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

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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.

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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.[1] 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.[2]

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

[1] See http://www.edreform.com/Fast_Facts/K12_Facts/

[2] 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.

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, which in our framework means maximizing expected net revenue. 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 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. Lacking individual-level data, we 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 predicted market share and peer characteristics for each school and grade. 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 company, peer characteristics are determined by aggregate household choices and are similar to the local spillovers in Bayer and Timmins (2007).[3] 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.[4] The fact that D.C. contains a single public school district facilitates research design and data collection. Finally, the city is relatively large and contains substantial variation in household demographics, thus providing scope

[3] General equilibrium analyses of school choice include Benabou (1996), Caucutt (2002), de Bartolome (1990), Epple and Romano (1998), Fernandez and Rogerson (1998), and Nechyba (1999, 2000). Calabrese et al (2006), Ferreyra (2007) and Ferreyra (2009) estimate general equilibrium models. Relative to these prior analyses, our econometric framework in this paper provides a model of choice among the entire set of schools within a district as well as a model of charter school entry.

[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.

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[5], 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 followed a similar approach (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, we match school peer characteristics. While the BLP approach is usually focused on the parameters that explain the observed market shares, ours must fulfill the additional requirement of explaining who chooses each school in our data. 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 Hessians in order to achieve these goals, we rely on an efficient combination of solvers and do not require analytical Hessians, whose derivation is involved and prone to errors. We are currently exploring the use of MPEC to impose all equilibrium conditions at once rather than in three separate stages. 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). Most of this literature assumes a reduced-form function for demand,[6] whereas we specify a full model of household choice of school. In addition, a major focus of that 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

[5] See, for instance, Bettinger (2005) Bifulco and Ladd (2006), Booker et al (2007, 2008), Buddin and Zimmer (2005a, 2005b), Clark (2009), Hanushek et al (2007), Holmes et al (2003), Hoxby (2004), Hoxby and Rockoff (2004), Hoxby and Murarka (2009), Imberman (2009, forthcoming), Sass (2006), Weiher and Tedin (2002), and Zimmer and Buddin (2003).

[6] A recent exception is Carranza et al, who have a BLP demand-side model.

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 1992 and 2007 the District of Columbia Public Schools (DCPS) had seven 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 permanent 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 consists of information on every public, charter and private school in Washington, D.C. between 2003 and 2007. 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.[7] We direct readers interested in further detail of the dataset to Appendix I.

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.[8] We have 700, 228 and 341 observations for public, charter and private schools respectively. Our 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 assess-

[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.

[8] A campus is identified by its name and not its geographic location. For instance, if a campus moves but retains its name, then it is still considered the same campus.

[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 from 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.

ments. For private schools we have school type (Catholic, other religious and non-sectarian) and tuition by grade.

In Washington, D.C. 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).

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), phone calls to charters that are still open and achievement data at the campus level. The resulting campus-level 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. We obtained tuition information for many private schools from their web sites. Though this information is current, in our empirical application we assume that relative tuitions among private schools have not changed since 2003 and express tuitions in dollars of 2000.

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 (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.

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. During 2003-2007, it is estimated that the population grew from 577,000 up to 586,000 in 2007, although the school-age population declined

from 82,000 to 76,000.[11] 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 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 Asssessment 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 doubled, from 30 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.

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 actually 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 afluent neighborhoods.

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.

[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).

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.[12]

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 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.[13] 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.[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 offered 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 6). 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.

[12] 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.

[13] This does not necessarily mean that charter schools have smaller class sizes; rather, it may mean that they have fewer classrooms per grade.

[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.

2.1.4 Relocations, closings and multiple-campus charters

Very few public and private schools opened, closed or relocated during the sample period relative to the total number of those schools (see Table 2). Charter schools, in contrast, displayed more action on those fronts, especially in terms of relocation. It is quite common for charter schools to add grades over time until completing the grade coverage stated in the charter. Of the 30 campuses that entered between 2003 and 2006, 26 added grades during the sample period, mostly at higher grades. 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 a higher enrollment.

Of the 63 campuses in our sample, 28 pertain to a multi-campus organization, for a total of 45 schools. In general, these organizations run multiple campuses in order to serve different grade levels.[15] The 10 multi-campus schools in our sample accounted for by 46 percent of the charter enrollment during the sample period. Relative to single-campus charters, multi-campus charters are more likely to focus on a core curriculum, 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 more curriculum specialization.

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, it features a rich variation over time and across schools that 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. Public and private schools react very slowly to changes in the market environment. Hence, the prospective

[15] 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 (College).

entrant takes the locations, grades served, and focus of public and private schools as given (it also takes private school tuitions as given).

To make their decisions, both incumbents and potential entrants forecast their 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 are even more uncertain 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 of school. Our school choice framework draws from Bayer and Timmins (2007).

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 $\widetilde{D}$ elements. In our empirical application D has 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).
- $\ell \in \{1, ..., L\}$ 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.[16]
- I is the income of the student's family.
- ε 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 treat multiple campus of the same organization as separate entitites because in practice 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:

- κ_{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.

[16] 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.

- y_j denotes time-invariant school characteristics such as type (public, charter, Catholic, other religious, nonsectarian) and focus (core, language, arts, vocational, other). Henceforth, for presentational clarity, we will refer to y_j as "focus."

- p_{jgt} is tuition. Public and charter schools cannot charge tuition, but private schools can. Private school tuition can vary by grade.[17]

- $\overline{D}_{jt}$ represents peer characteristics of the student body at the school. Unlike school characteristics y_j and p_{jgt}, $\overline{D}_{jt}$ is the outcome of household choices. It is the average over the vectors D of the students who attend the school and hence has $\widetilde{D}$ elements as well. In our empirical application, $\overline{D}_{jt}$ stores percent of white, hispanic and non-poor students. These characteristics may change over time, as household choices change.

- ξ^p_{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.

- ξ^a_{jgt} is an unobserved (to us) characteristic of the school and grade that affects children's achievement (in contrast, ξ^p_{jgt} affects household satisfaction with the school and grade for reasons other than achievement). Thus, ξ^a_{jgt} 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:

$$U_{ijgt} = \delta^p_{jgt} + \mu^p_{ijgt} + \varepsilon_{ijgt} \tag{1}$$

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

$$\delta^p_{jgt} = y_j\beta^p + \overline{D}_{jt}\alpha^p + \xi^p_{jgt} \tag{2}$$

Here, α^p and β^p are vectors of parameters. In what follows, we refer to ξ^p_{jgt} 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:

$$\mu^p_{ijgt} = E(A_{ijgt})\phi + D_i y_j \tilde{\beta}^p + D_i \bar{D}_{jt}\tilde{\alpha} + x_{ijt}\gamma + \varphi \log(I_i - p_{jgt}) \tag{3}$$

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 $\bar{D}_{jt}$, 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.

[17] Recall that our tuition data is for the school year 2010/11, and is expressed in dollars of 2000. Hence, it does not vary over time in our empirical application.

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 ν_{ijgt}, which parents do not observe at the time of choosing a school:

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

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 ξ^a_{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 $\bar{D}$ below:

$$Q_{jgt} = y_j\beta^a + \bar{D}_{jt}\alpha^a + \xi^a_{jgt} \tag{5}$$

Substituting (5) into (4), we obtain

$$A_{ijgt} = y_j\beta^a + \bar{D}_{jt}\alpha^a + D_i\omega^a + y_j D_i \tilde{\beta}^a + \xi^a_{jgt} + \nu_{ijgt} \tag{6}$$

Since parents observe ξ^a_{jgt} but ν_{ijgt} has not been realized yet at time they choose a school, their expectation of (4) is:

$$E\left[A_{ijgt}\right] = y_j\beta^a + \bar{D}_{jt}\alpha^a + D_i\omega^a + y_j D_i \tilde{\beta}^a + \xi^a_{jgt} \tag{7}$$

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

$$\mu^p_{ijgt} = y_j\beta^a\phi + \bar{D}_{jt}\alpha^a\phi + D_i\omega + y_j D_i\tilde{\beta} + D_i\bar{D}_{jt}\tilde{\alpha} + x_{ijt}\gamma + \varphi\log(I_i - p_{jgt}) + \phi\xi^a_{jgt} \tag{8}$$

where $\omega = \omega^a\phi$. The coefficient of the interaction of y_j and D_i is $\tilde{\beta} = \tilde{\beta}^p + \phi\tilde{\beta}^a$. 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 ($\phi\tilde{\beta}^a$).

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

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

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

$$\delta_{jgt} = y_j\beta + \bar{D}_{jt}\alpha + \xi_{jgt} \tag{10}$$

In this expression, the coefficient of y_j captures both household preference for school focus and impact of focus on achievement: $\beta = \beta^p + \phi\beta^a$. 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 $\bar{D}_{jt}$ 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: $\xi_{jgt} = \xi^p_{jgt} + \phi\xi^a_{jgt}$. 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:

$$\xi_{jgt} = \xi_j + \xi_g + \xi_t + \Delta\xi_{jgt} \tag{11}$$

In this decomposition, the school-specific component ξ_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 ξ_j as the permanent quality of the school. The grade-specific component ξ_g captures elements that are common to a given grade across schools and over time. For instance, retention rates tend to be higher in 9th grade than in any other grade. The time-specific component ξ_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 much higher than the school average.

The household-specific component of (9) is:

$$\mu_{ijgt} = D_i\omega + y_j D_i\tilde{\beta} + D_i\bar{D}_{jt}\tilde{\alpha} + x_{ijt}\gamma + \varphi\log(I_i - p_{jgt}) \tag{12}$$

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:

$$U_{i0gt} = \varphi\log(I_i) + \xi_{0gt} + D_i\omega_0 + \varepsilon_{i0gt} \tag{13}$$

Since we cannot identify ξ_{0gt} and ω_0 separately from the ξ_{jgt} terms of the "inside" goods or from ω, we apply the following normalizations: $\xi_{0gt} = 0$ and $\omega_0 = 0$.

Let J^i_{gt} 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^i_{gt} 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:

$$P_{jgt}\left(y_j, y_{-j}, \bar{D}_{jt}, \bar{D}_{-jt}, \xi_{jgt}, \xi_{-jgt}, p_{jgt}, p_{-jgt}, X_{ijt}; \theta^d\right) = \frac{\exp(\delta_{jgt} + \mu_{ijgt})}{\exp(\varphi\log(I_i)) + \sum_{k=1}^{J^i_{gt}} \exp(\delta_{kgt} + \mu_{ikgt})} \tag{14}$$

where θ^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 $h(D, I, \ell \mid g)$ be the joint distribution of demographics, income and location conditional on a particular grade. Recall that each location ℓ 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:

$$\widehat{N}_{jgt} = \int_\ell \int_I \int_D P_{jgt}(\cdot)dh(D, I, \ell \mid g) \tag{15}$$

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

$$\widehat{S}_{jgt}(y_j, y_{-j}, \bar{D}_{jt}, \bar{D}_{-jt}, \xi_{jgt}, \xi_{-jgt}, p_{jgt}, p_{-jgt}; \theta^d) = \frac{\widehat{N}_{jgt}}{M_{gt}} \tag{16}$$

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

$$\widehat{\bar{D}}_{jt}(y_j, y_{-j}, \bar{D}_{jt}, \bar{D}_{-jt}, \xi_{j\cdot t}, \xi_{-j\cdot t}, p_{j\cdot t}, p_{-j\cdot t}; \theta^d) = \frac{\sum_{g \in \kappa_{jt}} \widehat{N}_{jgt} \int_{\ell} \int_{I} \int_{D} DP_{jgt}(\cdot) dh(D, I, \ell \mid g)}{\widehat{N}_{jt}} \tag{17}$$

where the dot in ξ 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, $\widehat{\bar{D}}$.

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):

$$q_{jt} = y_j \alpha^q + \bar{D}_{jt} \phi^q + y_j \bar{D}_{jt} \omega^q + \xi_j^q + \xi_t^q + \Delta \xi_{jt}^q \tag{18}$$

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 schock 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 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 the number of schools. Hence, there is not enough variation in our data to identify a model of strategic decisions on the part of public or private schools. At least during our sample period, these schools seem to have reacted very slowly to changes in the environment. Thus, we do not model decision-making on the part of public and private schools; rather, we take their behavior as given from the data. We assume that in any given time period they make decisions before charters do, and hence charters take public and private schools' decisions 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.

For these reasons, our supply-side model focuses on 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.[18] In particular, charters must forecast their *equilibrium*

[18] Reimbursement is the per-student stipend that charters receive in lieu of funding.

demand, namely the demand they will face after households re-sort across schools in response to charter actions.

Below we provide a few institutional details on charter entry to illuminate our modeling choices regarding entry. Then we describe the information structure facing charters and describe the problem of entrants and incumbents. We finalize by describing the timing of the entry-exit-relocation game and by describing the equilibrium of the model.

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 that it will be able 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 the school needs in order to be viable given the expected fixed costs.

If the application is approved, the charter receives approval notice in April or May of (X-1) and must start negotiations with the authorizer on a few issues, including the building. At the time of receiving the approval notice, the school should have secured a building, or else the negotiations with the authorizer 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 also 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 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-specific process motivates the timing of entry-exit-relocation events we describe below. Broadly speaking, schools make entry, exit and relocation decisions first, and households choose schools later. Although schools face uncertainty when making choices, the uncertainty is resolved by the end of the period and households make choices with complete information.

3.2.2 Information structure

To illustrate the information problems facing charters, recall that we have defined an entry point for charters as a combination of location ℓ, focus y and grade level κ, and consider a prospective entrant for entry point $(\ell,\ y, \kappa)$. In order to determine whether to enter or not, she needs to forecast her equilibrium demand taking into account the choice set available to households and the characteristics of these choices. However, the entrant faces two sources of uncertainty. First, she does not know the choice set available to households because she does not know which other schools will enter, exit or relocate. Second, she does not know, for herself or others, a characteristic that households take into account when choosing schools, namely their demand shock ξ_{jgt}. This dual uncertainty affects both potential entrants and incumbent charters.

The timing of entry-exit-relocation events we describe below specifies the information available to a school about others' actions at each point in time and thus addresses the first source of uncertainty. As for the second source, recall that we have decomposed the demand shock as $\xi_{jgt} = \xi_j + \xi_g + \xi_t + \Delta\xi_{jgt}$. We assume that both prospective entrants and incumbents observe ξ_g because it is time-invariant and common to all schools that offer g. We also assume that ξ_t becomes public knowledge at the begining of period t and is thus observed by prospective entrants and incumbents. While incumbents observe their permanent quality ξ_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 schools, hosts open houses, hires a principal and teachers, participates in charter fairs, engages in fundraising, etc.

Finally, we assume that at the beginning of t no school observes its school-grade-year deviation $\Delta\xi_{jgt}$. We assume that ξ_j and $\Delta\xi_{jgt}$ are independent and that $\Delta\xi_{jgt}$s are independent across grades for a given school-year. Further, we assume that the distributions of ξ_j and $\Delta\xi_{jgt}$ are common knowledge, equal to $N(\mu_\xi, \sigma^2_\xi)$ and $N(0, \sigma^2_{\Delta\xi})$ respectively. For convenience we sometimes refer to these distributions as N_{ξ_j} and $N_{\Delta\xi_{jgt}}$ respectively. Thus, ξ_{jgt} is distributed $N(\xi_j + \xi_g + \xi_t, \sigma^2_{\Delta\xi})$ for all incumbent public, private and charter schools, and $N(\mu_\xi + \xi_g + \xi_t, \sigma^2_\xi + \sigma^2_{\Delta\xi})$ for potential charter entrants.

In order to forecast her demand for a given period, a charter must integrate over the distribution of its own $\Delta\xi_{jgt}$ and that of other schools, and must do so for each grade she serves. Since charters compete with all schools in the city, this is high-dimensional integral. For instance, there were 180 schools offering 1st grade in 2007. Thus, we reduce the computational burden by evaluating other schools' $\Delta\xi_{jgt}$ at their mean, equal to $\mu_\xi + \xi_g + \xi_t$ for entrants and $\xi_j + \xi_g + \xi_t$ for incumbents.

3.2.3 Charter entrants

Recall we have assumed one prospective entrant per entry point per period. Prospective entrant j in location ℓ, grade level κ and focus y forms her beliefs about the expected demographic composition at her school as a solution of the following system of equations

$$\widehat{\widehat{D}}_{jt} = \int_{\xi_{j.t}} \widehat{\widehat{D}}_{jt}(y, y_{-j}, \widehat{\widehat{D}}_{jt}, \widehat{\widehat{D}}_{-jt}, \xi_{j\cdot t}, \xi_{-j\cdot t}, p_{-j\cdot t}; \theta^d) dN_{\xi_j}(\mu_\xi, \sigma^2_\xi) \prod_{g\in\kappa_{jt}} dN_{\Delta\xi_{jgt}}(0, \sigma^2_{\Delta\xi}) \tag{19}$$

where $\widehat{\widehat{D}}_{-jt}$ are the beliefs of other schools about their peer characteristics, formed similarly to $\widehat{\widehat{D}}_{jt}$.

Given these beliefs, the prospective entrant's predicted market share for grade g in case of entering is

$$E\left[\widehat{S}_{jgt} \mid (\ell, y, \kappa)\right] = \int_{\xi_{jgt}} \widehat{S}_{jgt}(y, y_{-j}, \widehat{\widehat{D}}_{jt}, \widehat{\widehat{D}}_{-jt}, \xi_{jgt}, \xi_{-jgt}, p_{-jgt}; \theta^d) dN(\mu_\xi + \xi_g + \xi_t, \sigma_\xi^2 + \sigma_{\Delta\xi}^2) \quad (20)$$

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

Let R_{gt} denote the reimbursement per student in grade g that a charter school obtains.[19] Let V_κ denote variable costs per student; these may differ by grade level, κ. Let ζ be an entry fee that is only paid when entering. Let $F_{\ell t}$ denote fixed costs which must be paid every year that the school is open. These may vary by location and time to capture varaition in the main component of fixed costs, which is the cost of facilities.

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

$$\pi^e_{\ell y \kappa t}(\theta^s) = \sum_{g \in \kappa} M_{gt} E\left[\widehat{S}_{jgt} \mid (\ell, y, \kappa)\right](R_{gt} - V_\kappa) - \zeta - F_{\ell t} + \nu^e_{\ell y \kappa t} \quad (21)$$

where $\theta^s = \left\{\mu_\xi, \sigma_\xi, \sigma_{\Delta\xi}, \zeta, V_\kappa, F_{\ell t}, w\right\}$ refers to the collection of supply-side parameters to be estimated, and $\nu^e_{\ell y \kappa t}$ 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 ν^e_{0t}.[20]In the θ^s vector, parameter w denotes relocation costs and is used below in our model of incumbents. We assume that the error terms $\nu^e_{\ell y \kappa t}$ and ν^e_{0t} are i.i.d. type I extreme value.

In practice, a charter school may serve only a single grade in the first year and grow into its full grade level over time. Our characterization in (21) assumes that the school decides on entry based on whether it expects non-negative net revenues were it serving its full set of grades from the beginning of its operations.

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.

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 ℓ, with focus y and grade level κ makes the decision that solve the following problem:

[19] 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.

[20] 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.

$$\pi_{jt}^{i}\left(\theta^{s}\right)=\max\left\{\begin{array}{ll}\pi_{jt,stay}^{i}=\sum_{g\in\kappa}M_{gt}E\left[\widehat{S}_{jgt}\mid(\ell,y,\kappa)\right](R_{gt}-V_{\kappa})-F_{\ell t}+\nu_{jt\ell}^{i} & \text{if stays in location }\ell\\ \pi_{jt,move}^{i}=\sum_{g\in\kappa}M_{gt}E\left[\widehat{S}_{jgt}\mid\left(\ell^{'},y,\kappa\right)\right](R_{gt}-V_{\kappa})-F_{\ell^{'}t}-w+\nu_{jt\ell^{'}}^{i} & \text{if moves to location }\ell^{'}\\ \pi_{jt,exit}^{i}=\nu_{jt0}^{i} & \text{if exits}\end{array}\right\} \tag{22}$$

where $\nu_{jt\ell}^{i}$ is ideosyncratic 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 ν_{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 ξ_j is common knowledge as is the set of grade-specific demand shocks ξ_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 ξ_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.[21]

Step 6: (*Households' school choice*) At the end of t, households observe the demand shocks ξ_{jgt} of all the schools operating in the market, including new entrants and incumbents. Households choose schools based on this information.

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 sort across schools given the supply of schools. In equilibrium, the resulting school peer

[21] Step 4 can only be repeated a finite number of times.

characteristics are consistent with households' choices, and no household wishes to alter its choice. The other stages of the game represent the strategic interaction of the schools. In particular, we assume that they play Perfect Bayesian Equilibrium. In equilibrium, every school forms consistent beliefs about the equilibrium strategies of competing schools, households' choices and the resulting peer compositions. Every charter school chooses the strategy that maximizes its payoff conditional on these beliefs.

4 Data and Estimation

To estimate the model, we proceed in three stages. First, we estimate demand-side parameters θ^d. Second, we estimate supply-side parameters θ^s. Third, we estimate proficiency rate parameters θ^q. Below we describe the data used to estimate the model and each of 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; 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^S=8,112 school-grade-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 data on 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 (by grade) 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. 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 ℓ 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.[22]

[22] 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.

Once we have this joint distribution, we randomly draw $ns = 100$ households for each market.[23] 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 assigment 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. 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 constrast, 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 θ^d, we must first calculate the predicted school-grade-year market shares and school-year demographic compositions. 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

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

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 $\widehat{S}_{jgt} = \frac{\widehat{N}_{jgt}}{M_{gt}}$. Thus, the school's predicted enrollment is equal to $\hat{N}_{jt} = \sum_{g \in \kappa_{jt}} \hat{N}_{jgt}$, and predicted school peer characteristics are as follows:

$$\widehat{\bar{D}}_{jt} = \frac{\sum_{g \in \kappa_{jt}} \left(\frac{M_{gt}}{ns} \right) \sum_{i=1}^{ns} D_i \hat{P}_{jgt} (\cdot)}{\hat{N}_{jt}} \tag{24}$$

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.

We assume that $E\left(\bar{D}_{jt} \mid X_t\right) = \widehat{\bar{D}}_{jt}$. Thus, observed peer characteristics $\bar{D}_{jt}$ are different from their expected value due to sampling (and perhaps measurement) error:

[23] 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.

$$\bar{D}_{jt} = \widehat{\bar{D}}_{jt} + u_{jt} \tag{25}$$

Since parents observe the unobserved (to us) school characteristics $\Delta\xi_{jgt}$ and make ther decisions accordingly, the school demographic composition $\bar{D}_{jt}$ that results from household choices is correlated with $\Delta\xi_{jgt}$. Let Z^X_{jgt} be a row vector of L^X instruments, and Z^D_{jt} be a row vector of L^D instruments. In our preferred specification, $L^X = 332$ and $L^D = 137$. Recall that $J^X = 8,112$ and $J^D = 1,269$. Vertically stacking all observations yields matrices Z^X, with dimension J^X by L^X, and Z^D, with dimension J^D by L^D.

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:

$$E\left[\Delta\xi_{jgt} \mid Z^X_{jgt}\right] = 0 \tag{26}$$

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

$$E\left[u_{jt} \mid Z^D_{jt}\right] = 0 \tag{27}$$

Recall that vector u_{jt} has $\widetilde{D}$ elements, one for each peer characteristic. Hence, these conditional moments yield the following $(L^X + L^D * \widetilde{D})$ moment conditions:

$$E\left[\left(Z^X_{jgt}\right)' \Delta\xi_{jgt}\right] = 0 \tag{28}$$

$$E\left[\left(Z^D_{jt}\right)' u^d_{jt}\right] = 0 \tag{29}$$

where u^d_{jt} indicates the sampling error in a specific demographic characteristic d (for instance, in percent white students). Vertically stacking all observations yields vectors and rearranging elements yields vectors $\Delta\xi$ and u with J^X and $\left(J^D * \widetilde{D}\right)$ rows respectively. The first set of J^D rows in vector u correspond to the first demographic characteristic; the second set set to the second demographic characteristic, and so forth for the $\widetilde{D}$ demographics. In order to interact the sampling error for each demographic characteristic with every instrument in Z^D we introduce matrix $\widetilde{Z}^D$, which is block diagonal and repeats Z^D along the diagonal for a total of $\widetilde{D}$ times. We use the term "share moments" to refer to (28) and "demographic moments" to refer to (29).

The sample analogs of (28) and (29) are the following vectors:

$$\begin{aligned} \lambda_X(\Delta\xi) &= \frac{1}{J^X} Z^{X\,\prime} * \Delta\xi \\ \lambda_D(\Delta\xi, \theta^d) &= \frac{1}{J^D} \widetilde{Z}^{D\,\prime} * u \end{aligned} \tag{30}$$

with L^X and $\left(L^D * \widetilde{D}\right)$ 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 δ that equates predicted and observed market shares each time that a value of θ^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 by including the demographic moments as well.

Since u_{jt} is sampling error, it is independent of the elements upon which households base their choices. One such element is $\Delta\xi_{jgt}$. Hence, we assume $E\left[u_{jt} \mid \Delta\xi_{jgt}\right] = 0$ for all the grades in school j, and write our MPEC problem as follows:

$$\begin{aligned} & \min_{\Delta\xi,\, \theta^d} \begin{bmatrix} \lambda_X(\Delta\xi) \\ \lambda_D(\Delta\xi, \theta^d) \end{bmatrix}' \begin{bmatrix} V_X & 0 \\ 0 & V_D \end{bmatrix} \begin{bmatrix} \lambda_X(\Delta\xi) \\ \lambda_D(\Delta\xi, \theta^d) \end{bmatrix} \\ & s.t. \\ S &= \hat{S}(\Delta\xi, \bar{D}; \theta^d) \end{aligned} \tag{31}$$

where the sample moments are defined as in (30). The MPEC algorithm simultaneously searches over values for $\Delta\xi$ and θ^d; given values for these, it calculates the predicted market shares and peer characteristics. The constraint of the MPEC problem ensures 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.

In order to implement optimal GMM we must calculate the optimal weighting matrix. Thus, we first solve our first-stage MPEC problem, described by (31) for arbitrary V_X and V_D matrices. Let $\left(\tilde{\theta}^d, \Delta\tilde{\xi}\right)$ be the this problem's solution. Based on first-stage results we constuct the optimal weighting matrix for the second-stage MPEC and solve the following problem:

$$\begin{aligned} & \min_{\Delta\xi,\, \theta^d} \begin{bmatrix} \lambda_X(\Delta\xi) \\ \lambda_D(\Delta\xi, \theta^d) \end{bmatrix}' \begin{bmatrix} W_X & 0 \\ 0 & W_D \end{bmatrix} \begin{bmatrix} \lambda_X(\Delta\xi) \\ \lambda_D(\Delta\xi, \theta^d) \end{bmatrix} \\ & s.t. \\ S &= \hat{S}(\Delta\xi, \bar{D}; \theta^d), \end{aligned} \tag{32}$$

with the elements of the weighting matrix given by

$$\begin{aligned} W_X &= \left\{ \frac{1}{(J^X)^2} \left[Z^X .* (\Delta\tilde{\xi} * e'_{L^X}) \right]' * \left[Z^X .* (\Delta\tilde{\xi} * e'_{L^X}) \right] \right\}^{-1} \\ W_D &= \left\{ \frac{1}{(J^D)^2} M^{D\,\prime} * M^D \right\}^{-1} \end{aligned} \tag{33}$$

where $.*$ denotes element-by-element matrix multiplication, and matrix M^D is of size $J^D \times (L^D * \widetilde{D})$. The content of this matrix is

$$M^D = \left[\; Z^D .* (\tilde{u}^1 * e'_{L^D}) \quad \ldots \quad Z^D .* (\tilde{u}^{\tilde{D}} * e'_{L^X}) \; \right]$$

where u^d $d = 1, ..., \tilde{D}$, is the size J^D vector of sampling error for demographic characteristic d and e_T is a vector with ones of size T. This formulation assumes that the $\Delta\xi_{jgt}$ shocks are independent across schools and grades and over time, but allows for correlation among sampling errors of percent white, hispanic and non-poor for a given school-year. In future versions we will allow $\Delta\xi_{jgt}$ to be correlated over time for a given school-grade.

Let $\left(\hat{\theta}^d, \Delta\hat{\xi}\right)$ be the solution to this problem. To estimate the standard errors of our parameter estimates $\hat{\theta}^d$, we first calculate the derivatives of the sample moments λ_S and λ_D with respect to $\hat{\theta}^d$ as follows:

$$
\begin{aligned}
Q_{\partial\lambda_X} &= \frac{1}{J^X}\, Z^{X\,\prime} * \frac{\partial \hat{S}^{-1}(S,\bar{D};\hat{\theta}^d)}{\partial(\theta^d)'} \\
Q_{\partial\lambda_D} &= \frac{1}{J^D}\left(-Z^{D\,\prime}\right) * \frac{\partial \hat{\bar{D}}(\Delta\hat{\xi};\hat{\theta}^d)}{\partial(\theta^d)'}
\end{aligned}
\tag{34}
$$

where the vector function $\hat{S}^{-1}(S,\bar{D};\hat{\theta}^d) = \Delta\xi$ is the solution of the share equation. The variance-covariance matrix of $\hat{\theta}^d$ is then equal to

$$
V(\hat{\theta}^d) = \left\{ \begin{bmatrix} Q_{\partial\lambda_X} \\ Q_{\partial\lambda_D} \end{bmatrix}' \begin{bmatrix} W_X & 0 \\ 0 & W_D \end{bmatrix} \begin{bmatrix} Q_{\partial\lambda_X} \\ Q_{\partial\lambda_D} \end{bmatrix} \right\}^{-1}
$$

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, ξ_j in (10), we apply a minimum-distance procedure as in Nevo (2000, 2001) in order to estimate β and ξ_j separately. Recall that $J = 281$ is the number of schools in the data. Denote by B the $J \times 1$ vector of school-specific dummy variables estimated by GMM; by y the $J \times Y$ vector of time-invariant characteristics (governance and focus), and by ξ the $J \times 1$ vector of school-specific demand shocks. From (10) and (11) we can see that our school fixed effects capture the total effect of time-invariant characteristics: $B = y\beta + \xi$. Following Nevo (2000, 2001), we assume that $E\left(\xi_j \mid y_j\right) = 0$, which allows us to recover the estimates of β and ξ as $\hat{\beta} = \left(y' V_B^{-1} y\right)^{-1} y' V_B^{-1} \hat{B}$ and $\hat{\xi} = \hat{B} - y\hat{\beta}$ respectively, where $\hat{B}$ is the vector of school dummy coefficients contained in $\hat{\theta}^d$ and estimated through GMM, and V_B is the variance-covariance matrix of these estimates.

4.3 Supply estimation

In the second stage of estimation we match the entry, exit and relocation decisions of charters in order to estimate the supply parameters $\theta^s = \left\{\mu_\xi, \sigma_\xi, \sigma_{\Delta\xi}, \zeta, V_\kappa, F_{\ell t}, w\right\}$. In our empirical application we consider $L = 40$ locations or neighborhood clusters,[24] $Y = 5$ focuses and $K = 3$ grade levels for a total of 600 entry points. Over our sample period, these amount to 3,000 instances of possible charter entry, exit or relocation.[25] Yet as Table 2 illustrates there are only 30 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. We will then check the accuracy of this approximation through Monte Carlo simulations of the steps of the game at the estimated values of θ^s.

We estimate θ^s through Maximum Likelihood Estimation (MLE). Denote by $\tilde{I}_t$ the information available to the econometrician on market structure for period t. The likelihood function is then

$$
\tilde{L}\left(\theta^s\right) = \prod_{t=1}^{T} \left[\left\{ \prod_{j=1}^{C_t} \Pr\left(d_{jt} = \hat{d}_{jt} \mid \tilde{I}_t\right) \right\} \left\{ \prod_{\ell=1}^{L} \prod_{y=1}^{Y} \prod_{\kappa=1}^{K} \Pr\left(d_{\ell y\kappa} = \hat{d}_{\ell y\kappa} \mid \tilde{I}_t\right) \right\} \right] \tag{35}
$$

[24] A neighborhood cluster is a collection of Census tracts that is often used by DC planning agencies to proxy for a "neighborhood." While D.C. includes 188 Census tracts, it only has 40 neighborhood clusters. Thus, the use of neighborhood clusters rather than Census tracts or block groups eases computational burdens.

[25] In our data there is at most one entry per entry point and year.

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 $\tilde{L}(\theta^s)$, $\Pr\left(d_{jt} = \hat{d}_{jt} \mid \tilde{I}_t\right)$ is the conditional probability that incumbent j chooses action $\hat{d}_{jt}$ given the observed market structure. 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

$$\Pr\left(d_{jt} = \hat{d}_{jt} \mid I_t\right) = \frac{\exp\left(\bar{\pi}^i_{jt\hat{d}_{jt}}\left(\tilde{I}_t\right)\right)}{\sum_{\ell=0}^{L} \exp\left(\bar{\pi}^i_{jt\ell}\left(\tilde{I}_t\right)\right)} \tag{36}$$

where $\bar{\pi}^i_{jt\ell}\left(\tilde{I}_t\right)$ is the mean profit of incumbent j at time t if it locates in ℓ. The profit is given by (22). The other set of probabilities in $\tilde{L}(\theta^s)$, $\Pr\left(d_{\ell\kappa y} = \hat{d}_{\ell\kappa y} \mid \tilde{I}_t\right)$, describes entry behavior in each entry point (ℓ, y, κ). The probability of entering is given by

$$\Pr\left(d_{\ell\kappa y} = enter \mid \tilde{I}_t\right) = \frac{\exp\left(\bar{\pi}^e_{\ell y\kappa}(\tilde{I}_t)\right)}{1 + \exp\left(\bar{\pi}^e_{\ell y\kappa}(\tilde{I}_t)\right)} \tag{37}$$

where $\bar{\pi}^e_{\ell y\kappa}(\tilde{I}_t)$ is the mean profit from (21). Since the probabilities in (37) and (36) also depend on the demand side parameters θ^d, we use our estimates of these parameters when conducting MLE.

4.4 Proficiency Rate Estimation, and Summary

Although we cannot identify the parameters of the achievemet function, [26] 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:

$$\bar{q}_{jt} = y_j\alpha^q + \bar{D}_{jt}\phi^q + y_j\bar{D}_{jt}\omega^q + \xi^q_j + \xi^q_t + \Delta\xi^q_{jt} + v^q_{jt} \tag{38}$$

Here, the error term is the addition of the a school-year unobserved shock on proficiency $\Delta\xi^q_{jt}$ and school-year sampling or measurement error in proficiency rates v^q_{jt}. Since $\Delta\xi^q_{jt}$ may be correlated with the demand shocks $\Delta\xi_{jgt}$ observed by parents when choosing schools, $\bar{D}_{jt}$ is likely to be correlated with ξ^q_{jt}, 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 α^q and the school fixed effects ξ^q_j. This issue is similar to the one we face when estimating utility function parameters, and we therefore solve it in a similar way.

To summarize, our estimation approach proceeds in three stages. First, we exploit orthogonality conditions related to demand shocks and demographic 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.

[26] 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.

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 $\bar{D}_{jt}$, which are an outcome of household choices, and $\Delta\xi_{jgt}$.

To address this correlation, we instrument for $\bar{D}_{jt}$ using the observed peer characteristics of "similar but distant" schools. The idea behind this instrument is that the peer characteristics of "similar" schools are correlated, but their grade-year specific valuations are not if the schools are "distant." Consider, for instance, two elementary public schools located in neighborhoods with the same average household income, but four miles apart from each other. The fact that the schools are located in similar neighborhoods means that they will attract observationally similar students, but because they are far away, grade-specific idiosyncrasies (such as who teaches a specific grade) will not be correlated.

We define "similarity" as follows. For charters belonging to a multi-campus organization, similar schools are other charters in the same organization. The idea is that campuses of the same organization may be perceived as belonging to the same "brand" yet their specific grade-year valuations are not correlated because the campuses operate independently and serve different grade levels. This idea is similar to that of Nevo (2000, 2001), who instruments for the price of a brand in one market with the price of the same brand in other, distant markets. For single-campus charters, similar schools are other charters with the same focus and grade level.[27] For public schools, similar schools are other public schools that serve the same grade level and are located in neibghborhoods with similar demographics (in particular, similar average household income). For private schools, similar schools are other private schools of the same type (Catholic, other religious or nonsectarian), grade level, tuition range, and neighborhood demographic characteristics. To be considered "distant", an elementary school must be farther away than 2 miles; a middle school must be farther away than 2.5 miles, and a high school must be farther away than 3 miles.[28]

Note that the set of similar-but-distant schools for a given school-grade-year varies across grades within a school. For instance, the set of similar-but-distant schools for the 4th grade of Adams Elementary School is 2004 is the set of schools that are "similar" to Adams, as described above, and offer 4th grade. This set may not be the same as for Adams's 5th grade since grade configuration varies substantially across schools and even over time for some schools. This is particularly true of charters, for which entry, relocations and grade additions affect the set of similar schools.

Thus, our Z^X matrix contains the following instruments: percent white, percent hispanic and percent low-income in the five most similar-but-distant schools;[29] interactions between grade-level dummies and the demographics of the most similar-but-distant school; and campus-, grade- and year-level dummies.[30]

[27] We also use this similarity notion for multi-campus charters for the years in which they only have one campus open.

[28] Filardo et al (2008) report median distance traveled from children in each neighborhood cluster to school, by grade level. Most median distances fall below the thresholds we are using.

[29] We gave to each school in the set of similar-but-distant schools an index that was increasing in distance and similarity. Hence, the schools from the set that were most similar yet located at the greatest distance were included as instruments.

[30] To avoid highly collinear instruments, we regressed each one on all the others and eliminated those for which more than 85 percent of their variation could be explained by the other instruments.

As for Z^D, the sampling error in school-year average peer characteristics must be mean independent of its columns. Since characteristics of the schools that affect households' choices are valid instruments, matrix Z^D contains campus dummies.[31]

Finally, matrix Z^Q used for the proficiency rate estimation is similar to Z^X and contains the following instruments: percent white, percent hispanic and percent low-income in each of five most similar-but-distant schools, and campus- and year-level dummies.

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 $(\alpha^a, \beta^a, \omega^a, \tilde{\beta}^a)$. The parameters of the baseline component of utility, (α, β) in equation (10), are identified. Parameters α 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 α^a not being identified, ϕ is not identified either as discussed below. Since we cannot identify α^a, the individual components of α are not identified. A similar reasoning applies to β (baseline utility of time-invariant school characteristics) and its individual components. Given that the default demographic group is (black, low income), α and β reflect black and low-income households' preferences. Parameters α are identified by the extent to which black and low-income students mix with students from other races and economic status in schools, and parameters β are identified by the variation in the fraction of black and low-income students among schools of different types and focuses.

Parameters $\left(\tilde{\alpha}, \tilde{\beta}, \gamma, \omega, \varphi\right)$ of the household-specific component of utility in (12) are identified. Parameter ω is the utility from the portion of achievement due to a student's own characteristics: $\omega = \omega^a\phi$. While ω is identified, ω^a is not as discussed above. Hence, the weight of achievement on utility ϕ is not identified either. Since ω_0 is normalized to zero for the outside good and the default demographic group is (black, low income), ω 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 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 ϕ nor $\tilde{\beta}^a$ are identified, as we saw above. Thus, $\tilde{\beta}^p$ is not identified either. From the perspective of counterfactual analysis of the impact of policies on school choice, identification of the components of α, β 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 and by their enrollment patterns across schools of different types and focuses. Parameter γ is the disutility of geographic distance between the household's residence and the school, and is identified by the geographic distribution of households and schools and the extent to which schools' demographic composition matches that of nearby neighborhoods. In

[31] We use a set of 137 campus dummies rather than the full set of 281 campus dummies in Z^D. The reason is that the remaining orthogonality conditions are redundant and lead to an ill-posed second stage MPEC problem. Applying a greedy algorithm, we removed the set of campus dummies that most contributed to a high condition number for the W_D matrix in the second stage MPEC problem. After removing those dummies and re-running the first stage, the second-stage W_D matrix has a condition number of the order of 1e4.

general, variation in school type, focus and location is critical to the identification of preference parameters. Parameter φ 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 ξ_j are identified by having multiple grades and years per school (all of them are included in the estimation). Since $\xi_{0gt} = 0$ for the outside good, ξ_j represents the difference in utility from attending school j relative to the outside good. Grade fixed effects ξ_g are identified by having multiple schools and year per grade. Since first grade is the omitted category, ξ_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 ξ_t are identified by having multiple schools and grades per year. Since 2003 is the omitted year, ξ_t is the difference in the utility of going to school rather than choosing the outside good in year t relative to 2003.

A formal condition for identification is that the matrix of derivatives of the sample moments with respect to the parameters, $Q_{\partial\lambda} = \begin{bmatrix} Q_{\partial\lambda_X} \\ Q_{\partial\lambda_D} \end{bmatrix}$ have full rank. Evaluated at our parameter estimates, this matrix indeed has full rank.[32]

Proficiency rate parameters in (38)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 ζ is identified by the frequency of entry in the data. The fixed cost $F_{\ell t}$ is identified by the variation in entry patterns across locations and over time holding entrant and demand characteristics constant. Variable costs V_κ are identified by the pattern of entry by grade level holding other things constant. Moving costs w are identified by the frequency of moves. Finally, the parameters of the distribution of demand shocks, μ_ξ, σ_ξ and $\sigma_{\Delta\xi}$ are identified by the frequency of entry, exit and moves in the data, and by the distribution of ξ_j for the actual entrants (which we estimate based on demand-side fixed effects). Note, however, that we cannot estimate these parameters entirely based on the distribution of the estimated ξ_j's for the actual entrants because they parameters pertain to the distribution of unobserved school quality for *all* charters, including those that do not enter.

4.7 Computational Considerations

Currently we have estimated the demand side of the model. Obtaining these estimates involves solving the MPEC problem in (32). This is a problem with 8,446 unknowns – 334 parameters in θ^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

[32] 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.

order derivatives. In contrast, Dube et al (2011) supplied second-order derivatives to the KNITRO solver and used the Interior/Direct algorithm.

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 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 θ^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.[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.[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

Currently we have estimated the demand side of our model. Our demand-side model fits the data on peer characteristics very well. Across 1,269 school-year observations, the correlation between observed and predicted percent white, percent hispanic and percent non-poor students equals .96, .96 and .94 respectively. Most of our parameters estimates are significant and of the expected sign, as explained below.

[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.

[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.

Table 8 presents our parameter estimates. 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. These interaction effects are crucial to the fit of the data: without them, the correlations between observed and predicted peer characteristics are of the order of 0.6.[35] At the same time, the variation in our data is not enough to identify some of the parameters, most notably the interaction between the constant term and household demographics which capture heterogeneity across demographic groups in the value of being enrolled in school versus consuming the outside good.

In terms of school type, blacks, whites and non-poor households are indifferent between public and charter schools, but hispanics strictly prefer charters. All households prefer public over Catholic schools, although whites have a less negative valuation of Catholic schools than the other groups. All households prefer public over other religious private schools. While blacks are indifferent between public and private non-sectarian schools, other households prefer public over private non-sectarian schools. These findings are robust to a number of alternative specifications.

As for focus, all households prefer core over language with the exception of the non-poor, who prefer language. Whites and hispanics prefer arts over core and blacks are indifferent between the two, but non-poor households prefer core. Blacks are indifferent between vocational and core, but hispanics and non-poor prefer core. All households prefer core over "other" focus with the exception of whites.

While blacks are indifferent between increasing the fraction of white and black students in the school, all other groups prefer an increase in the fraction of white rather than black students. Increasing the fraction of hispanics rather than blacks is preferred only by hispanics, although whites are more favorable to hispanics than blacks. The estimates imply that whites prefer to mix with other whites rather than blacks or hispanics; hispanics prefer to mix with hispanics or whites but not blacks; and blacks are indifferent about mixing with whites rather than other blacks but strictly prefer to mix with other blacks rather than hispanics. Estimated preferences over peers' races are thus aligned with those in Hastings et al (2009), who documents that parents have preferences for peers of the same demographics. Our estimates also echo those in Bayer et al (2007), who documents households' preference to self-segregate based on demographics.

As for non-poor students, no demographic group prefers to mix with them rather than low-income students, although non-poor students are less disinclined to mixing with other non-poor students. These findings are robust to a number of alternative specifications.While somewhat surprising, they might be explained by the fact that we are also controlling for tuition. It is possible that controlling for tuition, households prefer to have an increase in poor rather than non-poor students.

Finally, the coefficient on distance is negative and significant indicating that households prefer shorter travels to school. To the extent that there is actually some residence-based assignment to public schools in D.C., this coefficient may attribute to preferences what is really an institutional requirement. Without data on these requirements, though, it is hard to tease out these different elements. The coefficient on the consumption of other goods is positive and significant, indicating negative sensitivity with respect to price. In future versions we will investigate the variation in price (tuition) elasticity among households, and in cross-price elasticities among schools.

Thus, while households have relatively similar preferences for school type, their preferences over school focus are quite different. Their preferences over peer characteristics are also heteroge-

[35] Results from this and alternative specifications are available from the authors upon request.

neous – whereas all attach positive value to having greater fraction of whites in the school (with blacks being indifferent between additional blacks and whites), only hispanics attach positive value to having a greater fraction of Hispanics. These parameter estimates help explain some of the enrollment patterns observed in the data. For instance, Table 6 shows a significant presence of hispanics in language schools. However, this presence is apparently not due to their preference for language relative to core (their disutility from language relative to core is robust across many different specifications). Rather, it seems driven by the fact that most language schools are charters, which is the most preferred school type for hispanics, and that they attract a large fraction of hispanic students.

To summarize, our estimates show substantial variation in household preferences over school characteristics. This variation creates an entry opportunity for charters, as different households prefer different focuses and peer characteristics. In future versions we will study the distribution of household willingness to pay for these characteristics to develop further insights on these preferences.

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. First, 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. A related concern is that our school fixed effects could be capturing not only unobserved school quality but also school capacity, and hence might be estimating high "quality" for schools that are simply large and have high market shares.

Second, 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. Third, in reality charters choose whether to be single- or multi-campus organizations in a choice that probably resembles a store chain's decision to open a new franchise. We plan on investigating this issue further.

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. Given that 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). DCPS has made some vacant public school buildings available for charters (Filardo et al, 2008). As public school enrollment continues to decline the supply of facilities for charters should increase. Moroever, 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 prefered. 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, given their loss of market share to charters over the past few years, public schools will be forced to respond at some point. Thus, we will study the effects of alternative responses.

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, at some point they might begin to respond, particularly if new charter entrants continue to target a more affluent, less disadvantaged student population. The question of interest is how private schools would compete in that context.

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.

From a methodological perspective, we will explore the use of MPEC to impose all equilibrium constraints at once rather than in three separate stages. In addition, we have begun investigating the consequences of relaxing the BLP assumption that market shares are observed without error. While this is a plausible assumption in markets with many consumers relative to the number of products, it may not be so in markets such as ours that consist of approximately 6,000 children per grade-year and at least 40 or 50 schools per grade. Currently we assume that market shares are observed without error but school demographics are observed with error. Thus, we have designed an estimator for the case in which both shares and demographics are observed with error. We are exploring the performance of this estimator in ongoing work.

Finally, Filardo et al (2008) contains tabulations of aggregate data for D.C. during our sample period that we are interested in matching in the estimation. For instance, they report the average distance to school traveled by children in each neighborhood cluster in D.C. Since our model predicts this distance, we can match it to the observed data. Matching additional data might be necessary given the lack of institutional information regarding school assignments. For instance, we have noticed that the predicted distance to school with our current estimates is too high relative to that reported in Filardo et al (2008), most likely as a consequence of not knowing public school assignment rules. Matching distance traveled to school would solve this problem and, in so doing, would help us produce more credible counterfactuals.

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 are able to capture the fact that peer characteristics are the outcome of parental choices, and that parents, in turn, respond to this composition 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

[1] Altonji, Joseph, C. Huang and Chris Taber (2011). "Estimating the Cream Skimming Effect of Private School Vouchers on Public School Students." Working Paper, University of Wisconsin-Madison.

[2] Bayer, Patrick and Christopher Timmins (2007). "Estimating Equilibrium Models of Sorting Across Locations" Locations," *Economic Journal*, 117(March), 353-374.

[3] Bayer, Patrick, Fernando Ferreira, and Robert McMillan (2007). "A Unified Framework for Measuring Preferences for Schools and Neighborhoods," *Journal of Political Economy*, vol. 115, No. 4, 588-638.

[4] Benabou, Roland (1996). "Heterogeneity, Stratification and Growth: Macroeconomic Effects of Community Structure," *American Economic Review*, 86, 584–609.

[5] Berry, Steven, James Levinsohn, and Ariel Pakes (1995). "Automobile Prices in Market Equilibrium," *Econometrica*, 63, 841-890.

[6] Bettinger, Eric P. (2005). "The Effect of Charter Schools on Charter Students and Public Schools," *Economics of Education Review*, 24, 113-147.

[7] Bifulco, Robert and Christian Buerger (2012). The Influence of Finance and Accountability Policies on Charter School Locations. Working Paper, Syracuse University .

[8] Bifulco, Robert and Helen F. Ladd (2006). "The Impacts of Charter Schools on Student Achievement: Evidence from North Carolina," Education Finance and Policy, 1 (1), 123-138.

[9] Booker, Kevin, Scott Gilpatric, Timothy Gronberg, and Dennis Jansen (2007). "The Impact of Charter School Attendance on Student Performance," Journal of Public Economics, 91 (5/6), 849-876.

[10] Booker, Kevin, Scott Gilpatric, Timothy Gronberg, and Dennis Jansen (2008). "The Effect of Charter Schools on Traditional Public School Students in Texas: Are Children Who Stay Behind Left Behind?," Journal of Urban Economics, 64 (1), 123-145.

[11] Buckle, Jack and Mark Schneider (2007). Charter Schools: Hope or Hype?, Princeton and Oxford: Princeton University Press.

[12] Buddin, Richard and Ron Zimmer (2005a). "Is Charter School Competition in California Improving the Performance of Traditional Public Schools?," RAND Working Paper.

[13] Buddin, Richard and Ron Zimmer (2005b). "Student Achievement in Charter Schools: A Complex Picture," Journal of Policy Analysis and Management, 24 (2), 351-371.

[14] Calabrese, Stephen, Dennis Epple, Thomas Romer, and Holger Sieg (2006). "Local Public Good Provision: Voting, Peer Effects, and Mobility,", Journal of Public Economics, 90, 6-7 (August): 959-81.

[15] Cardon, James H. (2003). "Strategic Quality Choice and Charter Schools," Journal of Public Economics, 87 (3), 729-737.

[16] Carranza, Juan Esteban, Jean-Francois Houde and Robert Clark (2011). "Dynamic Entry and Firm Reconfiguration in Canadian Gasoline Markets." Working Paper, ICESI University.

[17] Caucutt, Elizabeth (2002). "Educational Policy when There Are Peer Group Effects—Size Matters," International Economic Review, 43, 195–222

[18] Clark, Damon (2009). "The Performance and Competitive Effects of School Autonomy," Journal of Political Economy, 117 (4), 745-783.

[19] de Bartolome, C. (1990). "Equilibrium and Inefficiency in a Community Model with Peer Group Effects," Journal of Political Economy, 98, 110–133.

[20] Downes, Thomas A. and Shane M. Greenstein (2006). "Understanding the Supply Decisions of Nonprofits: Modelling the Location of Private Schools," RAND Journal of Economics, Vol. 27(2), Summer, pp. 365-390.

[21] Draganska, Michaela, Michael Mazzeo, and Katja Seim (2009). "Beyond Plain Vanilla: Modeling Joint Product Assortment and Pricing Decisions," Quantitative Marketing and Economics, 7(2), 105-146.

[22] Draganska, Michaela, Sanjog Misra, Victor Aguirregabiria, Pat Bajari, Liran Einav, Paul Ellickson, Dan Horsky, Sridhar Narayanan, Yesim Orhun, Peter Reiss, Katja Seim, Vishal Singh, Raphael Thomadsen, and Ting Zhu (2008). "Discrete choice models of firms' strategic decisions," Marketing Letters, 19, 399–416.

[23] Dubé, Jean-Pierre, Jeremy Fox, and Che-Lin Su (2011). "Improving the Numerical Performance of BLP Static and Dynamic Discrete Choice Random Coefficients Demand Estimation," Forthcoming, *Econometrica*.

[24] Dunne, Timothy, Shawn Klimek, Mark Roberts and Daniel Yi Xu (2009). "Entry, Exit and the Determinants of Market Structure," NBER Working Paper 15313.

[25] Epple, Dennis and Romano, Richard (1998). "Competition Between Private and Public Schools, Vouchers, and Peer-Group Effects". American Economic Review, March, 88(1), pp. 33-62.

[26] Fernandez, Raquel and Richard Rogerson (1998).: "Public Education and Income Distribution: A Dynamic Quantitative Evaluation of Education-Finance Reform," American Economic Review, 88, 813–833.

[27] Ferreyra, Maria M. (2007). "Estimating the Effects of Private School Vouchers in Multi-District Economies". American Economic Review, 97 (3): 789-817.

[28] Ferreyra, Maria M. (2009). "An empirical Framework for Large-Scale Policy Evaluation, with an Application to School Finance Reform in Michigan". American Economic Journal: Economic Policy, vol. 1 no. 1: 147–80.

[29] Filardo, Mary, Marni Allen, Nancy Huvendick, Ping Sung, David Garrison, Margery Turner, Jennifer Comey, Barika Williams and Elizabeth Guernsey (2008). "Quality Schools and Healthy Neighborhoods: A Research Report." Available at www.brookings.edu.

[30] Glomm, Gerhard, Douglas Harris, and Te-Fen Lo (2005). "Charter school location," Economics of Education Review, 24, 451–457.

[31] Hanushek, Eric A., John F. Kain, Steven G. Rivkin, and Gregory F. Branch (2007). "Charter School Quality and Parental Decision Making With School Choice," Journal of Public Economics, 91 (5/6), 823-848.

[32] Hastings, Justine, Thomas J. Kane and Douglas O. Staiger (2009). "Heterogeneous Preferences and the Efficacy of Public School Choice." Working Paper, Brown University.

[33] Holmes, George M., Jeff DeSimone, and Nicholas G. Rupp (2003). "Does School Choice Increase School Quality?," NBER Working Paper No. 9683.

[34] Hoxby, Caroline M. (2004). "Achievement in Charter Schools and Regular Public Schools in the United States: Understanding the Differences," Dept. of Economics, Harvard University, mimeo.

[35] Hoxby, Caroline M. and Jonah E. Rockoff (2004). "The Impact of Charter Schools on Student Achievement," Dept. of Economics, Harvard University, mimeo.

[36] Hoxby, Caroline M. and Sonali Murarka (2009). "Charter Schools in New York City: Who Enrolls and How They Affect Their Students' Achievement," NBER Working Paper No.14852.

[37] Imberman, Scott A. (forthcoming). "Achievement and Behavior of Charter Students: Drawing a More Complete Picture," Review of Economics and Statistics.

[38] Imberman, Scott A. (2009). "The Effect of Charter Schools on Achievement and Behavior of Public School Students", Working paper, University of Houston.

[39] Mazzeo, Michael (2002). "Product Choice and Oligopoly Market Structure," RAND Journal of Economics, vol. 33, No. 2, summer, 1-22.

[40] Mehta, Nirav (2012). Competition in Public School Districts: Charter School Entry, Student Sorting, and School Input Determination. Working Paper, Western Ontario University.

[41] National Alliance for Public Charter Schools (2010). "How State Charter Laws Rank Against the New Model Public Charter School Law," January, downloaded from www.publiccharters.org.

[42] Nechyba, Thomas J. (1999). School Finance Induced Migration and Stratification Patterns: The Impact of Private School Vouchers," Journal of Public Economic Theory, v. 1, pp. 5–50.

[43] Nechyba, Thomas J. (2000). "Mobility, Targeting and Private School Vouchers," American EconomicReview, 90, 130–146.

[44] Nevo, Aviv (2000). "Mergers with Differentiated Products: The Case of the Ready-To-Eat Cereal Industry," RAND Journal of Economics, vol. 31, No. 3, Autumn, 395-421.

[45] Nevo, Aviv (2001). "Measuring Market Power in the Ready-To-Eat Cereal Industry," Econometrica, v. 69, No. 2 (March), 307-342.

[46] Petrin, Amil (2002). "Quantifying the Benefits of New Products: The Case of the Minivan," Journal of Political Economy, vol. 110, 705-729.

[47] Rincke, Johannes (2007). "Policy diffusion in space and time: The case of charter schools in California school districts," Regional Science and Urban Economics, 37, 526–541.

[48] Sass, Tim R. (2006). "Charter Schools and Student Achievement in Florida," Education Finance and Policy, 1 (1), 123-138.

[49] Seim, Katja (2006). "An Empirical Model of Firm Entry with Endogenous Product-Type Choices, " RAND Journal of Economics, vol. 37, No. 3, Autumn, 619-640.

[50] Skrainka, Benjamin (2011). A Large-Scale Study of the Small Sample Performance of Random

[51] Coefficient Models of Demand. Working Paper, University of Chicago.

[52] Su, Che-Lin and Kenneth L. Judd (2011). "Constrained Optimization Approaches to Estimation of Structural Models," Forthcoming, *Econometrica*.

[53] Suzuki, Junichi (2010). "Land Use Regulation as a Barrier to Entry: Evidence from the Texas Lodging Industry," Working Paper, University of Toronto.

[54] Weiher, Gregory R. and Kent L. Tedin (2002). "Does Choice Lead to Racially Distinctive Schools? Charter Schools and Household Preferences," Journal of Policy Analysis and Management, 21 (1), 79.

[55] Zimmer, Ron and Richard Buddin (2003). "Academic Outcomes," in Charter School Operations and Performance, RAND, pp. 37-62.

TABLE 1a
Demographics and Achievement at Public, Charter and Private Schools

	All Schools			Public Schools			Charter Schools			Private Schools		
	Avg.	**10th pctile.**	**90th pctile.**	**Avg.**	**10th pctile.**	**90th pctile.**	**Avg.**	**10th pctile.**	**90th pctile.**	**Avg.**	**10th pctile.**	**90th pctile.**
Pct. White	17.20	0	78.71	7.61	0	30.6	2.80	0	5.00	56.12	0	85.1
Pct Black	73.84	15.67	100	81.89	37.47	100	89.69	68.00	100	38.16	7.27	99.21
Pct. Hispanic	8.96	0.24	26.00	10.49	0	34.47	7.51	0	26.00	5.72	0	10.92
Pct. Low Income	56.88	3.24	87.63	64.68	27.44	88.56	70.47	50.30	95.00	23.74	1.48	76.58
Reading Prof.	41.34	15.47	72.97	41.18	14.55	77.52	41.93	25.32	63.39	n/a	n/a	n/a
Math Prof.	41.55	13.51	73.98	41.25	12.80	75.27	42.66	21.05	67.16	n/a	n/a	n/a
Tract Income	$61,970	$27,400	$136,600	$55,600	$27,400	$104,800	$43,400	$20,800	$65,600	$95,000	$32,700	$139,700

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

	Catholic	**Other Religious**	**Nonsectarian**
Avg. Pct. White	42.91	66.91	67.52
Avg. Pct Black	49.02	30.39	27.84
Avg. Pct. Hispanic	8.07	2.70	4.64
Avg. Tuition	$7,800	$19,700	$20,900
Tract Income	$76,000	$120,500	$102,800

Notes: See Table 1a.

TABLE 2
School Openings and Closings

	Public Schools				Charter Schools				Private Schools			
Year	**Total**	**Opened**	**Closed**	**Moved**	**Total**	**Opened**	**Closed**	**Moved**	**Total**	**Opened**	**Closed**	**Moved**
2003	142	0	0	0	30	3	0	0	70	0	0	0
2004	143	2	1	0	39	10	1	2	68	0	2	0
2005	142	0	1	0	46	8	1	6	70	2	0	2
2006	137	0	5	4	54	9	1	7	67	1	4	0
2007	136	0	1	4	60	6	0	5	68	0	2	3

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

	Public Schools			Charter Schools			Private Schools		
	Percent (1)	**Pct. of Students (2)**	**Avg. Enrollment (3)**	**Percent (4)**	**Pct. of Students (5)**	**Avg. Enrollment (6)**	**Percent (7)**	**Pct. of Students (8)**	**Avg. Enrollment (9)**
Elementary	68.57	55.02	277	42.11	27.69	192	17.30	8.14	116
Elementary/Middle	4.29	4.97	400	21.05	22.76	315	51.91	36.03	171
Middle	14.43	16.46	393	11.84	13.59	334	0.59	0.32	39
Middle/High	n/a	n/a	n/a	6.14	7.41	352	5.87	5.39	226
High	12.71	23.55	639	14.91	21.16	413	7.33	18.63	626
Elem./Middle/High	n/a	n/a	n/a	3.95	7.38	545	17.01	31.71	459

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

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

Charter Schools

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

Private Schools

	Elementary	Middle	High
Avg. Pct. White	58.74	36.70	68.33
Avg. Pct. Black	38.52	56.39	26.29
Avg. Pct. Hispanic	2.73	6.91	5.39
Avg. Pct. Low Income	28.12	41.91	11.32
Avg. Tract Hh. Income	$82,800	$75,050	$109,700

Note: “elementary”, “middle” and “high” correspond to the three-type category described in the text.

TABLE 5a
Program Focus by School Type

Focus	Public Schools (1)	Charter Schools (2)	Private Schools (3)
Core	83.00	47.37	91.79
Arts	1.43	9.65	1.47
Language	4.29	7.02	1.76
Vocational	1.43	7.89	0
Other	9.86	28.07	4.99

TABLE 5b
Program Focus by School Level

	Public Schools				Charter Schools				Private Schools			
Focus	**All Levels**	**Elementary**	**Middle**	**High**	**All Levels**	**Elementary**	**Middle**	**High**	**All Levels**	**Elementary**	**Middle**	**High**
Core	83.00	86.67	95.42	44.94	47.37	41.67	65.33	33.33	91.79	81.36	88.35	97.21
Arts	1.43	0	3.82	5.62	9.65	20.83	0	3.51	1.47	8.47	0	0
Language	4.29	6.04	0.76	0	7.02	13.54	4	0	1.76	1.69	0	2.70
Vocational	1.43	0	0	11.24	7.89	0	1.33	29.82	0	0	0	0
Other	9.86	7.29	0	38.20	28.07	23.96	29.33	33.33	4.99	8.47	11.65	0

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 6
Student Demographics and Achievement by School Level and Program Focus

a. Elementary Schools

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

b. Middle Schools

	Core (1)	Arts (2)	Language (3)	Vocational (4)	Other (5)
Pct. Public	50.16	100	27.58	0	0
Pct. Charter	20.07	0	15.18	100	100
Pct. Private	29.77	0	57.24	0	0
Avg. Percent White	12.72	28.35	58.58	0	17.08
Avg. Percent Black	79.99	57.72	15.66	100	74.03
Percent Hispanic	7.29	13.93	25.76	0	8.89
Avg. Percent Low Income	61.66	25.51	24.83	92	57.75
Avg. Pct. Proficient Reading	39.10	73.80	57.15	21.43	53.46
Avg. Pct. Proficient Math	39.40	68.74	50.63	20	48.97
Avg. Tract Hh. Income	$58,500	$73,900	$86,000	$34,400	$47,000

c. High Schools

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

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 7
Early versus Recent Charter Entrants

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

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

Variable	Baseline Utility	Interactions with Hh. Demog. Charact.		
		White	Hispanic	Non-Poor
Constant	*-0.203**			
	(0.035)			
Charter	*-0.035*	-0.015	0.288*	0.012
	(0.024)	(0.047)	(0.026)	(0.020)
Catholic	*-0.555**	0.153*	-0.671*	-0.707*
	(0.022)	(0.050)	(0.032)	(0.012)
Other Religious	*-0.851**	-1.343*	-2.016*	-1.101*
	(0.038)	(0.098)	(0.062)	(0.030)
Nonsectarian	*0.000*	-0.655*	-0.473*	-3.065*
	(0.044)	(0.070)	(0.049)	(0.118)
Language	*-0.388**	-0.415*	-0.753*	1.034*
	(0.060)	(0.130)	(0.083)	(0.143)
Arts	*0.012*	1.394*	0.226*	-0.573*
	(0.050)	(0.096)	(0.060)	(0.038)
Vocational	*0.032*		-2.700*	-0.449*
	(0.074)		(0.289)	(0.046)
Other Focus	*-0.320**	1.133*	-0.182*	-0.541*
	(0.026)	(0.049)	(0.033)	(0.015)
Percent White	2.250	5.520*	1.476*	2.472*
	(2.867)	(0.137)	(0.090)	(0.105)
Percent Hispanic	-5.921*	3.020*	8.083*	-1.596*
	(2.210)	(0.125)	(0.086)	(0.093)
Percent Non-Poor	-8.626*	0.905*	-0.123	4.103*
	(0.809)	(0.105)	(0.080)	(0.059)
Distance	-1.177			
	(0.107)			
(Income-Tuition)	0.443			
	(0.199)			

Notes: Based on 11,919 (=8,112 + 3,807) 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 δ, except in the case of the coefficients on distance and log(income-tuition). (*) are significant at the 5% significance level. Estimates in Italics were obtained through minimum-distance estimation.

FIGURE 1
Number of Public, Charter and Private School Campuses

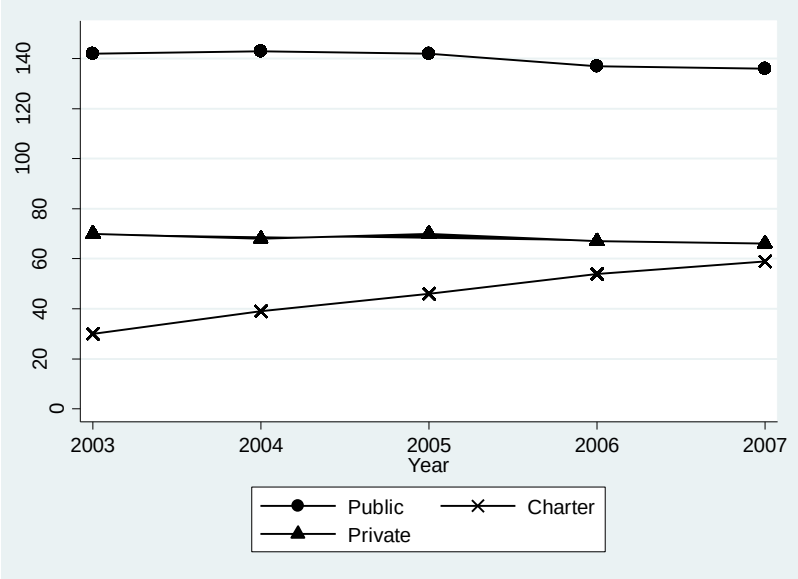


FIGURE 2
Enrollment in Public, Charter and Private School Campuses

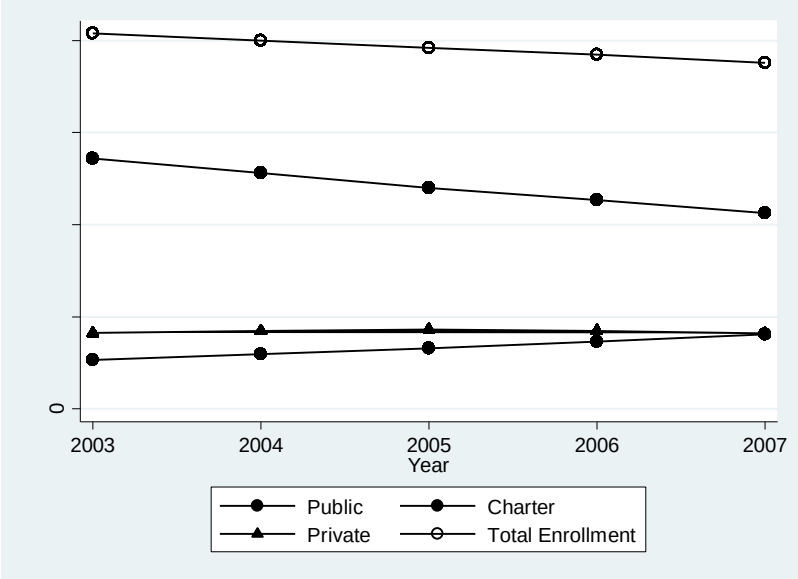
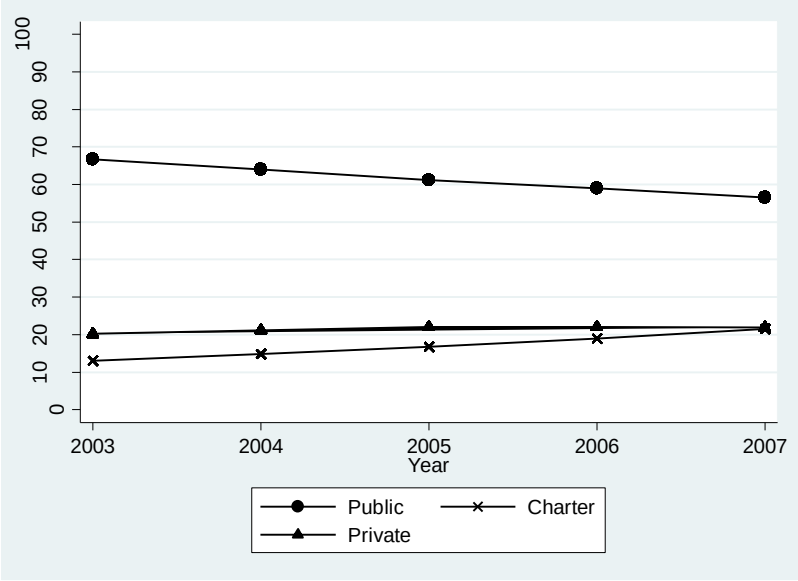
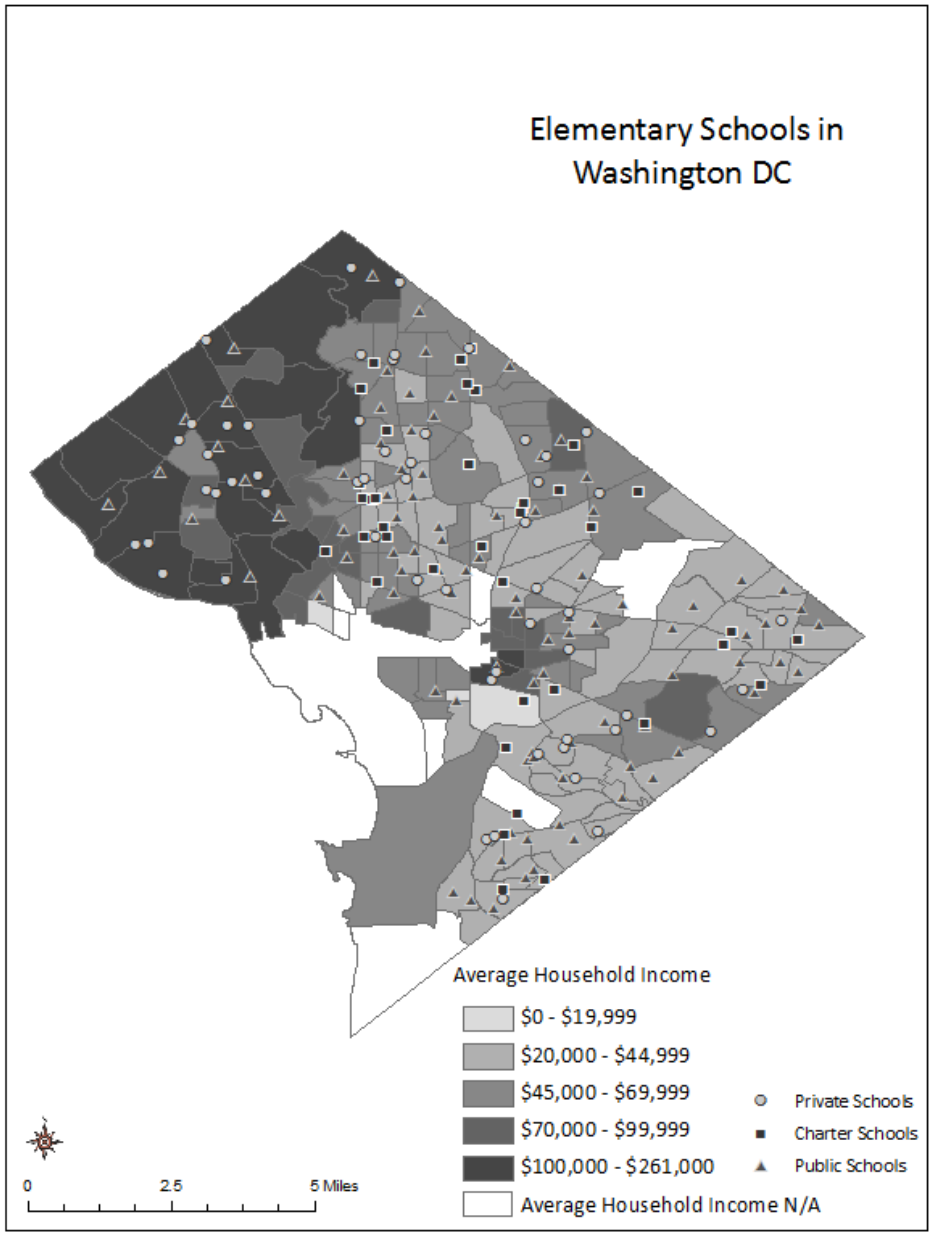


FIGURE 3
Enrollment Shares for Public, Charter and Private Schools



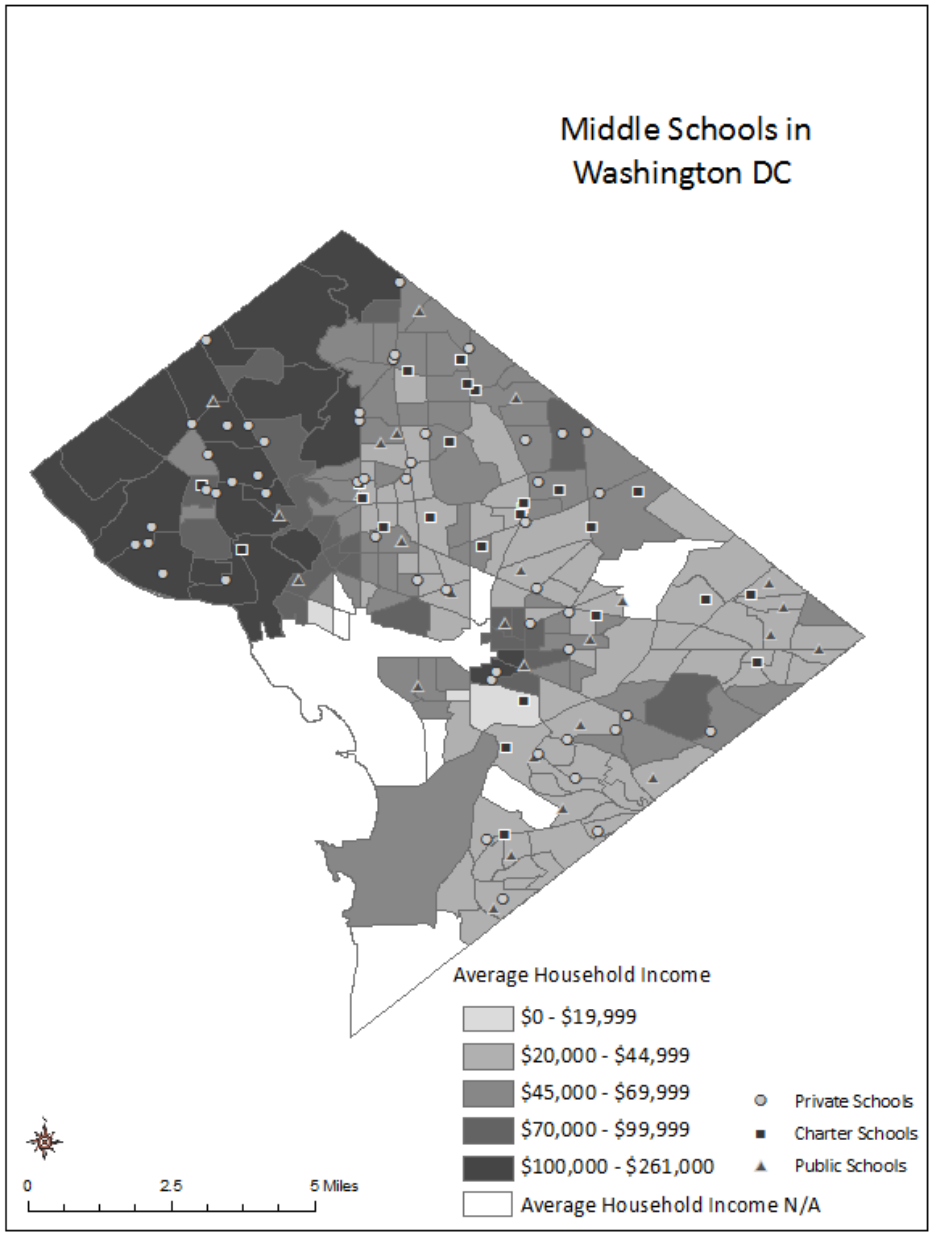
Notes: percentages calculated relative to total enrollment, aggregated over all schools and grades.

FIGURE 4a
Geographic Location of Elementary Schools in DC in 2007



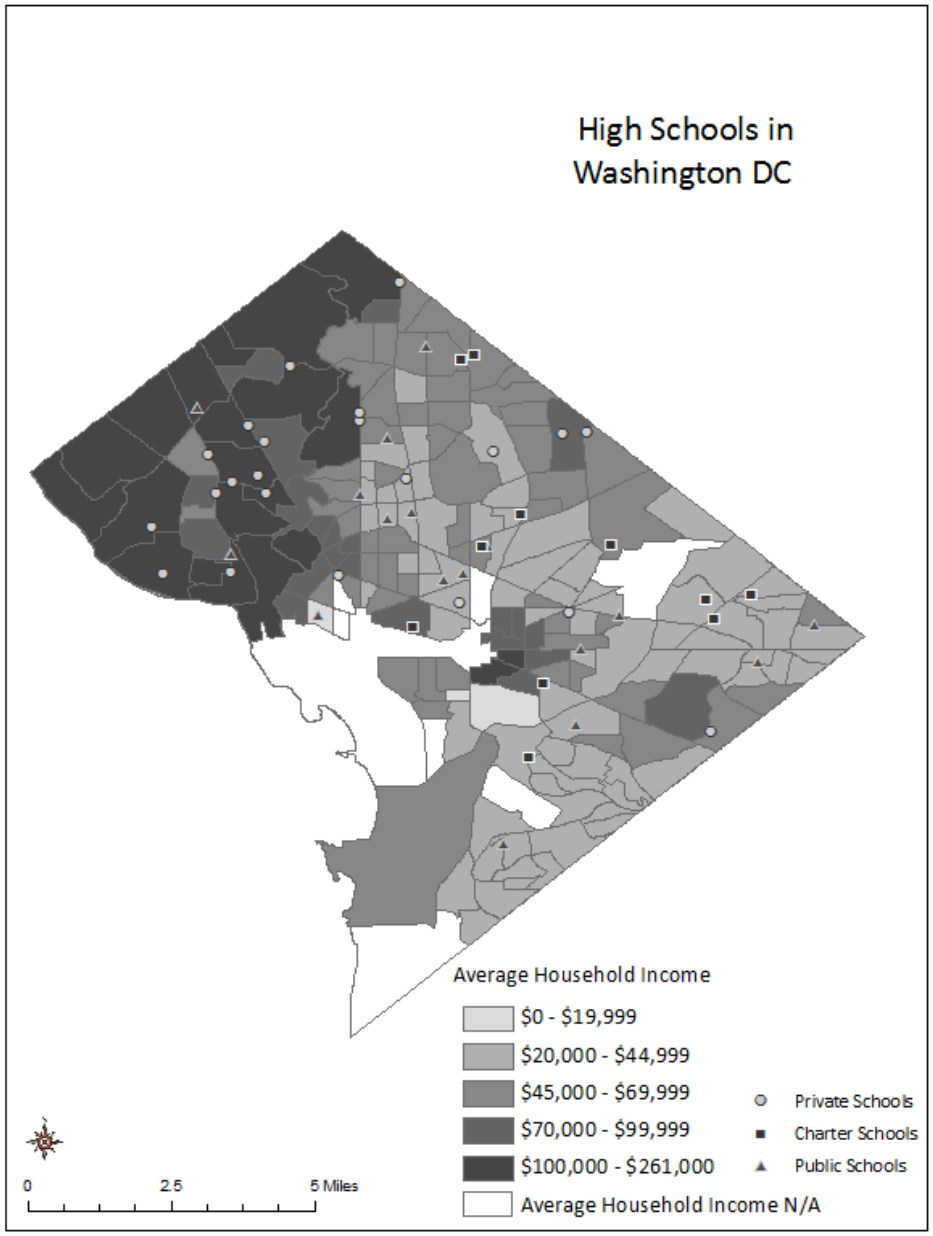
Note: Elementary schools include elementary, elementary/middle, and elementary/middle/high schools.

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***

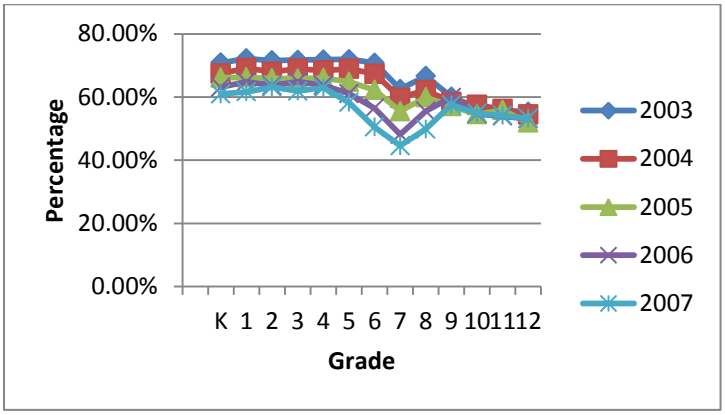


FIGURE 5b - ***Charter Schools: Aggregate Enrollment Share by Grade***

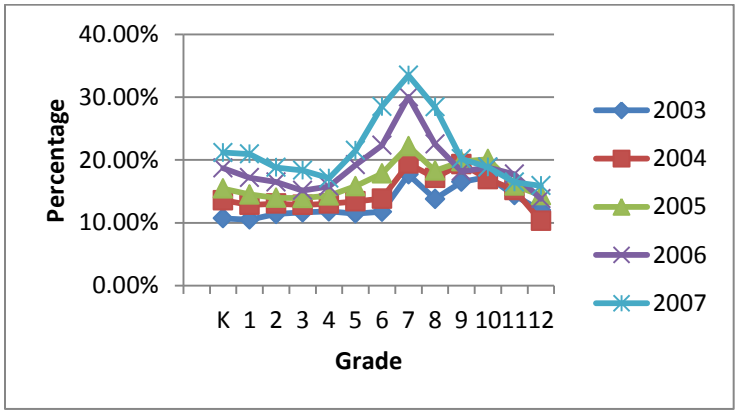
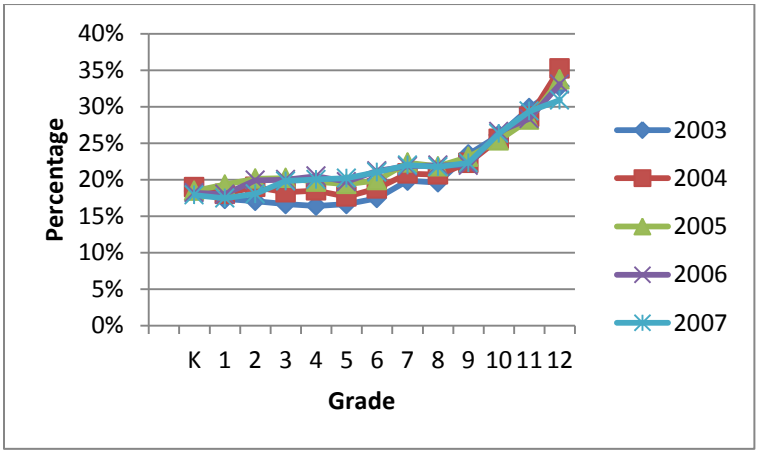


FIGURE 5c - ***Private Schools: Aggregate Enrollment Share by Grade***



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

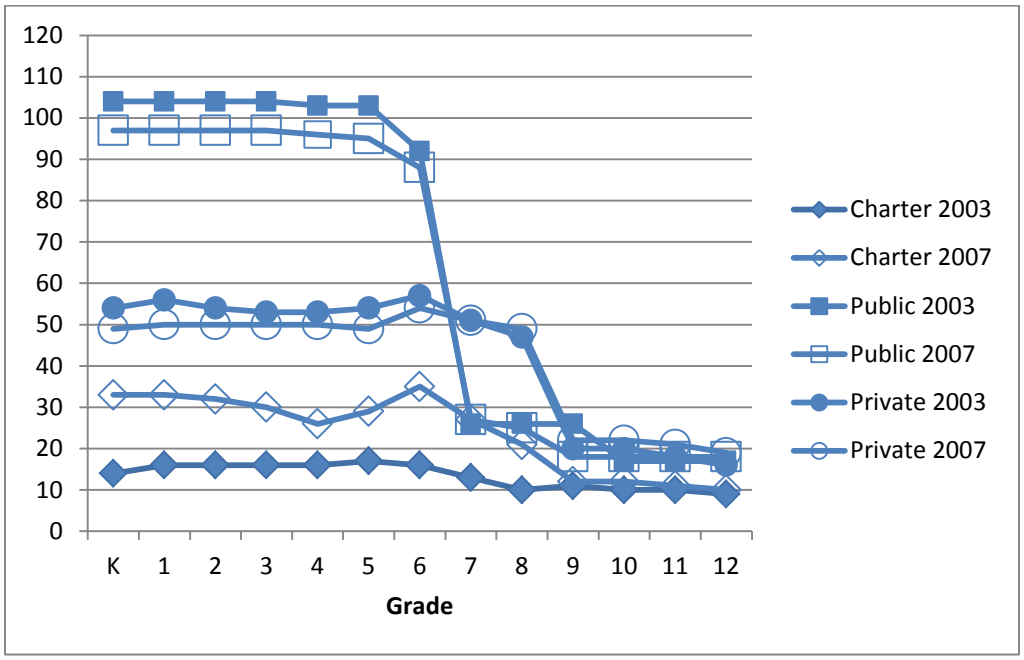
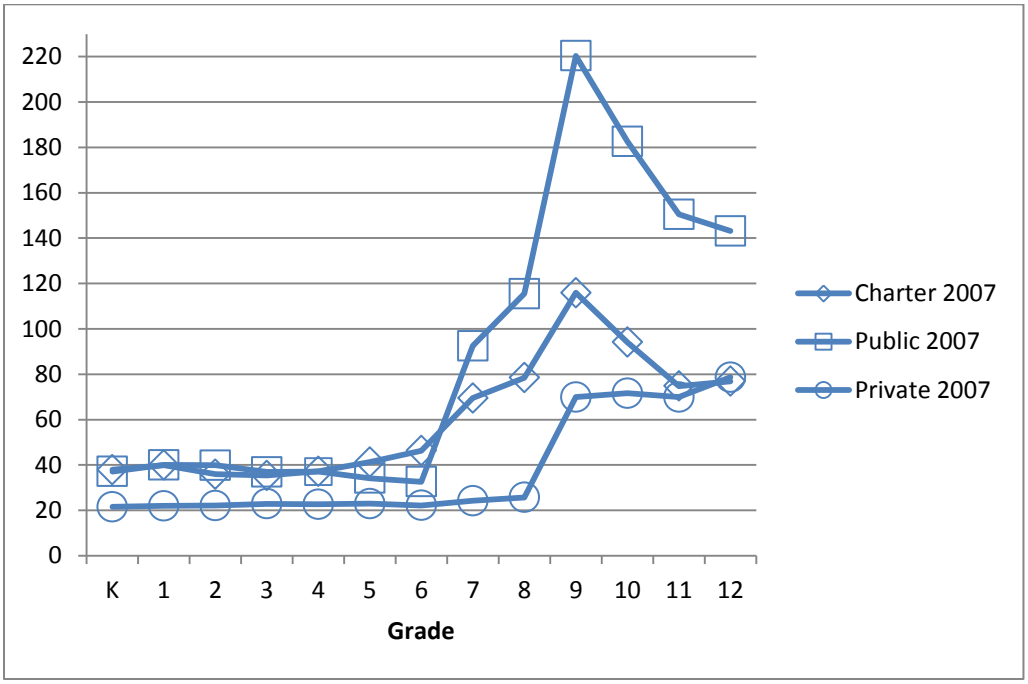


FIGURE 7
Average Grade Enrollment in Public, Private and Charter Schools in 2007



1 Appendix I. School-Level Data

1.1 Public Schools

The starting point for this dataset was audited enrollments from the District of Columbia Office of State Superintendent of Education (OSSE), available at http://osse.dc.gov. From here we obtained the list of public schools along with their grade-level enrollment.

Our list only includes regular schools. This means that relative to the original OSSE list, we alternative schools, special education schools, and early childhood centers.We excluded schools listed as alternative by the OSSE, schools that report their program as alternative in the Common Core of Data (CCD), and schools listed as alternative during the corresponding years by DCPS. We also excluded schools that offer residential programs, such as Ballou Stay and Spingarn Stay. In total, we eliminated 11 alternative schools from the original OSSE lists. We excluded schools listed as special ed by OSSE and schools that report their type as special ed in the CCD. Some schools report their type as special ed only during one or two years during our sample period, in which case we called the individual schools to gauge their type and removed them from the data if they were special ed. In total, we eliminated 22 special ed schools from the original OSSE lists. Early childhood centers include one or several of the following: pre-school, pre-kindergarten, and kindergarten, and do not include regular grades. We excluded early childhood centers as long as they never had enrollment in regular grades (1 through 12) during the sample period. For instance, if an early childhood center added first grade in 07, then the school was included for all 5 years.

Below is the list of information and sources for each school, along with the construction of the corresponding variables:

- **Address**: geographic address of the school. The main source for this variable was the CCD. When the address was not consistent over time, we used Google Earth and Google Maps to see whether the different addresses corresponded to the same geographic location or not. If not, we consulted the school's web site, or called the school to track down the history of its location. In the absence of other information, we used the most recently reported address. We geocoded all addresses.
- **School enrollment:** total school enrollment, excluding ungraded and adult students. Source: own calculations based on OSSE.
- **Grade-level enrollment** (grades preschool through 12). Source: OSSE.
- **Focus:** the school's curricular focus. Source: Filardo et al (2008).
- **Percent of white students**: percent of White students in the school. Source: own calculations based on CCD. For the few cases in which the CCD data was not available, we used the demographics reported to fulfill No Child Left Behind (NCLB) requirements (see http://www.nclb.osse.dc.gov/). Note, however, that the NCLB requirements pertain to the students enrolled in the grades tested for the sake of NCLB accountability, not to the entire student body. When using the NCLB web site, we computed percent of white students as the ratio between the number of white students in the grades tested and the total number of students in those grades.
- **Percent of black students, percent of Hispanic students, percent of students of other ethnicities:** constructed similarly to percent of white students.
- **Percent of low income students:** calculated as the percent of students who receive free or reduced lunch. Source: own calculations based on CCD. For the few cases in which the CCD data was not available we used the demographics reported in fulfillment of NCLB requirements.

- **Reading proficiency:** percent of students who are proficient in Reading.
  Source: http://www.nclb.osse.dc.gov/. In 03 and 04, proficiency levels were determined according to the Stanford-9 assessment. To be considered proficient, a student was supposed to score at the national 40th percentile or higher. Since 05, proficiency has been determined according to DC CAS (Comprehensive Assessment System). See http://www.nclb.osse.dc.gov/faq.asp for more information.

- Prior to 05, the grades tested were 3, 5, 8 and 10 (according to the School Performance Reports for PCBS-authorized charter schools, and according to our own calculations comparing grade-level enrollment with number of students tested). Since 05, the grades tested have been 3, 4, 5, 6, 7, 8 and 10 (according to http://www.nclb.osse.dc.gov/aboutayp.asp, School Performance Reports and our own calculations comparing grade-level enrollment with number of students tested).

- The achievement website, http://www.nclb.osse.dc.gov/faq.asp , reports proficiency for elementary and secondary schools. According to http://www.nclb.osse.dc.gov/faq.asp, schools are classified as elementary or secondary as follows. Since 05, elementary schools are schools with a 3rd and/or 5th grade. If the school goes above the 6th grade it must also have a 3rd grade. Secondary schools are schools with no 3rd and a grade above 6th. Prior to 2006, schools with a wide grade range were required to meet both the elementary and secondary targets. The general rule for most schools was that they were classified as elementary if they had no grade above 6 and as secondary if they had no grade below 5. Schools that did not meet either of these criteria had to meet the targets at both levels.

- For some schools and years, proficiency data are not available for one of the following three reasons: 1) the school only includes early childhood enrollment; 2) the school only includes grades that are not tested (for instance, the school includes kindergarten and first grade only); 3) the school includes grades that are tested, but enrollment in those grades is below the minimum threshold for reporting requirements. The last reason is the most prevalent cause of missing proficiency. See below for the imputations made in those cases.

- **Math proficiency:** percent of students who are proficient in Math. Constructed similarly as reading proficiency.

- **Year of Opening:** year the school opened if it was not open in 03. Using the CCD "status" variable and web searches we verified the school's initial year, which is the first year for which we have records.

- **Year of Closing:** year the school closed if it was not open in 07. The variable stores the first year that the school was no longer open. We verified the content of this variable using the CCD "status" variable and web searches.

- **Year of Merge:** year the school merged with another school. The variable stores the first year that the school no longer operates separately, which is the first year for which we have joint records.

Ethnic composition and low-income status of the student body were missing for 2 and 4 (out of 701) observations respectively; these were schools with very low enrollment. To the cases of missing ethnic composition we imputed the school's average ethnic composition over the years for which we do have data. When possible, we imputed the predicted value coming from a school-specific linear trend.

Achievement was missing in 16 out of 701 observations. To these observations, we imputed the predicted achievement coming from the regression of school-level proficiency rates on year dummies, ethnic composition variables, percent of low income students, enrollment, and school fixed effects. In cases in which we had no proficiency data for the school at all, we ran a similar regression excluding school fixed effects and including dummies for school level, and used the resulting predicted values for our imputations.

1.2 Charter Schools

As with public schools, the starting point for this dataset was audited enrollments from the District of Columbia Office of State Superintendent of Education (OSSE), available at http://osse.dc.gov. From here we obtained the list of public schools along with their enrollment for preschool, pre-kindergarten, kindergarten, each grade between 1 and 12, and enrollment of ungraded and adult students.

For consistency with public schools, we excluded alternative schools. We identified alternative schools based on OSSE's classification, the schools' mission statements, and the self-reported program type in the CCD. We excluded schools in which ungraded or adult students constitute the majority of the student body, and schools with residential programs.

By law, charter schools cannot serve special education students exclusively. However, they can offer services targeted to specific populations even though their enrollment must be open to all students. Only one charter school in D.C., St. Coletta, serves special ed students exclusively, and was approved to that end by the Board of Education (BOE) when it was chartered. We excluded schools whose services target mostly special ed students. We identified those schools based on OSSE's classification, the schools' mission statements, the self-reported program type in the CCD, and phone conversations with staff from the Public Charter School Board (PCSB).

We excluded early childhood schools only if they never added regular grades. We also excluded online campuses.

Some non-early childhood charters opened an early childhood campus during the sample period. We only included these campuses if at some point they added regular grades. Community Academy-Amos II is an early childhood campus that did not include regular grades (at least not during our sample period) and is hence not included in our data. Similarly, Roots Academy opened an early childhood campus in 07, which we did not include in the data. KIPP-LEAP is an early childhood campus that opened in 07 and is not included either. In contrast, E.L. Haynes opened a campus in 07 for early childhood and first grade; this campus is included in our data.

Below is the list of variables for charter schools:

- **Address:** geographic location of the campus. For PCSB schools, the main source was the SPRs. For BOE schools, the main source was the CCD. We supplemented these sources with web and Internet archive searches, and phone calls to the individual schools. We geocoded all addresses.

- Several schools moved in the middle of the school year, temporarily relocated, or closed. We consulted the SPRs and various web sites to handle these cases. If the school moved in the middle of a school year, the address variable contains the more recent address. Some schools relocated some students for a few months during renovations. Since this was a temporary arrangement and parents knew it, we did not consider this a change in address.

- **Statement:** the school's mission statement. Source: schools' web sites, FOCUS, SPRs.

- **Focus**: the school's curricular focus. Source: school statements, and Filardo et al (2008).

- **School enrollment:** total school enrollment, excluding ungraded and adult students. Source: own calculations based on OSSE.
- **Grade-level enrollment** (grades preschool through 12). Source: OSSE.
- **Percent of white students: percent of White students in the school.** For PCSB charters, the source is the School Performance Reports (SPRs) when available. Only for one campus and year (Tri Community in 07), does the SPR not include demographic information, in which case we use the NCLB data from http://www.nclb.osse.dc.gov/ otherwise.
- For BOE charters in 2007, the source is the SPRs (in 2007, the PCSB began including the BOE-authorized charters in its reports). For BOE charters before 2007, the source is the NCLB web site. Note that the NCLB information pertains only to students in grades tested, not to the whole student body of a school. These sources were supplemented by the CCD when needed. When the school has multiple campuses but we only have one set of ethnic composition data, we impute it to all campuses.
- **Percent of black students, percent of Hispanic students, percent of students of other ethnicities:** constructed similarly to percent of white students.
- **Percent of low income students:** fraction of students on free or reduced lunch. For PCSB charters, the source is the SPRs. For BOE charters, the source is NCLB information in http://www.nclb.osse.dc.gov/. These sources were supplemented by the CCD when needed and possible. When the school has multiple campuses but we only have one set of low-income variables, we impute it to all campuses.
- **Reading proficiency:** percent of students who are proficient in Reading. See public schools for sources and construction. Some charters span elementary and secondary grades, and this affected their reporting. For instance, Capital City had to meet elementary and secondary targets before 05, and for those years it reported two sets of scores. Since 05, Capital City has had to meet only one target, has been considered an elementary school for the sake of reporting, and has had to report only one set of scores. In general, when the school had only one campus but separate proficiencies for elementary and secondary students, we combined them into a single proficiency indicator for comparability with other years in which we had a single proficiency indicator. For multi-campus charters we usually had achievement data for each campus. When we did not, we imputed the available data to all the campuses.
- As with public schools, we did not have proficiency data for some campus and years for the reasons enumerated above. In the case of many PCSB schools for which the NCLB web site did not report test scores due to low enrollment, we obtained proficiency rates from the SPRs. This was not possible for BOE schools with low enrollment since the SPRs only cover PCSB schools before 07. In cases in which we could not find proficiency data, we made imputations (see below).
- **Math proficiency:** percent of students who are proficient in Math. Constructed similarly as reading proficiency.
- **Year of Opening:** year the campus opened. Source: SPRs, FOCUS, web searches. The variable stores the first Fall that the school is open.
- **Year of Closing:** year the school closed, even if it closed after 07. The variable stores the first year that the school is no longer open. The sources are Center for Education Reform (http://www.edreform.com/accountability/charters/CER_ClosedCharterSchools2009.pdf), current SPRs and PCSB listings of charter schools, current NCLB reports, and web searches.

- Note that Washington Academy was taken over by Howard Road in Spring 08 – i.e., in the middle of school year 07. Hence, the year of closing is 2007 for Washington Academy because it the first year for which Washington Academy no longer exists. In fact, for the school year 07/08, data were reported by Howard Road, and the SPRs report data for Howard Road campuses noting that they were former campuses of Washington Academy. We chose not to add campuses to Howard Road for 07 because the campuses did not physically move – they simply changed ownership.

- **Reason for Closing:** reason for closing (academic / financial / mismanagement). Source: Center for Education Reform, SPRs, web searches.

Percent of low-income students was missing for 9 out of 230 observations respectively. These schools had low enrollments. To most of these cases we imputed the school's average percent of low-income students, the average being calculated over the years for which the school does have data.

In the case of missing proficiency rates (36 out of 230 observations), we made imputations similar to those described for public schools, the only difference being that we used school-fixed effects (as opposed to campus-fixed effects) in the predicting regressions.

1.3 Private Schools

The starting point for this dataset was the list of private schools from the Private School Survey (PSS). Since the PSS is biennial, we included the 2003, 2005 and 2007 waves in our data.

PSS classifies schools as regular, vocational, special ed, and other/alternative. 92 percent of the schools in our dataset are regular, and the remaining schools are classified as other/alternative. Although an alternative public school is usually a school for students with behavioral problems, an alternative private school is often a school that offers a specialized rather than a regular curriculum. In these cases, we kept alternative schools. We eliminated vocational schools because they enrolled exclusively ungraded students. We also eliminated special ed schools, early childhood centers (as long as they never had enrollment in regular grades during the sample period), and schools that only teach ungraded students. Most of the schools we eliminated are early childhood centers.

Since 2004 was not included in PSS, we assigned 2004 values to the variables through linear interpolation of 2003 and 2005, and similarly for 2006. For instance, we calculated the percent of White students for a school in 2004 as the average of percent white in 2003 and 2005.

Some schools did not report to the survey for some waves. For instance, Edmund Burke has data for 2001, 2005 and 2007 but not for 2003, which means that we need to make some data imputations for 2003, 2004 and 2006. The imputed data for 2003 is the average between 2001 and 2005. Treating the imputed 2003 as actual data, we then imputed data for 2004 as the average between 2003 and 2004.

If a school does not appear again in PSS after a particular wave, we assumed that the last year of operation was the year of the last wave in our data. Similarly, if a school appears in a particular wave but not in any of the following waves, we assume that its last year is the year of the last wave for which we have data.

Below is the list of information and sources for each campus, along with the construction of the corresponding variables:

- **Address:** geographic location of the campus. We supplemented PSS with web and Internet archive searches, and phone calls to the individual schools. We geocoded all addresses.

- **Type:** Catholic, other religious or non-sectarian. Source: PSS.

- **School enrollment**: total school enrollment, excluding ungraded and adult students. Source: own calculations based on PSS.
- **Grade-level enrollment:** number of students in each grade between K and 12.
- **Percent of white students:** percent of White students in the school. Source: own calculations based on the reported number of White students and the total enrolment. Since the number of students for each ethnicity spans grades K through 12, we used K-12 enrollment as well in the denominator.
- **Percent of black students, percent of Hispanic students, percent of students of other ethnicities:** constructed similarly to percent of white students.
- **Percent of low income students**: since PSS does not collect this information, we imputed it based on a logistic regression for public and charter schools of percent low income on school ethnic composition, enrollment, and average household income of the school's tract. As a check, we compared the resulting predictions with data from OSSE on the percent of students receiving free and reduced lunch in private schools. Our predictions compare favorably with the OSSE data.
- **Tuition:** annual tuition by grade for the 2010/11 school year. Source: web searches. When tuition information was not available, we imputed tuition based on the predicted values arising from the regression of tuition on grade, school type (based on the nine-type private school classification used by PSS), average household income of the tract where the school is located, school enrollment, and a quadratic term in school enrollment. Both observed and predicted tuitions are expressed in dollars of 2000.

2 Appendix II. Proficiency Rate Regression

As described in the paper (eq. (6)), student i's achievement in school j, grade g and time (the variable A_{ijgt}) is a function of school time-invariant characteristics y_j, student body $\bar{D}_{jt}$, the student's own characteristics D_i, and the student-school interaction $y_j D_i$. We assume that the probability q_{ijgt} that i passes the proficiency test is monotonically related to her achievement, and is given by the following specification:

$$q_{ijgt} = y_j \beta^q + \bar{D}_{jt}\alpha^q + D_i \omega^q + y_j D_i \tilde{\beta}^q + \xi^q_{jgt} + v^q_{ijgt}, \tag{1}$$

where v^q_{ijgt} is a zero-mean idiosyncratic shock. A student who passes is deemed "proficient".

The school-level expected share of proficient students is

$$q_{jt} = \frac{\sum_{g\in\kappa_{jt}} \sum_{i\in I_{jgt}} q_{ijgt}}{|I_{jt}|},$$

where I_{jt} is the set of students enrolled in school j at year t. Averaging q_{ijgt} over students and grades we obtain the following:

$$q_{jt} = y_j \beta^q + \bar{D}_{jt}\phi^q + y_j \bar{D}_{jt}\tilde{\beta}^q + \xi^q_{jt}, \tag{2}$$

where the identity $\bar{D}_{jt} = \frac{\sum_{g\in\kappa_{jt}} \sum_{i\in I_{jgt}} D_i}{|I_{jgt}|}$ is applied. The following new variables are introduced: $\phi^q = \alpha^q + \omega^q$ and $\xi^q_{jt} = \frac{\sum_{g\in\kappa_{jt}} \sum_{i\in I_{jgt}} (\xi^q_{jgt} + v^q_{ijgt})}{|I_{jt}|}$.[1]

[1] This averaging is possible because the probability of passing the test is specified as a linear function.

In (2), we decompose shock ξ^q_{jt} as follows

$$\xi^q_{jt} = \xi^q_j + \xi^q_t + \Delta\xi^q_{jt}.$$

Substituting the above expression into (2) we obtain the following expression for the expected share of proficient students:

$$q_{jt} = y_j\beta^q + \bar{D}_{jt}\phi^q + y_j\bar{D}_{jt}\tilde{\beta}^q + \xi^q_j + \xi^q_t + \Delta\xi^q_{jt}. \tag{3}$$

Let $\bar{q}_{jt}$ be the observed proficiency rates. They are related to the expected proficiency rates in the following way:

$$\bar{q}_{jt} = y_j\alpha^q + \bar{D}_{jt}\phi^q + y_j\bar{D}_{jt}\omega^q + \xi^q_j + \xi^q_t + \Delta\xi^q_{jt} + v^q_{jt} \tag{4}$$

where $v^q_{jt} = \bar{q}_{jt} - q_{jt}$ incorporates sampling and measurement error and is conditionally mean independent of all the explanatory variables in (4). However, it is possible that $\Delta\xi^q_{jt}$ is correlated with $\Delta\xi_{jgt}$, and as consequency that $\bar{D}_{jt}$ is correlated with $\Delta\xi^q_{jt}$. Hence, we use IV estimation for (4).

3 Appendix III. Market Size and Outside Good

In this appendix we first describe the estimation of the joint distribution of household location, child age and race, parental income and child poverty status for year 2000 and the adjustments needed for years 2003-2007. Then we describe the construction of choice sets for households in different locations.

In what follows we use the term "demographic type" to refer to a combination of race (Black, White and Hispanic), income (16 values for income, each one representing the midpoint of the corresponding Census income bracket), and poverty status (eligible for free- or reduced-lunch, and not eligible). This yields a total of 96 demographic types. Our goal is to estimate the number of children in each of these types for each of the 13 grades and 433 locations in our data.

Since each grade is a market, calculating market size amounts to determining the number of children who are eligible for each grade in Washington, D.C. in each year between 2003 and 2007. Given our data on aggregate enrollment by grade and year, the share of the outside good for a given grade and year is equal to (market size – aggregate enrollment) / market size.

The main difficulty in calculating market size is that we do not have direct information on the number of children eligible for each grade in each year. In the absence of this information, the mere count of children by age and year would be helpful, but we do not have this information either. Instead, to calculate market size we rely on the following pieces of data:

1. The 2000 count of children by age (see Table A1);
2. The intercensal estimates of the number of children 5-13 and 14-17 year old brackets (see Table A2);
3. The 2000 count of enrolled and not enrolled children, and the resulting percent of children who are not enrolled. The latter is our best proxy for the outside good share for year 2000;
4. Observed enrollment for each grade and year (see Table A4).

To estimate the number of children by age in each year, one could apply the annual rates of growth implied by Table A2 to the 2000 observed number of children in each age (see Table A1). Since these rates of growth differ by age groups, one could apply to each age the rate that corresponds to its age group. In principle, the resulting number of children per age should be at least as large as the observed enrollment in the corresponding grades (see Table A4). When we apply this procedure, for grades 4-8 we estimate a number of children (or potential enrollment) that is lower than the actual enrollment, thus implying a negative share of the outside good. One possible explanation is the existence of different growth rates within the age group 5-13. For instance, children who are 5-13 years old in 2003 would have been 2-10 years old in 2000. As Table 1 shows, there is a fair amount of variation in the number of children in each age between 2 and 10. Thus, it is plausible that each individual age would grow at a different annual rate. Another possible explanation is the existence of complex patterns of grade retention.

Since we do not have data to disentangle these possibilities, after evaluating a number of solutions we opted for inflating the observed enrollment for each grade g and year t by a factor ϑ_{gt} in order to calculate potential enrollment by grade. These factors are chosen so that their implied outside good shares by age match up with 2000 Census outside good shares (see Table A3) We opted for this solution not only because it was simple, but also because our most direct evidence on the outside good share comes from the 2000 Census. Thus, we calculate market size for (g, t) as observed aggregate enrollment for $(g, t) * \vartheta_{gt}$. For computational reasons we imposed the constraint that the resulting outside share by grade should be greater than or equal to 0.01.

For the calculation of our adjustment factor, we modified the 2000 Census outside good shares slightly to accommodate some features of our data. In particular, our enrollment data is based on regular schools (thus excluding special ed or alternative schools, which are more prevalent in middle or high school than elementary school), and excludes schools that are specialized in early childhood (i.e., that do not include grades above kindergarten). Thus, we used an outside good share of 3% for grades K through 8 (corresponding to ages 5-14 in the 2000 Census) and 10% for grades 9 through 12 (corresponding to ages 14-17 in the Census).

Our solution has the appealing feature of delivering an estimated number of children whose annual growth rate is consistent with the growth rates implied by the intercensal Census estimates (see Table A2). In particular, potential enrollment given our solution grows at the following rates between 2003 and 2007: -13% for grades K through 8, and 7% for grades 9 through 12. These rates line up with the Census growth rates for the corresponding age groups (equal to -13% and 13%, respectively) for the same period.

4 Appendix IV. Household Characteristics and Choice Sets

In this appendix we first describe the estimation of the joint distribution of household location, child age and race, parental income and child poverty status for year 2000 and the adjustments needed for years 2003-2007. Then we describe the construction of choice sets for households in different locations.

In what follows we use the term "demographic type" to refer to a combination of race (Black, White and Hispanic), income (16 values for income, each one representing the midpoint of the corresponding Census income bracket), and poverty status (eligible for free- or reduced-lunch, and not eligible). This yields a total of 96 demographic types. Our goal is to estimate the number of children in each of these types for each of the 13 grades and 433 locations in our data.

4.1 Household Types for Year 2000

The main challenge in measuring the number of households in each (grade, demographic type) combination at the block group level is the fact that we do not observe the joint distribution of child age, race, household income and poverty status at the block group level. Instead, the Census provides us with the following information:

- tract-level joint distribution of age and race;
- tract-level joint distribution of age bracket, race and poverty status[2];
- tract-level joint distribution of family income (by brackets) and race;
- block group-level joint distribution of age brackets and race.

Thus, we use this information to calculate the number of households in each demographic type, for each grade and location. Recall that Washington, D.C. includes 433 block groups and 188 Census tracts. The calculations described below apply to the 185 tracts that do have children aged 5-18 and the corresponding block groups. We proceeded as follows:

1. Note that for each block group we observe the joint distribution of age brackets and race, and at the tract level we observe the joint distribution of individual ages and race. We assume that for a given age bracket and race, the distribution of individual ages is the same for all the block groups that belong to a tract. Hence, for each block group, age bracket and race we imputed the distribution of individual ages of the corresponding tract and race.

2. For each tract we observe the joint distribution of age brackets, race and poverty status. We assume that for a given tract, the distribution of race and poverty status is the same for all individual ages within a given age bracket. We also assume that the joint distribution of age, race, and poverty status is the same for all the block groups located within a given tract. Hence, for each block group, individual age and race, we imputed the poverty distribution of the corresponding tract.

3. Based on steps (1) and (2), we calculated the number of children in each (age, race, poverty status) combination in each block group. For a given block group, denote this number as n_{arp}, where a=age; r=race; p=poverty status.

4. The tract-level income distribution for families is not adjusted by family size and hence does not reflect income per child. In the absence of data on the joint distribution of family income and size, we calculated tract-level average family income and size by race and constructed the city-level joint distribution of average family income and size. Then we reweighted the original tract-level family income distribution to reflect differences in family size by income bracket.

[2] Federal guidelines (see http://www.fns.usda.gov/cnd/governance/notices/iegs/iegs.htm) establish eligibility for free- or reduced-price lunch based on household size and income. To qualify for free (reduced) lunch, a child must live in a household whose income is below 130 (185) percent of the Federal poverty guidelines for that household size. We pool children eligible either for free or reduced lunch into a single category. Since the Census reports the number of children in each age bracket and race whose household income falls below 130%, or between 130% and 185% percent of the poverty guideline given their household size, we can calculate the number of children eligible for free- or reduced-lunch as the total number of children whose household income falls below 185% of the poverty guideline. Thus, "poverty status" is a binary variable that describes whether the child is eligible for free- or reduced-lunch or not. In some parts of the paper, we use "low-income" to describe a child who is eligible for free- or reduced lunch.

5. For each tract we observe the joint distribution of family income and race, but not the joint distribution of family income, race and poverty status. To determine how many of the n_{arp} children in the corresponding *(a, r, p)* combination a given block group fall in each income bracket, we perform an imputation which we can illustrate through the following example for a hypothetical block group and tract. In this block group, 20% of 5-year old White children are poor, and the remaining 80% are not. In the corresponding tract, 5% of White families have incomes below \$20,000; 15% have incomes between \$20,000 and \$40,000, and the remaining 80% have incomes between \$40,000 and \$60,000. Thus, we assigned a family income of \$10,000 (i.e., the midpoint for the income bracket between \$0 and \$20,000) to a quarter of the 5-year old White children, where 1/4 = 5% / 20%. Similarly, we assigned a family income of \$30,000 (i.e., the midpoint for the income bracket between \$20,000 and \$40,000) to three-quarters of the 5-year old, White children, where $\frac{3}{4}$ = 15% / 20%. To the 80% of 5-year old White children who are not poor, we assigned an income of \$50,000 (i.e., the midpoint of the income bracket between \$40,000 and \$60,000).

6. Based on step (4), for each block group we calculated the number μ_{lam} of children of each age and demographic type m, where the demographic type is given by a (race, income, poverty status) combination.

Calculating the number of children aged 18-years old in each demographic type and location is challenging for D.C. because the number of 18-year olds is much higher than the number of 17-year olds, and the demographics of these two ages are quite different as well. Similarly, the age bracket 18-24 has different demographics than the age bracket 12-17. We believe this is because many 18 year olds in D.C. attend college and do not come from D.C. Hence, we determined the number of 18-year olds at the block group level as the average number of children by age in the 12-17 year old bracket. We assigned to 18-year olds the same demographics as the average of the 12-17 year old bracket.

4.2 Household Types for Years 2003-2007

We obtained the market size for each grade and year as explained in Appendix III. This gave us the number of children eligible to attend each grade. Recall that we assume that each grade draws equally from the two most frequent ages in the grade, and only from those ages (for instance, 50% of second graders are 6 years old, and 50% are 7 years old). We also assume that while the marginal distribution of child age may change over time, the distribution of demographic types conditional on age remains constant. We assume, then, that all demographic types of a given age grow at the same rate ϑ_{at}.

Based on these assumptions, for year t we were able to calculate the number of children of each age, N_{at}, as follows. Let $\vartheta_{at} = N_{a,t}/N_{a,2000}$ be the proportional growth for age a between year 2000 and year t, $t = 2003, \ldots 2007$. The household type measures μ_{lamt} for $t = 2003, \ldots 2007$ is then equal to $\mu_{lamt} = \mu_{lam}\vartheta_{at}$, where μ_{lam} are the Census 2000 measures whose calculation was described above.

4.3 Sampling from the Distribution of Household Characteristics

Once we know the measure for each demographic type, age and year, we draw 100 children for each grade and year, 50 for each of the two most frequent ages in the grade. We sampled from the distribution of household types for each age and year. The sampling was probability-weighted, with the weights being equal to the measure of the household type and age in the corresponding year.

4.4 School Choice Sets

To determine the set of schools that are eligible to a household based on her location, the critical issue is determining the public school associated to each block group for each grade and year. To arrive at this association, we first associated block groups with attendance zones, and then attendance zones with schools. We have a set of associations for 2003 and 2004 (prior to the attendance zone boundary changes), and another for 2005-2007. We refer to these as the 2003 and 2005 associations, respectively. The associations were done using GIS software.

While the task was relatively straightforward for 2005, it was not so for 2003. For instance, in 2003 some attendance zones contain no schools, while others contain two; some attendance zones contain a school within their physical boundary that does not have the same name as the attendance zone; etc. To fix these problems, we defined a "main" and a "secondary" school when needed for each attendance zone and school level. For a given attendance zone, the main school is the school whose name matches the attendance zone's, or the school that lies within the physical boundaries of the school and does not have the same name as the attendance zone, but does not have another attendance zone named after the school. The additional school (when it exists) is the school that does not have a specific attendance zone associated to it and lies within a zone that does have a main school. Overall, additional schools are quite rare in the data.

We determined main and additional schools based on conversations with GIS experts from DCPS. Those conversations also provided a solution to the problem that the attendance zones' map contains holes – i.e., some block groups are not associated to any attendance zone. We assigned those block groups to the closest public school for each level.

TABLE A1
Number of children by age

Age	Number
0	6306
1	6123
2	6352
3	6332
4	6657
5	6692
6	6985
7	7095
8	7068
9	7069
10	6887
11	6039
12	5674
13	5636
14	5426
15	5469
16	5578
17	5787
18	5595

Note: data from the 2000 Census. For each age, the count is an aggregate over Census tracts. For the count of 18-year olds, see Appendix IV.

TABLE A2
Number of Children by Age Bracket

	2000	2003	2004	2005	2006	2007	% Change 07 w.r.t 03
Total Population	571,744	577,777	579,796	582,049	583,978	586,409	1.49%
Children Below 5 yrs.	32,404	33,357	34,167	34,771	34,677	35,794	7.31%
Elem. Sch. Age Children (5-13)	59,746	59,561	57,186	55,078	53,873	52,068	-12.58%
High Sch.-Age Children (14-17)	22,504	23,145	24,534	25,156	26,049	26,198	13.19%

Note: for 2000, counts are from the 2000 Census. For the other years, counts are from Census Bureau estimates.

TABLE A3
Children Enrolled and Not Enrolled in School, by Age Bracket

	Enrolled	Not Enrolled	Total	Pct. Not Enrolled
Age 5-9	33,854	945	34,799	2.72%
Age 10-14	29,916	526	30,442	1.73%
Age 15-17	15,502	1,188	16,690	7.12%

Note: data from the 2000 Census, aggregated over Census tracts.

TABLE A4
Total Enrollment by Grade and Year

Grade	2003	2004	2005	2006	2007	% change 07 w.r.t. 03
K	6,630	6,392	6,558	6,294	5,908	-11%
1	6,923	6,735	6,417	6,606	6,293	-9%
2	6,806	6,419	6,354	6,096	6,121	-10%
3	6,656	6,400	6,032	5,944	5,781	-13%
4	7,002	6,387	6,133	5,780	5,658	-19%
5	7,021	6,647	6,063	5,890	5,567	-21%
6	6,770	6,564	6,343	5,822	5,686	-16%
7	6,504	6,465	6,259	6,079	5,608	-14%
8	5,988	6,075	6,048	5,905	5,795	-3%
9	6,655	7,070	6,882	7,146	6,896	4%
10	5,587	5,844	6,031	5,864	5,992	7%
11	4,711	4,915	4,998	5,079	5,000	6%
12	4,249	4,021	4,269	4,432	4,840	14%
TOTAL PS-12	87,160	85,983	84,480	83,110	81,277	-7%
Total G1-G8	53,670	51,692	49,649	48,122	46,509	-13%
Total G9-G12	21,202	21,850	22,180	22,521	22,728	7%
Census estimates - ages 5-13	59,561	57,186	55,078	53,873	52,068	-13%
Census estimates - ages 14-17	23,145	24,534	25,156	26,049	26,198	13%

Note: enrollment counts are based on our own calculations by aggregating over public, private and charter schools for each grade and year. Rows with Census estimates for ages 5-13 and 14-17 are the same as in Table A2 and have been inserted here for comparison with enrollment totals for grades 1 through 8 and 9 through 12 respectively.