of instruments used to this end.

In the equation above, it is not possible to estimate the coefficient on school time-invariant characteristics $\alpha^q$ and the school fixed effects $\xi_j^q$. This issue is similar to the one we face when estimating utility function parameters, and we therefore solve it in a similar way. Hence, to estimate the parameters of the proficiency rate function we first run an instrumental variables (IV) regression of passing rate on campus and year fixed effects, school demographic composition and interactions between school demographic compositions and time-invariant school characteristics. Then we regress the campus fixed effects estimates on time-invariant school characteristics. The residuals from this second regression are our estimates of $\xi_j^Q$. We use the term "value added" to refer to these residuals.

To summarize, to estimate the parameters of our model we proceed in three stages. First, we exploit orthogonality conditions related to demand shocks and demographic and neighborhood sampling errors in order to estimate utility function parameters. Second, we match charter school decisions in order to estimate supply-side parameters. Third, we estimate the proficiency rate parameters.

4.5 Instruments

For the identification of the demand-side and proficiency rate parameters, the main concern is the endogeneity of peer characteristics in the utility and proficiency rate functions. Much of this concern is alleviated by the inclusion of school-, grade- and time-specific dummy variables following the demand shock decomposition in (11). However, the concern remains that when households choose schools, they observe the school-grade-time specific deviation $\Delta \xi_{jgt}$, which we do not observe. This induces correlation between student peer characteristics $D_{jt}$, which are an outcome of household choices, and $\Delta \xi_{jgt}$.

To address this correlation, we instrument for a school’s $D_{jt}$ using local demographics of school’s neighborhood as of year 2000 (recall that our sample is between 2003 and 2007). To the extent that these demographics are correlated with the demand shocks $\xi_{jgt}$, this correlation is absorbed by the campus fixed effect $\xi_j$. Hence, we expect $\Delta \xi_{jgt}$ to be mean-independent of local demographics. Thus, our $Z^X$ matrix contains the following instruments pertaining to the local neighborhood: percent of school-age children of each race and poverty status, average family income, average house value, percent of owner-occupied housing units, average number of children per family, number of public, private and charter schools, percent of families in each income bracket, ward indicators, and interactions between some of these variables with school type and grade level. In addition, $Z^X$ contains campus, grade and year dummies.

Matrix $Z^D$ contains the instruments for the sampling error in school-year student demographics. These instruments include school type, focus, and interactions of school type with ward. Matrix $Z^C$ contains the following instruments for sampling error in neighborhood-level variables: neighborhood-level number of public and charter schools, average family income, racial composition of school-age children, age distribution of school-age children, and ward-level dummies. Finally, matrix $Z^Q$ used for the proficiency rate estimation contains local demographics for the school’s neighborhoods, similar to $Z^X$. It also includes campus- and year-level dummies.

30 DC includes 8 electoral wards. These wards represent fairly different neighborhoods.
4.6 Identification

We first discuss the identification of demand-side and proficiency rate parameters, and then of supply-side parameters. Lack of individual achievement data prevents us from identifying the achievement function parameters \((\alpha^o, \beta^o, \omega^o, \tilde{\beta}^o)\). Nonetheless, the parameters of the utility function are identified.

The parameters of the baseline component of utility, \((\alpha, \beta)\) in equation (10), are identified. All moments contributed to the identification of these parameters. Parameters \(\alpha\) capture both the household preference for peer characteristics and the impact of peer characteristics on student achievement: \(\alpha = \alpha^p + \phi \alpha^a\). In addition to \(\alpha^a\) not being identified, \(\phi\) is not identified either as discussed below. Since we cannot identify \(\alpha^o\), the individual components of \(\alpha\) are not identified. A similar reasoning applies to \(\beta\) (baseline utility of time-invariant school characteristics) and its individual components. Given that the default demographic group is (black, low income), \(\beta\) reflects black and low-income households’ preferences. Parameters \(\alpha\) are identified by the extent to which black, low-income students mix with other races and economic status in school, and parameters \(\beta\) are identified by the variation in the fraction of black and low-income students among schools of different types and focuses.

Parameters \((\tilde{\alpha}, \tilde{\beta}, \gamma, \omega, \varphi)\) of the household-specific component of utility in (12) are identified. The identification of these parameters comes from the demographic and neighborhood moments. Parameter \(\omega\) is the utility from the portion of achievement due to a student’s own characteristics: \(\omega = \omega^a \phi\). While \(\omega\) is identified, \(\omega^o\) is not as discussed above. Hence, the weight of achievement on utility \(\phi\) is not identified either. Since \(\omega_0\) is normalized to zero for the outside good and the default demographic group is (black, low income), \(\omega\) is the difference in relative utility of going to school versus not going for other demographic groups relative to the default. It is identified by the variation across demographic groups in the fraction of school-age children who are enrolled in school.

Parameter \(\tilde{\alpha}\) is identified. Parameter \(\tilde{\beta}\) is the coefficient on the interaction between household demographics and school focus. It is a weighted average of the household’s preference for the school focus and focus impact on achievement: \(\tilde{\beta} = \tilde{\beta}^p + \phi \tilde{\beta}^a\). While \(\tilde{\beta}\) is identified, neither \(\phi\) nor \(\tilde{\beta}^o\) are identified, as we saw above. Thus, \(\tilde{\beta}^o\) is not identified either. From the perspective of counterfactual analysis of the impact of policies on school choice, identification of the components of \(\alpha, \beta\) and \(\tilde{\beta}\) is not required.

Parameters \(\tilde{\alpha}\) and \(\tilde{\beta}\) are the difference between white, hispanic and non-poor households relative to default households in preferences over peer characteristics and time-invariant school characteristics. These parameters are identified by the extent to which these groups mix with others in schools and by their enrollment patterns across schools of different types and focuses. Parameter \(\gamma\) is the disutility of geographic distance between the household’s residence and the school. It is identified by the neighborhood-level variation in distance traveled to school and fraction of children enrolled in charters. In general, variation in school type, focus and location is critical to the identification of preference parameters. Parameter \(\varphi\) is the utility from the consumption of all other goods. It is identified by the variation in household income, school tuition and peer characteristics across schools.

School fixed effects \(\xi_j\) are identified by having multiple grades and years per school (all of them are included in the estimation). Since \(\xi_{qgt} = 0\) for the outside good, \(\xi_j\) represents the difference in utility from attending school \(j\) relative to the outside good. Grade fixed effects \(\xi_g\) are identified by having multiple schools and year per grade. Since first grade is the omitted category, \(\xi_g\) is the difference in the utility of going to school rather than choosing the outside good for grade \(g\) relative to first grade. Year fixed effects \(\xi_t\) are identified by having multiple schools and grades.
per year. Since 2003 is the omitted year, \( \xi_t \) is the difference in the utility of going to school rather than choosing the outside good in year \( t \) relative to 2003.

From a formal perspective, a condition for identification is that the matrix of derivatives of the sample moments with respect to the parameters have full rank. Evaluated at our parameter estimates, this matrix indeed has full rank.\(^{31}\)

Proficiency rate parameters in (39) are identified by the variation in focus across schools and in student demographics across schools and over time. Having multiple observations per school and multiple observations per year allows us to identify the school and year fixed effects, respectively.

On the supply side, the charter entry fee \( \zeta \) is identified by the frequency of entry in the data. Fixed costs \( F \) are identified by the number of charter schools relative to the number of students and entry points in the data. Variable costs \( V \) are identified by the size distribution across schools. Moving costs \( w \) are identified by the frequency of moves. The parameters of the distribution of permanent quality, \( \mu_{\xi} \) and \( \sigma_{\xi} \), are identified by the variation in school fixed effects for charters that have entered.\(^{32}\) The standard deviation of the deviation from mean demand shocks, \( \sigma_{\Delta \xi} \), is identified by the variation in school-grade-year market shares above and beyond that which can be explained by observable school characteristics.

### 4.7 Computational Considerations

Currently we have estimated the demand and academic proficiency sides of the model. While the estimation of the academic proficiency function is straightforward, the estimation of the demand-side parameters is not because this requires solving the MPEC problem in (35). This problem has 8,452 unknowns – 340 parameters in \( \theta^d \) (including 281 campus fixed effects) and 8,112 elements in the \( \Delta \xi \) vector – and 8,112 equality constraints (equalities between predicted and observed market shares).

We coded the MPEC problem in MATLAB using the code from Dube et al (2011) as a starting point. Rather than code analytical first-order and second-order derivatives for the MPEC problem, we chose to use the automatic differentiation capabilities in TOMLAB's TomSym package (included in the Base module). This enabled us to experiment with different model specifications and instruments by only modifying the objective function and the constraints, and leaving TomSym to recompute the derivatives. Automatic differentiation can be memory intensive, especially for second-order derivatives, but our problem size and our choice of the SNOPT and MINOS solvers available from TOMLAB made it efficient and easy. SNOPT and MINOS require only analytic first order derivatives (which were computed by TomSym in our case). In contrast, Dube et al (2011) supplied second-order derivatives to the KNITRO solver and used the Interior/Direct algorithm. Avoiding the provision of analytical first- or second-order derivatives greatly facilitated our use of MPEC.

We used both the SNOPT and MINOS solvers in the following manner: we ran a few hundred major iterations of SNOPT to establish the basis variables (the variables of interest for the optimization problem) and to approach a local minimum, and then handed over the problem to MINOS in a "warm-start" fashion to converge to the local optimum. This combination allows

\(^{31}\)The condition number for this matrix is in the order of 1e3. We ran multiple specifications and computed this matrix for each one. Based on a QR decomposition of this matrix we eliminated the parameters that created high collinearity among the columns of the matrix. The parameters we eliminated are in fact those for which we would expect weak identification given our data. This process allowed us to arrive at our preferred specification.

\(^{32}\)In principle, it might seem that estimating the distribution of \( \xi_j \) off the charters that have actually entered would lead to biased estimates by not taking into account the quality of the potential entrants that have not entered. This bias does not exist, however, because we assume that potential entrants do not observe their quality \( \xi_j \) when they decide on entry.
us to exploit the virtues of each solver and solve the problem in the most efficient way. Broadly speaking, SNOPT is better suited for a large numbers of unknowns, but makes progress only by changing its limited-memory approximation of the full Hessian of the Lagrangian between major iterations. Once it gets to the point at which it no longer updates the Hessian approximation, it stops making progress. In contrast, MINOS works with the exact Lagrangian and can also make many updates to a full quasi-Newton approximation of the reduced Lagrangian. Hence, MINOS can make progress even when SNOPT cannot provided the size of the problem is not too large. At the same time, MINOS only works well if started sufficiently close to a local minimum. Hence, SNOPT starts the problem with the full set of unknowns, quickly solves for $\Delta \xi$ and establishes $\theta^d$ as the basis variables. After having reduced the size of the problem, it hands the optimization problem over to MINOS.

This approach proved fast and accurate, allowing us to obtain results with 5 or 6 decimal digits of precision.\textsuperscript{33} For our preferred specification, SNOPT-MINOS took 10.5 hours for the first stage MPEC problem, and 3.5 hours for the second stage MPEC problem on a workstation with a 2.8 GHZ AMD Opteron 4280 processor with 64GB of RAM.\textsuperscript{34} The computational time compares favorably with what Dube et al (2011) and Skrainka (2011) report for BLP problems, particularly taking into account that our problem has complicating features relative to straightforward BLP. The first is that our objective function includes demographic moments in addition to share moments. The second is that we have a relatively large number of products (schools) relative to the number of markets (grade-years). In a typical industrial organization context there are many markets relative to products. This gives rise to a sparser Jacobian, which in turn speeds up performance (see Dube et al 2011 for a discussion of how the speed advantage of MPEC declines as the sparsity of the Jacobian falls). The third complicating feature is the presence of some very small market shares, an issue related to the large number of schools relative to the number of students.

5 Estimation Results

5.1 Demand Side

Table 8 presents our preference parameter estimates. Most of our estimates are significant and of the expected sign, as explained below. The "baseline utility" column displays the estimates of the parameters in equation (10). Given the parameterization of household demographics, these parameters represent the preferences of black, low-income households. The remaining columns present estimates of the parameters in equation (12), which reflect differences in the preferences of white, hispanic and non-poor households with respect to the preferences of black, low-income households. Given our sample size and data variation, we have only been able to identify some of those interactions.

\textsuperscript{33}The precision is determined by a combination of the algorithm’s optimality tolerance, the condition number of the Jacobian at the optimum, and the size of the dual variables. We used an optimality tolerance of 1e-6 and re-scaled the problem as needed to ensure that the dual variables had order unity. The output logs report the Jacobian’s condition number, and these were checked. SNOPT and MINOS work best if the objective function gradients, the Jacobian of the constraints, and the dual variables are of order unity. This is easily achieved by multiplying the objective function and constraints by constant factors. We found that the solvers are 3-5 times faster by employing this scaling.

\textsuperscript{34}The workstation had many cores, but the SNOPT-MINOS solvers are single-threaded and so use only one core. The solvers had a peak memory consumption of 10GB when the derivatives were symbolically computed, and then worked with 5GB of RAM. On our 64GB workstation we could therefore run multiple jobs at once from multiple starting points.
Our estimates show that preferences over school types are quite heterogeneous across races and poverty status. For charters that do not belong to multi-campus organizations, blacks are 50% less likely to choose charters than public schools. However, they are 13% more likely to choose a multi-campus charter than a public school. Whites and non-poor households are less likely to choose charter than public schools, yet hispanics are 42 percent more likely to choose charters than public schools.

Blacks prefer public over Catholic schools, but whites are 81 percent more likely to choose Catholic over public schools. While blacks prefer public over non-Catholic private schools, whites are almost indifferent among those schools. Hispanics have a stronger preference than blacks for Catholic schools. These estimates make sense in light of the distribution of school choices by student race and poverty status displayed in Table 1c, according to which 60 or 70 percent of black, hispanic and low-income students attend public schools, and whites are almost evenly split among public, catholic, other religious and private non-sectarian schools. Note as well that households experience more utility from having their children in school rather than consuming the outside good at the middle and high school level than at the elementary level.

In terms of curricular focus, most students are indifferent among focuses. These estimates are consistent with the pattern of focus choices by student race and poverty status displayed in Table 6b, which shows that approximately 80 percent of students of each race and poverty status chooses a core curriculum. Given that 19 percent of Hispanic students chooses language, it is surprising that the coefficient on the interaction of language and hispanic is negative (though not significant). Yet given that hispanics exhibit a strong same-race preference, as described below, their choice of language-focused schools may not be due to language per se but rather to the fact that those schools attract other Hispanics.

Both whites and hispanics have strong same-race preferences. For instance, an additional 10 percentage points of white students in a school (with a concomitant reduction in percent of black students) makes a white family 144 percent more likely to choose the school. Similarly, an additional 10 percentage points of Hispanic students in a school (with a concomitant reduction in percent of black students) makes a Hispanic family 61 percent more likely to choose the school. This is consistent with the fact that the average black student in the public system in D.C. attends a school that is 90 percent black, the average white student attends a school that is 40 white, and the average hispanic student attends a school that is 37 percent hispanic (Filardo et al, 2008). It is also consistent with the pattern of school choices by student demographic characteristics displayed in Table 1c and with the student body characteristics by school type displayed in Table 1a. Further, our estimated racial preferences are in line with those in Hastings et al (2009), who documents that parents have preferences for peers of the same demographics, and with Bayer et al (2007), who documents households’ preference to self-segregate based on demographics. Non-poor households also prefer to attend schools with other non-poor households, though this preference is not as strong as the racial preferences described above.

We have allowed preferences for distance to vary depending on school type (public, charter or private). The disutility of traveling an extra mile to a public school is quite large, as having to travel an additional mile to a public school makes a family 68 percent less likely to attend that school than another public schools. However, according to our estimates there is no disutility in traveling to a charter or a private school. These estimates are consistent with the fact that children travel longer to charter than to public schools, and with the expectation that they would travel more to private than to public schools. Nonetheless, these estimates must be interpreted with caution because approximately 50 percent of children in public schools attend their assigned neighborhood schools. Consequently, we expect the preference for distance to public school to be downward biased.
Coefficient $\varphi$ in (31) captures sensitivity of private school enrollment to tuition. Our attempts to estimate this coefficient were not met with success, as the coefficient was poorly identified in the sample. After trying several specifications we settled for a linear specification in tuition, or $\varphi p_{jgt}$. Since tuition does not vary over time and barely varies across grades, we quantified tuition using the school average, $p_j$, and treated it as another time-invariant school characteristic. Hence, we estimated $\varphi$ via Minimum Distance Estimation, similarly to the coefficients on the other time-invariant school characteristics. The resulting coefficient on tuition is negative but not significant. The noise in the estimate is to be expected given that we measure tuition with error (as we have school-average tuition rather than tuition by grade) and only have data for 2002 (expressed in dollars of 2000) rather than for each year. Nonetheless, the magnitude of this coefficient is reasonable. According to our estimates, a $1000$ decline in tuition makes households 21 percent more likely to attend a (private) school. Families would be willing to pay $6,074$ to attend a public school that is one mile closer. They would also be willing to pay $663$ to attend a multi-campus charter rather than a public school. Whites would be willing to pay $4,704$ for an extra ten percentage points of white students in the school, and Hispanics would be willing to pay $2,500$ for an extra ten percentage points of Hispanic students in the school.

Overall, our model fits the data well. The correlation between observed and predicted value is equal to 0.91, 0.94 and 0.92 for school percent of white, hispanic and non-poor students respectively. It is equal to 0.81, 0.68 and 0.81 for neighborhood-level percent of students in charters, average distance traveled to public schools and average distance traveled to charter schools respectively. Distance traveled to public schools is quite difficult to fit given the absence of information on the enforcement of in-boundary enrollment. As Tables 9 and 10 show, our model captures students’ choices of school type and focus given their race and poverty status.

The main concern surrounding the utility function parameter estimates has to do with school capacity constraints. Consider, for instance, the negative coefficient on the charter indicator. If neither public nor charter schools faced capacity constraints, a negative coefficient on charter would indicate that households prefer public over charter schools holding other things constant. However, if charter schools have capacity limitations, a negative coefficient on charter could indicate either lack of preference for charter schools or lack of space in charters even though families prefer charter over public schools. In other words, it is possible that charter schools are in excess demand (i.e., that the number of families who wish to attend charters exceeds the number of available charter seats), yet if their capacity is lower than that of public schools, then the coefficient on charter is likely to be negative.

To disentangle the role of capacity, we need data on excess demand and/or school capacity. In the case of charters we need to know which schools are oversubscribed and by how much. In the case of public schools we need data on in- and out-of-boundary enrolment. We may also need data on capacity, which is a fluid concept in the case of charter schools given that they use building space differently than public schools. Unfortunately these data are not collected by any agency in D.C. In the absence of these data, we can only speculate as to the possible biases induced in our coefficients.

Capacity issues also arise in other markets. However, in ordinary markets price plays a rationing role, in the sense that excess demand leads to a higher price, which in turn clears the market. The absence of a price in the case of public and charter schools complicates matters. One might think that private schools are exempt of this problem because they charge a price, yet we believe this is true only to the extent that private schools behave like profit-maximizing firms. If they do not, then excess demand does not necessarily lead to a higher price. For instance, many Catholic schools face waiting lists yet they do not raise their price because they wish to remain affordable for families in the parish or the neighborhood, and hence ration access based on some
other mechanism (first come, first served; sibling preference; parish preference, etc.). The capacity issue, then, is potentially a concern for a large number of schools in the sample. To the best of our knowledge this problem has not been examined before in the context of demand estimation, and we are currently studying it.

To the extent that capacity is a problem, it would mostly affect the parameters of the common utility (corresponding to 2 in the model, and to the "Baseline Utility" column in Table 8 except for the distance coefficients in this column). Since the baseline utility parameters include campus fixed effects, and we regress these on time-invariant school characteristics to estimate school quality $\xi_j$, our estimates of school quality would probably be biased as well. While these time-invariant characteristics explain 68 percent of the variation in campus fixed effects, the residuals capture a number of unmeasured school characteristics (to the extent that they are constant over time) such as school culture, proximity to transportation, relations with the community, connections between the school and other organizations in D.C., existence of after-school and enrichment programs, features of the building site, characteristics of the school’s neighborhood which are not captured by student demographics, etc. Building capacity might be another unmeasured characteristic captured by school quality. With the exception of public schools in ward 3, which is the most economically advantaged in the city, most public schools lost enrollment between 2003 and 2007 and hence faced no capacity constraints, which would result in little bias in school quality estimates for public schools. But for charter schools facing excess demand we expect to underestimate school quality, which means that in the public-charter comparisons below we are likely underestimating the advantage of the best charter schools.

With these caveats in mind, Table 11 shows average public and charter school quality. When comparing all wards except for ward 3, average quality is (slightly) higher for charter than public schools, particularly for elementary/middle and middle schools. Faced with the choice between a public and a charter school of average quality, the difference is such that a family is 36 and 51 percent more likely to choose charters at the elementary/middle and middle school level, respectively. The differences are more dramatic for wards 7 and 8, the most disadvantaged in the city. Faced with the choice between a public and a charter school of average quality in wards 7 and 8, a household is 136, 49 and 125 percent more likely to choose charters for elementary/middle, middle and high schools. These differences are substantive, particularly when considering that charter school quality is likely underestimated for the best schools. In other words, school quality varies substantially across schools and plays a quantitatively large role explaining households’ choices of school.

To summarize, our preference estimates show substantial variation in household preferences over school characteristics. They also show substantial variation in school quality. Both variations create an entry opportunity for charters.

### 5.2 Academic Proficiency

Table 12 presents estimates of the passing rate function for math. Since our data consists of school-level passing rate in math tests for public and charter schools, we only have five school-year observations at most for each school. The change in the assessment instrument in 2005 led to large declines in passing rates. On average, passing rates were 52 and 51 percent in 2003 and 2004 respectively, and 29, 33 and 41 percent in 2005, 2006 and 2007 respectively. For some schools the swings in passing rates are particularly pronounced; since those schools have large enrollments the swings cannot be solely attributed to sampling error. Because of these data limitations, our achievement estimates should be taken with caution. We will only use these estimates to make predictions regarding achievement in our counterfactuals; in these predictions we will stress the direction of the change more than its magnitude.
Recall that in order to estimate the passing rate function, we regress the log odds of passing the math exam relative to not passing it, or \( \log(\text{pass rate} / (100-\text{pass rate})) \) on campus fixed effects, year fixed effects and school demographic characteristics. We instrument for the endogenous school demographic characteristics. We then regress school fixed effects on time invariant characteristics, and the residuals from this regression give us estimates of school value added (\( \xi_j^2 \) in (39)). Table 12 reports the resulting set of parameter estimates.

Our estimates indicate that school level affects proficiency, as the the relative odds of passing the math test are 54 lower in middle or high school than in elementary school. On average, charters have a negative effect in elementary school achievement (they lower the relative odds of passing by 73 percent compared to public schools) but not in middle or high school. Charters that belong to a multi-campus organization raise the relative odds of passing by 164 percent relative to single-campus charters. School curricular focus seems to make a difference, as "other focus" schools (many of which teach a curriculum specialized in math) raise the relative odds of passing by 233 percent. The coefficients on percent white and non-poor students are not significantly different from zero. The coefficient on percent Hispanic is significant but very small, as an extra 10 percentage points of Hispanic students raises the relative odds of passing by 0.09 percent.

In the Minimum Distance Estimation regression, only 23 percent of the variation in school fixed effects is explained by time-invariant school characteristics. This means that 77 percent of the variation in school value added is explained by unmeasured school characteristics such as leadership and culture, instructional style, management of human resources, policies to foster parental engagement, length of school day and year, use of instructional time, etc. The residuals from this regression – our estimates of school value added – are reasonable in that they induce a ranking of charter schools by value added that largely agrees with PCSB’s ranking (see, for instance, classification of schools by tier in http://www.dcpsb.org/data/images/pcsb%20book_dec1.pdf). For example, at the top of our ranking are Elsie Whitlow Stokes, Paul, the KIPP campuses, and DC Prep, which also top PCSB’s ranking.

School value added seems to play an important role in academic proficiency. Table 13 shows average value added for public and charter schools in all wards except for ward 3, and in wards 7 and 8. Attending a charter rather than a public school raises the relative odds of passing by 11 percent in all wards but 3, and by 12 percent in wards 7 and 8. The effect is larger for elementary/middle schools, where the relative odds of passing are 242 percent and 458 percent higher in all wards but 3, and wards 7 and 8 respectively. For middle schools the relative odds are higher by 77 and 75 percent in all wards but 3, and wards 7 and 8 respectively. For high schools in wards 7 and 8, relative odds are 31 percent higher.

The main concern with our proficiency rate estimates is that they could be biased due to the self-selection of students into schools. For instance, if highly motivated students selected into charters, this would lead to an overestimate of charter value added. Similarly, if students with high math ability selected into schools with a math focus, this would lead to an overestimate of the effect of "other focuses" (which includes math) and/or to an overestimate of the value added for those schools. Unfortunately these concerns cannot be addressed without individual level data. In addition, the direction of the bias is not clear. For example, while charters may attract the most motivated students, they may also attract students with persistently poor performance and disciplinary problems in public schools. In other words, there might be negative (rather than positive) selection into schools based on student unobservables.

To summarize, our academic proficiency estimates indicate substantial heterogeneity in school effectiveness due to school type, focus and value added. This, in turn, should encourage the entry of high-quality charters.
5.3 Counterfactual Analysis

Our structural estimates can be used to study a number of alternative policy scenarios. For illustrative purposes, Table 14 depicts some results from a policy consisting of the elimination of charter schools. In particular, we study how students would have sorted across schools in 2007 if charter schools had been closed that year. The table shows observed patterns of student sorting across schools, the model’s fit of the data, and the predicted sorting when charters are not allowed.

In 2007 charters attracted 22 percent of total student enrollment. In the counterfactual they attract zero percent. As the table shows, in the counterfactual most charter school students switch into public schools, and about 4% of all students switch from charters to Catholic schools. Most of these switches correspond to black and low-income students, who would make up for most of the enrollment in charter schools. The fact that a good fraction of students switch into Catholic schools when charters are not available suggests that at least some Catholic schools must have been hurt by charter expansion. This is consistent with the fact that after our sample period, the Archdiocese of Washington, D.C. converted seven Catholic schools into charters, and pointed to the proximity of charter schools as one reason for their decision (Bowen McShane 2011).

In addition to the effects on student sorting across schools, the elimination of charter would also have effects on student achievement. While we have not analyzed these yet, our achievement estimates indicate that for children leaving charter schools in all wards except 3, there could be large achievement losses at the elementary/middle and middle/school level, and the losses could be particularly large in wards 7 and 8.

6 Discussion, Extensions and Intended Counterfactuals

For all its richness, our data is limited in some regards. These limitations, most of which are due to the unavailability of the corresponding data, have forced us to ignore certain institutional features of charter schools in our model. As mentioned above, we do not observe school capacity or effective demand (i.e., the number of students who apply to the school). Thus, our model cannot capture a distinctive aspect of charter schools, namely that they must randomize access when oversubscribed. In addition, we do not observe the complete set of charter applications submitted to PCSB for authorization; we only observe the applications that were approved and entered the market. During the first part of our sample period there were two charter school authorizers in D.C., the BOE and the PCSB (see Section 2). Some have suggested that the BOE tended to authorize lower-quality applicants (Buckley and Schneider 2007). This, in turn, might have led prospective entrants to "shop" authorizers at the beginning of the sample period, and could have been reflected in a change in the distribution of school-specific quality when PCSB became the sole authorizer.

Once we complete our estimation, we will use our parameter estimates to conduct some counterfactuals. First, we will study the response of charter entry and student sorting to changes in per-student funding for charter schools. High schools are more costly to open and operate, and the relative lack of charter entry at the high school level might be related to poor funding. Further, since real estate is a prime concern for charters, we are particularly interested in examining the consequences of raising the facilities allowance for charters. On a related note, we will study the response of greater access to facilities (represented as a lower fixed cost in some locations). Although by law charter schools are the first claimant to vacant public school buildings, DCPS has not made those buildings available to charters on a regular basis. As public school enrollment continues to decline the supply of facilities for charters should increase. Moreover, in recent years
charters have had increasing access to "incubator facilities" where they are housed for a few years until they move to their permanent locations. We can capture the greater access to initial facilities through lower entry fees and/or lower fixed costs for certain locations.

While many states provide free transportation for children (even for those attending private or charter schools), D.C. does not provide any busing for public, private or charter school children. Thus, the provision of publicly-funded busing could alter household choices significantly. It could also alter the geographic pattern of charter entry and location. Furthermore, the charter landscape is heavily influenced by the preferences of the authorizer. Hence, changes in these preferences are likely to affect charter entry and student sorting. For instance, some claim that the authorizer today is less interested in approving vocational charters than it was a few years ago. Thus, it is of interest to study whether students would be less likely to attend charters if they were not of the exact focus that they preferred. Similarly, in recent years charter entry has been concentrated at the elementary and middle school level. The question, then, is whether lowering entry costs for charter high schools would encourage their entry.

DCPS has undergone important changes in recent years. These changes include school closings, consolidations, re-configuration of grades, and adoption of specialized curricula. We will study the effect of these changes on charter entry and student sorting. More generally, we will study the effects of a more responsive DCPS. Even if DCPS did not react much to charters during our sample period, at some point public schools will indeed be forced to respond. Thus, we will study the effects of alternative responses.

One might wonder to what extent the charter school landscape would be different if charter schools were centrally operated by the authorizer. Hence, we will explore how the market would differ if the charter sector were managed by an authorizer who acted as a central planner. A social planner might open either fewer or more charters, or target different entry points. This issue is similar to that study by Berry and Waldfogel (1999), who investigate whether there is too much entry of radio stations.

Washington, D.C. is home to a publicly-funded voucher program for private schools. Since the recipients of these vouchers are demographically similar to the students attending charters (Filardo et al, 2008), an expansion of the current program is likely to affect charter schools. Our model allows us to study this issue. A related issue is the general response of private schools to charters. While private schools did not seem particularly responsive during the sample period, the conversion of some Catholic schools into charters is an example of how some private schools have indeed begun to respond to charters. If new charter entrants continue to target a more affluent, less disadvantaged student population, other private schools might become more responsive as well.

Finally, one of the main demographic changes affecting most urban school districts in the United States is the loss of school-age children. Thus, we will explore the response of charters and household to exogenous demographic shocks that change the potential enrollment in the city as a whole or that change the income distribution of the families with school-age children.

7 Conclusion

In this paper we have developed a model of charter school entry and household choice of school and have devised an estimation strategy for the model. We estimate the model using a unique dataset for Washington, D.C., which incorporates information on all public, charter and private schools in D.C. between 2003 and 2007. Since we rely on an equilibrium framework, we model peer peer characteristics as an outcome of parental choices, with parents responding to those characteristics when making choices. We model charter entrants as being uncertain about their school-specific quality, and making their entry decisions based on their expected revenue given the opportunities
available to households.

Understanding the decisions made by charters and households helps us predict their responses to policy changes. Through our counterfactuals we will analyze alternative policies facing charter schools. Today, charter schools not only provide children with additional school choices but also provide researchers with new evidence on school management methods, educational curricula, and a number of aspects in which charters can diverge from public schools by virtue of the freedoms that have been granted to them. Thus, in future research we will further explore the innovation and competition induced by charters in the education market.

References


### TABLE 1a

**Demographics and Achievement at Public, Charter and Private Schools**

<table>
<thead>
<tr>
<th></th>
<th>All Schools</th>
<th>Public Schools</th>
<th>Charter Schools</th>
<th>Private Schools</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Pct. White</strong></td>
<td>17.20</td>
<td>0</td>
<td>78.71</td>
<td>7.61</td>
</tr>
<tr>
<td><strong>Pct Black</strong></td>
<td>73.84</td>
<td>15.67</td>
<td>100</td>
<td>81.89</td>
</tr>
<tr>
<td><strong>Pct. Hispanic</strong></td>
<td>8.96</td>
<td>0.24</td>
<td>26.00</td>
<td>10.49</td>
</tr>
<tr>
<td><strong>Pct Low Income</strong></td>
<td>56.88</td>
<td>3.24</td>
<td>87.63</td>
<td>64.68</td>
</tr>
<tr>
<td><strong>Reading Prof.</strong></td>
<td>41.34</td>
<td>15.47</td>
<td>72.97</td>
<td>41.18</td>
</tr>
<tr>
<td><strong>Math Prof.</strong></td>
<td>41.55</td>
<td>13.51</td>
<td>73.98</td>
<td>41.25</td>
</tr>
<tr>
<td><strong>Tract Income</strong></td>
<td>$61,970</td>
<td>$27,400</td>
<td>$136,600</td>
<td>$55,600</td>
</tr>
</tbody>
</table>

Notes: The unit of observation is a campus-year. “Reading Prof.” is the percent of students who are proficient in Reading. “Tract income” is the average household income in the Census tract where the school is located. Pct. Low Income for private schools is imputed as described in Appendix I. Proficiency data is not available for private schools. Weighted statistics; weight = Fall enrollment.
### TABLE 1b
Demographics of Private Schools by Private School Type

<table>
<thead>
<tr>
<th></th>
<th>Catholic</th>
<th>Other Religious</th>
<th>Nonsectarian</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg. Pct. White</td>
<td>42.91</td>
<td>66.91</td>
<td>67.52</td>
</tr>
<tr>
<td>Avg. Pct. Black</td>
<td>49.02</td>
<td>30.39</td>
<td>27.84</td>
</tr>
<tr>
<td>Avg. Pct. Hispanic</td>
<td>8.07</td>
<td>2.70</td>
<td>4.64</td>
</tr>
<tr>
<td>Avg. Tuition</td>
<td>$7,800</td>
<td>$19,700</td>
<td>$20,900</td>
</tr>
<tr>
<td>Tract Income</td>
<td>$76,000</td>
<td>$120,500</td>
<td>$102,800</td>
</tr>
</tbody>
</table>

Notes: See Table 1a.

### TABLE 1c
School Choice by Student Race and Poverty Status

<table>
<thead>
<tr>
<th></th>
<th>Public</th>
<th>Charter</th>
<th>Catholic</th>
<th>Other Religious</th>
<th>Nonsectarian</th>
</tr>
</thead>
<tbody>
<tr>
<td>White</td>
<td>27.76</td>
<td>3.02</td>
<td>23.64</td>
<td>21.13</td>
<td>24.45</td>
</tr>
<tr>
<td>Hispanic</td>
<td>72.12</td>
<td>14.79</td>
<td>8.37</td>
<td>1.57</td>
<td>3.14</td>
</tr>
<tr>
<td>Black</td>
<td>68.43</td>
<td>20.47</td>
<td>6.27</td>
<td>2.31</td>
<td>2.52</td>
</tr>
<tr>
<td>Non-Poor</td>
<td>50.73</td>
<td>11.83</td>
<td>14.49</td>
<td>10.53</td>
<td>12.42</td>
</tr>
<tr>
<td>Low-Income</td>
<td>70.18</td>
<td>20.84</td>
<td>5.62</td>
<td>1.64</td>
<td>1.72</td>
</tr>
<tr>
<td>All Students</td>
<td>61.89</td>
<td>17.00</td>
<td>9.40</td>
<td>5.42</td>
<td>6.28</td>
</tr>
</tbody>
</table>

Note: Each row indicates the fraction of students of the corresponding race or poverty status enrolled in each type of school. For each row, sum across columns equals 100. Data from all years has been pooled for the table.
### TABLE 2

**School Openings and Closings**

<table>
<thead>
<tr>
<th>Year</th>
<th>Public Schools</th>
<th>Charter Schools</th>
<th>Private Schools</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total</td>
<td>Opened</td>
<td>Closed</td>
</tr>
<tr>
<td>End 2002</td>
<td>142</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2003</td>
<td>142</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2004</td>
<td>143</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>2005</td>
<td>142</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>2006</td>
<td>137</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>2007</td>
<td>136</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Total 03-07</td>
<td>2</td>
<td>8</td>
<td>8</td>
</tr>
</tbody>
</table>

Notes: Each cell indicates number of campuses. A school’s opening year is its first year of operation; a school’s closing year is the year following the last. A school is counted as moving in year X if its address in X is different from its address in (X-1).

### TABLE 3

**Grade Levels at Public, Charter, and Private Schools**

<table>
<thead>
<tr>
<th></th>
<th>Public Schools</th>
<th>Charter Schools</th>
<th>Private Schools</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elementary</td>
<td>68.57</td>
<td>55.02</td>
<td>277</td>
</tr>
<tr>
<td>Elementary/Middle</td>
<td>4.29</td>
<td>4.97</td>
<td>400</td>
</tr>
<tr>
<td>Middle</td>
<td>14.43</td>
<td>16.46</td>
<td>393</td>
</tr>
<tr>
<td>Middle/High</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>High</td>
<td>12.71</td>
<td>23.55</td>
<td>639</td>
</tr>
<tr>
<td>Elem./Middle/High</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
</tr>
</tbody>
</table>

Notes: The unit of observation is a campus-year. For instance, on average during the sample period 68.57 percent of public schools are elementary, 4.29 are elementary/middle, etc. Among public school students, on average 55.02 percent attend elementary schools, 4.97 attend elementary/middle schools, etc.
## TABLE 4

*Demographics and Achievement by School Type and Level*

**Public Schools**

<table>
<thead>
<tr>
<th></th>
<th>Elementary</th>
<th>Middle</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg. Pct. White</td>
<td>9.10</td>
<td>5.22</td>
<td>6.32</td>
</tr>
<tr>
<td>Avg. Pct. Black</td>
<td>79.63</td>
<td>86.62</td>
<td>82.92</td>
</tr>
<tr>
<td>Avg. Pct. Hispanic</td>
<td>11.28</td>
<td>8.16</td>
<td>10.77</td>
</tr>
<tr>
<td>Avg. Pct. Low Income</td>
<td>68.09</td>
<td>67.74</td>
<td>53.94</td>
</tr>
<tr>
<td>Avg. Pct. Proficient Reading</td>
<td>46.90</td>
<td>37.13</td>
<td>31.50</td>
</tr>
<tr>
<td>Avg. Pct. Proficient Math</td>
<td>46.17</td>
<td>36.51</td>
<td>34.05</td>
</tr>
<tr>
<td>Avg. Tract Hh. Income</td>
<td>$54,300</td>
<td>$55,700</td>
<td>$58,400</td>
</tr>
</tbody>
</table>

**Charter Schools**

<table>
<thead>
<tr>
<th></th>
<th>Elementary</th>
<th>Middle</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg. Pct. White</td>
<td>3.87</td>
<td>3.93</td>
<td>0.84</td>
</tr>
<tr>
<td>Avg. Pct. Black</td>
<td>86.67</td>
<td>88.03</td>
<td>93.70</td>
</tr>
<tr>
<td>Avg. Pct. Hispanic</td>
<td>9.46</td>
<td>8.04</td>
<td>5.46</td>
</tr>
<tr>
<td>Avg. Pct. Low Income</td>
<td>74.48</td>
<td>67.44</td>
<td>66.17</td>
</tr>
<tr>
<td>Avg. Pct. Proficient Reading</td>
<td>41.93</td>
<td>48.88</td>
<td>34.89</td>
</tr>
<tr>
<td>Avg. Pct. Proficient Math</td>
<td>40.78</td>
<td>49.70</td>
<td>37.00</td>
</tr>
<tr>
<td>Avg. Tract Hh. Income</td>
<td>$44,600</td>
<td>$44,700</td>
<td>$41,200</td>
</tr>
</tbody>
</table>

**Private Schools**

<table>
<thead>
<tr>
<th></th>
<th>Elementary</th>
<th>Middle</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg. Pct. White</td>
<td>58.74</td>
<td>36.70</td>
<td>68.33</td>
</tr>
<tr>
<td>Avg. Pct. Hispanic</td>
<td>2.73</td>
<td>6.91</td>
<td>5.39</td>
</tr>
<tr>
<td>Avg. Pct. Low Income</td>
<td>28.12</td>
<td>41.91</td>
<td>11.32</td>
</tr>
<tr>
<td>Avg. Tract Hh. Income</td>
<td>$82,800</td>
<td>$75,050</td>
<td>$109,700</td>
</tr>
</tbody>
</table>

Note: “elementary”, “middle” and “high” correspond to the three-type category described in the text.
### TABLE 5a
**Program Focus by School Type**

<table>
<thead>
<tr>
<th>Focus</th>
<th>Public Schools (1)</th>
<th>Charter Schools (2)</th>
<th>Private Schools (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Core</td>
<td>83.00</td>
<td>47.37</td>
<td>91.79</td>
</tr>
<tr>
<td>Arts</td>
<td>1.43</td>
<td>9.65</td>
<td>1.47</td>
</tr>
<tr>
<td>Language</td>
<td>4.29</td>
<td>7.02</td>
<td>1.76</td>
</tr>
<tr>
<td>Vocational</td>
<td>1.43</td>
<td>7.89</td>
<td>0</td>
</tr>
<tr>
<td>Other</td>
<td>9.86</td>
<td>28.07</td>
<td>4.99</td>
</tr>
</tbody>
</table>

### TABLE 5b
**Program Focus by School Level**

<table>
<thead>
<tr>
<th>Focus</th>
<th>Public Schools</th>
<th>Charter Schools</th>
<th>Private Schools</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All Levels</td>
<td>Elementary</td>
<td>Middle</td>
</tr>
<tr>
<td>Core</td>
<td>83.00</td>
<td>86.67</td>
<td>95.42</td>
</tr>
<tr>
<td>Arts</td>
<td>1.43</td>
<td>0</td>
<td>3.82</td>
</tr>
<tr>
<td>Language</td>
<td>4.29</td>
<td>6.04</td>
<td>0.76</td>
</tr>
<tr>
<td>Vocational</td>
<td>1.43</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Other</td>
<td>9.86</td>
<td>7.29</td>
<td>0</td>
</tr>
</tbody>
</table>

Notes: the unit of observation is a campus-year. For instance, among elementary charter campuses, on average 41.67 percent focus on a core curriculum, 20.83 percent focus on arts, etc.
### TABLE 6a
Student Demographics and Achievement by School Level and Program Focus

#### Elementary Schools

<table>
<thead>
<tr>
<th></th>
<th>Core (1)</th>
<th>Arts (2)</th>
<th>Language (3)</th>
<th>Other (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pct. Public</td>
<td>87.80</td>
<td>0</td>
<td>61.22</td>
<td>74.76</td>
</tr>
<tr>
<td>Pct. Charter</td>
<td>7.80</td>
<td>98.60</td>
<td>26.53</td>
<td>18.10</td>
</tr>
<tr>
<td>Pct. Private</td>
<td>4.40</td>
<td>1.40</td>
<td>0.12</td>
<td>7.15</td>
</tr>
<tr>
<td>Avg. Percent White</td>
<td>9.86</td>
<td>1.12</td>
<td>12.18</td>
<td>20.68</td>
</tr>
<tr>
<td>Avg. Percent Black</td>
<td>82.01</td>
<td>94.92</td>
<td>38.12</td>
<td>74.99</td>
</tr>
<tr>
<td>Avg. Percent Hispanic</td>
<td>8.13</td>
<td>3.96</td>
<td>49.70</td>
<td>4.33</td>
</tr>
<tr>
<td>Avg. Percent Low Income</td>
<td>68.01</td>
<td>85.24</td>
<td>72.06</td>
<td>46.87</td>
</tr>
<tr>
<td>Avg. Pct. Proficient in Reading</td>
<td>45.06</td>
<td>36.77</td>
<td>50.54</td>
<td>59.06</td>
</tr>
<tr>
<td>Avg. Pct. Proficient in Math</td>
<td>44.43</td>
<td>31.83</td>
<td>52.27</td>
<td>55.69</td>
</tr>
<tr>
<td>Avg. Tract Hh. Income</td>
<td>$54,000</td>
<td>$38,900</td>
<td>$55,931</td>
<td>$63,000</td>
</tr>
</tbody>
</table>

#### Middle Schools

<table>
<thead>
<tr>
<th></th>
<th>Core (1)</th>
<th>Arts (2)</th>
<th>Language (3)</th>
<th>Vocational (4)</th>
<th>Other (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pct. Public</td>
<td>50.16</td>
<td>100</td>
<td>27.58</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Pct. Charter</td>
<td>20.07</td>
<td>0</td>
<td>15.18</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Pct. Private</td>
<td>29.77</td>
<td>0</td>
<td>57.24</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Avg. Percent White</td>
<td>12.72</td>
<td>28.35</td>
<td>58.58</td>
<td>0</td>
<td>17.08</td>
</tr>
<tr>
<td>Avg. Percent Black</td>
<td>79.99</td>
<td>57.72</td>
<td>15.66</td>
<td>100</td>
<td>74.03</td>
</tr>
<tr>
<td>Percent Hispanic</td>
<td>7.29</td>
<td>13.93</td>
<td>25.76</td>
<td>0</td>
<td>8.89</td>
</tr>
<tr>
<td>Avg. Percent Low Income</td>
<td>61.66</td>
<td>25.51</td>
<td>24.83</td>
<td>92</td>
<td>57.75</td>
</tr>
<tr>
<td>Avg. Pct. Proficient Reading</td>
<td>39.10</td>
<td>73.80</td>
<td>57.15</td>
<td>21.43</td>
<td>53.46</td>
</tr>
<tr>
<td>Avg. Tract Hh. Income</td>
<td>$58,500</td>
<td>$73,900</td>
<td>$86,000</td>
<td>$34,400</td>
<td>$47,000</td>
</tr>
</tbody>
</table>

#### High Schools

<table>
<thead>
<tr>
<th></th>
<th>Core (1)</th>
<th>Arts (2)</th>
<th>Vocational (3)</th>
<th>Other (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pct. Public</td>
<td>34.80</td>
<td>91.08</td>
<td>53.94</td>
<td>67.69</td>
</tr>
<tr>
<td>Pct. Charter</td>
<td>13.52</td>
<td>8.92</td>
<td>46.51</td>
<td>25.44</td>
</tr>
<tr>
<td>Pct. Private</td>
<td>51.68</td>
<td>0</td>
<td>0</td>
<td>6.87</td>
</tr>
<tr>
<td>Avg. Percent White</td>
<td>35.16</td>
<td>10.08</td>
<td>1.89</td>
<td>17.17</td>
</tr>
<tr>
<td>Avg. Percent Black</td>
<td>60.51</td>
<td>85.19</td>
<td>89.67</td>
<td>64.19</td>
</tr>
<tr>
<td>Avg. Percent Hispanic</td>
<td>4.33</td>
<td>4.73</td>
<td>8.44</td>
<td>18.64</td>
</tr>
<tr>
<td>Avg. Percent Low Income</td>
<td>36.55</td>
<td>31.27</td>
<td>67.25</td>
<td>47.73</td>
</tr>
<tr>
<td>Pct. Proficient Reading</td>
<td>21.11</td>
<td>59.53</td>
<td>20.96</td>
<td>53.00</td>
</tr>
<tr>
<td>Avg. Pct. Proficient Math</td>
<td>23.27</td>
<td>46.91</td>
<td>23.75</td>
<td>57.11</td>
</tr>
<tr>
<td>Avg. Tract Hh. Income</td>
<td>$79,800</td>
<td>$92,500</td>
<td>$43,414</td>
<td>$65,900</td>
</tr>
</tbody>
</table>

Note: Unit of observation is a campus-year. Weighted averages; weight = fall Enrollment. Average reading and math proficiency is computed over public and charter schools only.
TABLE 6b
Focus Choice by Student Race and Poverty Status

<table>
<thead>
<tr>
<th></th>
<th>Core</th>
<th>Arts</th>
<th>Language</th>
<th>Vocational</th>
<th>Other Focus</th>
</tr>
</thead>
<tbody>
<tr>
<td>White</td>
<td>82.66</td>
<td>1.15</td>
<td>3.98</td>
<td>0.27</td>
<td>11.93</td>
</tr>
<tr>
<td>Hispanic</td>
<td>61.39</td>
<td>1.51</td>
<td>18.59</td>
<td>2.27</td>
<td>16.23</td>
</tr>
<tr>
<td>Black</td>
<td>82.22</td>
<td>2.52</td>
<td>1.72</td>
<td>2.99</td>
<td>10.55</td>
</tr>
<tr>
<td>Non-Poor</td>
<td>79.46</td>
<td>2.11</td>
<td>2.95</td>
<td>1.88</td>
<td>13.58</td>
</tr>
<tr>
<td>Low-Income</td>
<td>81.10</td>
<td>2.26</td>
<td>4.14</td>
<td>2.90</td>
<td>9.60</td>
</tr>
<tr>
<td>All Students</td>
<td>80.40</td>
<td>2.20</td>
<td>3.63</td>
<td>2.47</td>
<td>11.30</td>
</tr>
</tbody>
</table>

Note: Each row indicates the fraction of students of the corresponding race or poverty status enrolled in each type of school. For each row, sum across columns equals 100. Data from all years has been pooled for the table.

TABLE 7
Early versus Recent Charter Entrants

<table>
<thead>
<tr>
<th></th>
<th>Early Entrants</th>
<th>Recent Entrants</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of campuses</td>
<td>27</td>
<td>36</td>
</tr>
<tr>
<td>Avg. Enrollment</td>
<td>432</td>
<td>169</td>
</tr>
<tr>
<td>Pct. Focused on Core</td>
<td>55.56</td>
<td>38.89</td>
</tr>
<tr>
<td>Pct. Elementary</td>
<td>18.52</td>
<td>61.11</td>
</tr>
<tr>
<td>Pct. Elementary/Middle</td>
<td>29.63</td>
<td>13.89</td>
</tr>
<tr>
<td>Pct. Elementary/Middle/High</td>
<td>11.11</td>
<td>0</td>
</tr>
<tr>
<td>Pct. Middle</td>
<td>11.11</td>
<td>16.67</td>
</tr>
<tr>
<td>Pct. Middle/High</td>
<td>7.41</td>
<td>5.56</td>
</tr>
<tr>
<td>Pct. High</td>
<td>22.22</td>
<td>2.78</td>
</tr>
<tr>
<td>Avg. Tract Hh. Income</td>
<td>$43,100</td>
<td>$46,500</td>
</tr>
<tr>
<td>Pct. belonging to multiple-campus charters</td>
<td>38.05</td>
<td>65.60</td>
</tr>
<tr>
<td>Pct. White Students</td>
<td>1.43</td>
<td>6.25</td>
</tr>
<tr>
<td>Pct. Black Students</td>
<td>92.40</td>
<td>85.64</td>
</tr>
<tr>
<td>Pct. Hispanic Students</td>
<td>6.18</td>
<td>8.11</td>
</tr>
<tr>
<td>Pct. Low Income Students</td>
<td>73.35</td>
<td>64.58</td>
</tr>
<tr>
<td>Pct. Proficient Reading</td>
<td>41.83</td>
<td>40.94</td>
</tr>
<tr>
<td>Pct. Proficient Math</td>
<td>40.47</td>
<td>37.72</td>
</tr>
</tbody>
</table>

Note: unit of observation is a campus. For each campus, demographics and school level correspond to the last year the campus is in the data. Weighted averages; weight is enrollment.
### TABLE 8
Parameter Estimates – Utility Function

<table>
<thead>
<tr>
<th>Variable</th>
<th>Baseline Utility</th>
<th>Interactions with Household Characteristics</th>
<th>White</th>
<th>Hispanic</th>
<th>Non-Poor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>3.560*</td>
<td></td>
<td>(0.384)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Charter</td>
<td>-0.662*</td>
<td></td>
<td>(0.140)</td>
<td></td>
<td>-0.481*</td>
</tr>
<tr>
<td>Catholic</td>
<td>-1.365*</td>
<td></td>
<td>(0.514)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Private Other Religious</td>
<td>-1.731</td>
<td></td>
<td>(1.258)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Private Nonsectarian</td>
<td>-2.048</td>
<td></td>
<td>(1.493)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Language</td>
<td>0.462</td>
<td></td>
<td>(0.514)</td>
<td></td>
<td>-0.522</td>
</tr>
<tr>
<td>Arts</td>
<td>0.234</td>
<td></td>
<td>(0.195)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vocational</td>
<td>-0.354*</td>
<td></td>
<td>(0.155)</td>
<td></td>
<td>0.213</td>
</tr>
<tr>
<td>Other focus</td>
<td>-0.358</td>
<td></td>
<td>(0.420)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tuition (in $1,000)</td>
<td>-0.190</td>
<td></td>
<td>(0.284)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Middle / high school</td>
<td>1.082*</td>
<td></td>
<td>(0.270)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Charter * middle / high school</td>
<td>-0.204</td>
<td></td>
<td>(0.126)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Charter * multicampus</td>
<td>0.788*</td>
<td></td>
<td>(0.204)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fraction White</td>
<td>4.823</td>
<td></td>
<td>(4.870)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fraction Hispanic</td>
<td>-2.910</td>
<td></td>
<td>(1.494)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fraction Non-Poor</td>
<td>-3.458*</td>
<td></td>
<td>(1.400)</td>
<td></td>
<td>4.095*</td>
</tr>
<tr>
<td>Distance (miles)</td>
<td>-1.154*</td>
<td></td>
<td>(0.035)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distance*charter (miles)</td>
<td>1.193*</td>
<td></td>
<td>(0.057)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distance*private (miles)</td>
<td>1.443*</td>
<td></td>
<td>(0.093)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Based on 12,378 (=8,112+3,807+459) observations. Except where noted, parameters are GMM estimates including campus, grade and year fixed effects. Asymptotic standard errors are given in parentheses. “Baseline utility” corresponds to parameters from $\delta$, except for the coefficients on distance, which correspond to $\mu$. Coefficients marked with (*) are significant at the 5% significance level. Estimates and standard errors in Italiacs were obtained through minimum-distance estimation of campus fixed effects on time-invariant school characteristics (number of observations in this regression = 281 campuses). Middle / high school = 1 if school level is one of the following: middle, high, middle/high, elementary/middle/high. Multicampus = 1 if the charter school belongs to a multi-campus organization.
**TABLE 9**

*School Choice By Student Race and Poverty Status – Observed and Predicted Values, All Years*

<table>
<thead>
<tr>
<th>Students</th>
<th>Public</th>
<th>Charter</th>
<th>Catholic</th>
<th>Other Religious</th>
<th>Non-Sectarian</th>
<th>Public</th>
<th>Charter</th>
<th>Catholic</th>
<th>Other Religious</th>
<th>Non-Sectarian</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>61.89</td>
<td>17.00</td>
<td>9.40</td>
<td>5.42</td>
<td>6.28</td>
<td>61.26</td>
<td>17.00</td>
<td>9.98</td>
<td>5.41</td>
<td>6.35</td>
</tr>
<tr>
<td>White</td>
<td>27.76</td>
<td>3.02</td>
<td>23.64</td>
<td>21.13</td>
<td>24.45</td>
<td>28.79</td>
<td>1.04</td>
<td>18.03</td>
<td>23.04</td>
<td>29.08</td>
</tr>
<tr>
<td>Black</td>
<td>68.43</td>
<td>20.47</td>
<td>6.27</td>
<td>2.31</td>
<td>2.52</td>
<td>66.01</td>
<td>19.81</td>
<td>8.54</td>
<td>2.75</td>
<td>2.87</td>
</tr>
<tr>
<td>Hispanic</td>
<td>72.12</td>
<td>14.79</td>
<td>8.37</td>
<td>1.57</td>
<td>3.14</td>
<td>67.34</td>
<td>16.14</td>
<td>10.60</td>
<td>2.72</td>
<td>3.20</td>
</tr>
<tr>
<td>Non Poor</td>
<td>50.73</td>
<td>11.83</td>
<td>14.49</td>
<td>10.53</td>
<td>12.42</td>
<td>54.79</td>
<td>11.87</td>
<td>13.62</td>
<td>8.89</td>
<td>10.81</td>
</tr>
<tr>
<td>Low Inc.</td>
<td>70.18</td>
<td>20.84</td>
<td>5.62</td>
<td>1.64</td>
<td>1.72</td>
<td>68.83</td>
<td>22.99</td>
<td>5.71</td>
<td>1.34</td>
<td>1.11</td>
</tr>
</tbody>
</table>

**TABLE 10**

*Focus Choice By Student Race and Poverty Status – Observed and Predicted Values, All Years*

<table>
<thead>
<tr>
<th>Students</th>
<th>Core</th>
<th>Arts</th>
<th>Language</th>
<th>Vocational</th>
<th>Other Focus</th>
<th>Core</th>
<th>Arts</th>
<th>Language</th>
<th>Vocational</th>
<th>Other Focus</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>80.40</td>
<td>2.20</td>
<td>3.63</td>
<td>2.47</td>
<td>11.30</td>
<td>79.64</td>
<td>2.17</td>
<td>3.78</td>
<td>2.76</td>
<td>11.63</td>
</tr>
<tr>
<td>White</td>
<td>82.66</td>
<td>1.15</td>
<td>3.98</td>
<td>0.27</td>
<td>11.93</td>
<td>83.02</td>
<td>1.30</td>
<td>3.25</td>
<td>0.16</td>
<td>12.27</td>
</tr>
<tr>
<td>Black</td>
<td>82.22</td>
<td>2.52</td>
<td>1.72</td>
<td>2.99</td>
<td>10.55</td>
<td>81.53</td>
<td>2.26</td>
<td>2.10</td>
<td>3.08</td>
<td>11.03</td>
</tr>
<tr>
<td>Hispanic</td>
<td>61.39</td>
<td>1.51</td>
<td>18.59</td>
<td>2.27</td>
<td>16.23</td>
<td>61.08</td>
<td>2.55</td>
<td>14.93</td>
<td>3.59</td>
<td>17.84</td>
</tr>
<tr>
<td>Non Poor</td>
<td>79.46</td>
<td>2.11</td>
<td>2.95</td>
<td>1.88</td>
<td>13.58</td>
<td>79.90</td>
<td>2.03</td>
<td>3.57</td>
<td>2.00</td>
<td>12.49</td>
</tr>
<tr>
<td>Low Inc.</td>
<td>81.10</td>
<td>2.26</td>
<td>4.14</td>
<td>2.90</td>
<td>9.60</td>
<td>79.33</td>
<td>2.35</td>
<td>4.03</td>
<td>3.65</td>
<td>10.63</td>
</tr>
</tbody>
</table>
## TABLE 11

**Public v. Charter School Quality**

<table>
<thead>
<tr>
<th>School Level</th>
<th>All Wards Except Ward 3</th>
<th>Wards 7 and 8</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Public</td>
<td>Charter</td>
</tr>
<tr>
<td>All</td>
<td>-0.007</td>
<td>-0.005</td>
</tr>
<tr>
<td>Elementary</td>
<td>-0.05</td>
<td>-0.11</td>
</tr>
<tr>
<td>Elementary/Middle</td>
<td>-0.07</td>
<td>0.24</td>
</tr>
<tr>
<td>Middle</td>
<td>0.05</td>
<td>0.42</td>
</tr>
<tr>
<td>Middle/High and High</td>
<td>0.16</td>
<td>-0.21</td>
</tr>
</tbody>
</table>

Note: school quality is the residual of the minimum-distance estimation regression of campus fixed effects on time-invariant school characteristics.
TABLE 12
Parameter Estimates – Math Proficiency Rate
(Dependent Variable = log(PassRate / (100-PassRate)))

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.056</td>
<td>(0.268)</td>
</tr>
<tr>
<td>Charter</td>
<td>-1.343*</td>
<td>(0.060)</td>
</tr>
<tr>
<td>Language</td>
<td>-1.016*</td>
<td>(0.195)</td>
</tr>
<tr>
<td>Arts</td>
<td>0.681*</td>
<td>(0.124)</td>
</tr>
<tr>
<td>Vocational</td>
<td>-0.421*</td>
<td>(0.034)</td>
</tr>
<tr>
<td>Other focus</td>
<td>1.202*</td>
<td>(0.159)</td>
</tr>
<tr>
<td>Middle / high school</td>
<td>-0.731*</td>
<td>(0.092)</td>
</tr>
<tr>
<td>Charter * middle / high school</td>
<td>1.380*</td>
<td>(0.027)</td>
</tr>
<tr>
<td>Charter * multicampus</td>
<td>0.974*</td>
<td>(0.066)</td>
</tr>
<tr>
<td>Percent White</td>
<td>-0.002</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Percent Hispanic</td>
<td>0.009*</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Percent Non-Poor</td>
<td>0.007</td>
<td>(0.009)</td>
</tr>
<tr>
<td>Year 2004</td>
<td>0.034</td>
<td>(0.78)</td>
</tr>
<tr>
<td>Year 2005</td>
<td>-1.255*</td>
<td>(0.075)</td>
</tr>
<tr>
<td>Year 2006</td>
<td>-1.068*</td>
<td>(0.079)</td>
</tr>
<tr>
<td>Year 2007</td>
<td>-0.648*</td>
<td>(0.083)</td>
</tr>
<tr>
<td>Mean of Dependent Vble.</td>
<td>-0.340</td>
<td></td>
</tr>
<tr>
<td>Mean of Passing Rate (%)</td>
<td>42.29</td>
<td></td>
</tr>
<tr>
<td>Std. Error of Regression Pseudo-R²</td>
<td>0.574</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.810</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Based on 871 school-year observations corresponding to schools with at least 2 years of data. PassRate is expressed between 0 and 100. Except where noted, parameters are IV estimates including campus (and year) fixed effects. Observations are weighted by total school enrollment. Standard errors are clustered at the school level. Coefficients marked with (*) are significant at the 5% significance level. Estimates and standard errors in Italics were obtained through minimum-distance estimation (regression of campus fixed effects on time-invariant school characteristics; number of observations = 193). Middle / high school = 1 if school level is one of the following: middle, high, middle/high, elementary/middle/high. Multicampus = 1 if the charter school belongs to a multi-campus organization. Omitted year is 2003. Pseudo-R² equal to the squared correlation between observed and predicted values of the dependent variable.
**TABLE 13**

*Public v. Charter School Value Added - Achievement*

<table>
<thead>
<tr>
<th>School Level</th>
<th>All Wards Except Ward 3</th>
<th>Wards 7 and 8</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Public</td>
<td>Charter</td>
</tr>
<tr>
<td>All</td>
<td>-0.12</td>
<td>-0.01</td>
</tr>
<tr>
<td>Elementary</td>
<td>-0.12</td>
<td>-0.48</td>
</tr>
<tr>
<td>Elementary/Middle</td>
<td>-0.47</td>
<td>0.76</td>
</tr>
<tr>
<td>Middle</td>
<td>-0.05</td>
<td>0.52</td>
</tr>
<tr>
<td>Middle/High and High</td>
<td>-0.04</td>
<td>-0.44</td>
</tr>
</tbody>
</table>

Note: school value added is the residual of the minimum-distance estimation regression of campus fixed effects on time-invariant school characteristics.

**TABLE 14**

*Counterfactual Analysis: No Charter Schools in 2007*

*School Choice – By Student Demographic Group*

<table>
<thead>
<tr>
<th>Students</th>
<th>Observed School Choice (%)</th>
<th>Predicted School Choice (%) With Charters</th>
<th>Predicted School Choice (%) Without Charters</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Public</td>
<td>Charter</td>
<td>Catholic</td>
</tr>
<tr>
<td>Black</td>
<td>62.43</td>
<td>26.62</td>
<td>5.97</td>
</tr>
<tr>
<td>Low Inc.</td>
<td>63.46</td>
<td>27.35</td>
<td>5.59</td>
</tr>
<tr>
<td>Non-Poor</td>
<td>49.23</td>
<td>15.03</td>
<td>14.08</td>
</tr>
</tbody>
</table>
FIGURE 1
Number of Public, Charter and Private School Campuses

FIGURE 2
Enrollment in Public, Charter and Private School Campuses
FIGURE 3
Enrollment Shares for Public, Charter and Private Schools

Notes: percentages calculated relative to total enrollment, aggregated over all schools and grades.
FIGURE 4a
Geographic Location of Elementary Schools in DC in 2007

Note: Elementary schools include elementary, elementary/middle, and elementary/middle/high schools.
FIGURE 4b
Geographic Location of Middle Schools in DC in 2007

Note: Middle schools include midle, elementary/middle, middle/high and elementary/middle/high schools.
FIGURE 4c
Geographic Location of High Schools in DC in 2007

Note: High schools include high, middle/high, and elementary/middle/high schools.
FIGURE 5a - Public Schools: Aggregate Enrollment Share by Grade

FIGURE 5b - Charter Schools: Aggregate Enrollment Share by Grade

FIGURE 5c - Private Schools: Aggregate Enrollment Share by Grade

Note: Shares are calculated relative to the total enrollment per grade, where total = aggregate enrollment over public, charter and private schools.
FIGURE 6
Number of Public, Charter and Private Schools by Grade in 2003 and 2007

FIGURE 7
Average Grade Enrollment in Public, Private and Charter Schools in 2007
FIGURE 8
Neighborhood Percent of Children in Charter Schools in 2006

Note: The map depicts cluster-level data. Percent is calculated relative to all children in the public system (traditional public + charter schools).
FIGURE 9
Neighborhood Average Distance Traveled to Public Schools in 2006

Note: The map depicts cluster-level data.
FIGURE 10

*Neighborhood Average Distance Traveled to Charter Schools in 2006*

Note: The map depicts cluster-level data.