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. We model the entry, exit and relocation of charters as well as the behavior of the regulatory agency that authorizes charter entry and continued operations. The regulator makes decisions based on charters' expected equilibrium demand. We estimate the model using school-level panel data for Washington, D.C. According to our estimates, household preferences over school characteristics are quite heterogeneous by race and poverty status. In addition, charter school quality surpasses that of public schools in the most disadvantaged areas of D.C. and at the middle and high school grade levels. At the same time, our estimates show that charters face higher fixed costs precisely when operating in those areas or serving those grade levels. 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 and 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 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 explore the effects that the entry, exit or relocation of a school has on others. We study the critical role of the chartering entity (henceforth, the regulator) in this market. Finally, we investigate 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 largely 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,

[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.

and with respect to private schools that can apply their own admission criteria. Addressing our research questions **is further complicated by t**he uncertainty faced by schools and the regulator about charters' demand. This uncertainty is more severe for new entrants, whose ability to run the new enterprise may not be known.

Thus, we develop and estimate an equilibrium model of household school choice, charter school entry and school interaction in a large urban school district. In the model, we view a charter entry point as a combination of location (neighborhood), grade level and thematic focus. For some entry points, prospective entrants submit entry applications to the regulator. Since charter funding is connected with enrollment, prospective entrants must be financially viable. Hence, the regulator forecasts enrollment and peer characteristics for the prospective entrant as a function of its geographic location, grades served and thematic focus, and approves the applications of charters that are expected to be financially viable.

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

We model schools as differentiated products and estimate the demand side of the model using an approach similar to Berry et al (1995), henceforth BLP. In particular, we allow for the existence of an unobserved school-grade-year quality component (such as teacher quality) that households observe when making choices but the researcher does not. This creates correlation between the resulting school peer characteristics and the unobserved quality component, similar to the correlation between unobserved quality and price in BLP. Unlike price, which is determined by the firm under consideration, peer characteristics are determined by aggregate household choices and are similar to the local spillovers in Bayer and Timmins (2007).[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. These school fixed effects are our estimates of school quality and capture unmeasured factors explaining household choices such as school climate and culture, length of school day and year, characteristics of the facilities, and ability to improve achievement. When estimating the parameters of the proficiency rate function we estimate a separate set of school fixed effects that capture schools' ability to raise passing rates in standardized tests and constitute our measure of school value added.

We have chosen to focus on a single, large urban district in order to study the behavior of charters 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

[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.

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 for charter entry.

Our estimates reveal large heterogeneity in preferences over school types on the part of households. For instance, black, Hispanic and low-income households have a stronger preference for charters than white, non-poor households. Our estimates also reveal substantial differences in school quality and value added by school type, level and location. For example, charters have a quality and value-added advantage relative to public school at the elementary/middle and middle school levels. The advantage is magnified in the most disadvantaged area of the city–the southeast, where public school quality is particularly low in middle and high school, and where public school value added is particularly low at all grade levels. Such heterogeneity in households' preferences and access to desirable schools, and in schools' quality and value added creates rich opportunities for charter entry.

At the same time, our estimates also reveal that charter schools face higher fixed costs exactly where they are most needed, in the southeast and at the high school level. Further, our estimates indicate that lowering application costs might stimulate additional charter entry in D.C., though less scrutiny at the entry stage on the part of the regulator might result in the entry of lower-performing charters, an outcome that the regulator wishes to avoid. Policies that raise per-pupil funding or lower fixed costs might be particularly effective for charter expansion.

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, Mehta (2012) who studies charter entry in North Carolina in a structural fashion, and Walters (2012), who estimates a structural model of school choice and academic achievement in Boston. We differ from Mehta (2012) in the following ways: a) we model heterogeneity in student race, income and poverty status; b) we endogenize student body characteristics as equilibrium outcomes determined by household choices; c) we model private schools as part of the choice set of households; d) 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; e) 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. While data on charter school lotteries and student-level achievement allows

[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.

[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).

Walters (2012) to conduct detailed estimation of preference and achievement parameters, he does not model charter school entry.

Second, we contribute to the school choice literature 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. Although others have studied school choice with endogenous peer characteristics (Ferreyra 2007, Altonji et al 2011), they have not relied on the full choice set available to households and have not modeled school unobserved quality.

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

Fourth, we contribute to the computational literature on the estimation of BLP models. We recast our demand-side estimation as a mathematical programming with equilibrium constraints (MPEC) problem following Dube et al (2011), Su and Judd (2011) and Skrainka (2011). Dube et al (2011) and Skrainka (2011) use methods based on supplying analytical gradients and Hessians to optimization software. We use an effective combination of two software solvers, SNOPT and MINOS, that require only first-order derivatives which we in turn compute using a symbolic differentiation tool. The researcher is therefore freed from the laborious and error-prone process of coding derivatives, and can more easily experiment with different model specifications. Thus, our research lies at the frontier of computational methods and estimation.

Finally, we contribute to the literature on firm entry in industrial organization. A review of this literature is provided in Draganska et al (2008). Whereas most of this literature assumes a reduced-form function for demand, we specify a structural model of household choice of school and allow for unobserved school quality.[6] In addition, a major focus of the entry literature is the strategic interaction between entrants and/or incumbents. We do not model public or private school decision making. The reason is that during our sample period public and private schools displayed very little entry or exit, a feature that would prevent the identification of a model of strategic decision making for them. Moreover, between 1998 and 2007 the District of Columbia Public Schools (DCPS) had six superintendents. This high turnover, coupled with financial instability, suggests that DCPS may not have reacted strategically to charters during our sample period.

An important contribution in this paper is the development of a supply-side model for charters. Our model is specifically tailored to the institutional realities of charter schools in Washington, D.C., where the regulator plays a crucial role both by authorizing charter entry and forcing the exit of under-performing charters. Hence, we further contribute to the entry literature by developing a game of interaction between charters and regulator that could be applied, with some adjustments, to other industries and settings that feature a prominent regulator.[7] In addition to being realistic, our model is analytically and numerically tractable. One last difference between our work and the entry literature is that we rely on panel data, which is quite rare in entry studies. By providing us with post-entry outcomes, the panel allows us to learn about the quality of both entrants and incumbents.

We use our parameter estimates to study the effect of changes in the regulatory, institutional and demographic environment on charter entry, household sorting across schools and student achievement. For instance, we explore whether greater availability of building sites for charters would spur the creation of more charter schools, where these would locate, which students they

[6] Recent efforts to model unobserved quality in entry models includes Carranza et al (2011), Berestenau et al (2011) and Seim et al (2009).

[7] For instance, Seim and Waldfogel (2012) estimate a structural model of entry into the liquor stores sector in Pennsylvania, where a state agency has the monopoly over the sector.

would attract, and how achievement would change among the pre-existing schools. Our counterfactuals and estimates suggest that the introduction of charter schools has enhanced household welfare, particularly for the most disadvantaged households.

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 describe our current and intended counterfactuals, and Section 7 concludes.

2 Data

Our dataset covers the 2003-2007 period. It includes annual school-level information on every public, charter and private school in Washington, D.C. for each year, and annual neighorhood-level information on school choice and distance traveled to school for 2003-2006. We have focused on the 2003-2007 time period to maximize the quality and comparability of the data over time and across schools. In addition, 2007 marked the beginning of some important changes in DCPS and hence constitutes a good endpoint for our study.[8] Appendix I provides interested readers with further details on our data.

We begin by describing our school-level data. While public and private schools have one campus each, many charters have multiple campuses. Hence, our unit of observation is a campus-year, where a "campus" is the same as a school in the case of schools that have one campus each.[9] 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,[10] percent of students of each ethnicity (Black, White and Hispanic),[11] and percent of low-income students (who qualify for free or reduced lunch). We also have the school's thematic focus, which we have classified into core curriculum, language (usually Spanish), arts, vocational and others (math and science, civics and law, etc.).

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

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

Data on enrollment and proficiency for public and charter schools comes from OSSE. For public schools, the source of school addresses and student demographics are the Common Core

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

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

[10] 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.

[11] Since students of other races (mostly Asian) constitute only 2.26 percent of the total K-12 enrollment, for computational reasons we added them to the white category.

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). Charter reimbursement rates come from D.C.'s Office of the Chief Financial Officer.

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

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

According to grades covered, we have classified schools into the following grade levels: elementary (if grades covered fall within the K-6 range, since most primary schools covered up to 6th grade in D.C. during our sample period), middle (if grades covered are 7th and/or 8th), high (if grades covered fall within the 9th - 12th grade range), and elementary/middle, middle/high, and elementary/middle/high (if grades fall into more than one level). This classification follows DCPS's criteria and incorporates mixed-level categories (such as middle/high), which are quite common among charters. When convenient, we employ an alternative classification with three categories: elementary (including all categories that encompass elementary grades: elementary, elementary/middle, elementary/middle/high), middle, and high (defined similarly). Note that a grade level is a *set* of grades and not a single grade.

The data appendices in Filardo et al (2008) are the source of our neighorhood-level data. D.C. planning agencies often use the concept of "neighborhood cluster" to proxy for a neighborhood. A cluster is a collection of Census tracts, and there are 39 clusters in DC (and 188 Census tracts). In what follows we use the word "neighborhood" to refer to a neighborhood cluster. For the children who reside in each neighborhood, we observe the fraction who attend charter schools relative to the total number of children enrolled in the public system, and the average distance traveled to public or charter schools. For the sake of charter relocations, we used Arc GIS to calculate network distance among clusters. An alternative (but larger) measure of neighborhood is that of wards. The city of Washington, D.C. has eight wards; ward 3, in the northwest, in the most advantaged, and wards 7 and 8, in the southeast, are the most disadvantaged. When convenient we split the city into three regions: west (ward 3 and some parts of ward 2), southeast (wards 7 and 8) and northeast.

2.1 Descriptive Statistics

The population in Washington, D.C. peaked in the 1950s at about 802,000, declined steadily to 572,000 in 2000, and bounced back to 602,000 in 2010. It is estimated that the population grew from

577,000 in 2003 up to 586,000 in 2007, although the school-age population declined from 82,000 to 76,000.[12] 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, with large economic disparities among the races. For instance, in 2006 median household income was $92,000 for Whites, but only $34,500 for Blacks (Filardo et al, 2008).

2.1.1 Basic trends in school choice

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

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

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

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. Charters are spread throughout the city except in the northwest (see Figures 4a-c), where private schools have a strong presence. Even though private schools tend to be located in more affluent neighborhoods than public or charter schools, there is substantial variation among the different types of private schools (see Table 1b). Relative to other private schools, Catholic schools are located in less affluent neighborhoods, enroll higher fractions of Black and Hispanic students and charge lower tuition.

Table 1c depicts the variation in school choices by student race and poverty status, and by school level. During our sample period, 62 percent of children are enrolled in public schools, 17 percent in charter schools and 21 percent in private schools. Approximately 70 percent of Black and Hispanic children attend public schools, compared to only 28 percent of Whites. Between 15 and 20 percent of Black and Hispanic students attend charters, relative to 3 percent of White students. Nearly three quarters of White students attend private schools, compared to less than 15 percent of Black and Hispanic students.

2.1.2 Variation by grade level

As Table 3 shows, most public schools are elementary. Public schools rarely mix levels, whereas about a third of charter schools and three quarters of private schools do so. At every level, private

[12] 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).

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.

As Figure 5 shows, market share for each school type differs across grade levels. 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.[13]

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 school grades, the difference is smaller for middle school grades because charter school supply grew the most for these grades over the sample period. Moreover, charter middle schools have fewer students per grade than public schools (see Figure 7), a feature that many students may find attractive.[14] Note in passing that while the number of public and private high schools is about the same, 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. Similarly, Table 1 shows that students from all races are less likely to choose public schools at the middle and high-school level than at the elementary level: whites tend to switch into private schools; blacks tend to switch into charters (and Catholic schools, to a lesser extent), and Hispanics tend to switch into charter and Catholic schools. 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.

2.1.3 Variation by focus

the vast majority of public and private schools offer a core (i.e., non-specialized) curriculum, yet more than half of charters offer a specialized curriculum (see Table 5a). Among public schools, high schools are more likely to offer a specialized curriculum. 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 arts-focused elementary schools are charters that attract very disadvantaged students and are located in low-income neighborhoods (see Table 6a). Language schools attract high fractions of Hispanic students, and vocational schools attract highly 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 high fractions of Whites. Perhaps for this reason, these schools also tend to have relatively high achievement.

[13] 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.

[14] This does not necessarily mean that charter schools have smaller class sizes, as charters may have the same (or bigger) class size yet fewer classrooms per grade.

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

2.1.4 Relocations, closings and multiple-campus charters

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

Of the three closings, two were due to academic reasons and one to mismanagement. The average relocation distance is 3.47 miles (median = 3.09 miles), and 5 of the 20 moves happened within the same cluster. When one considers all possible clusters that a charter could relocate to, the average potential relocation distance is equal to 5.31 miles.

Our sample includes 63 campuses and 45 schools, of which 35 contain only one campus. The 10 multi-campus schools account for 53 percent of all charter enrollment over the sample period. Multi-campus organizations typically run multiple campuses in order to serve different grade levels.[16] Relative to single-campus charters, multi-campus charters are more likely to focus on a core curriculum. They also attract slightly higher fractions of Black students and achieve higher proficiency rates.

2.1.5 Entry patterns

Tables 7a through 7d display charter school entry patterns between 2004 and 2007 (the years used for our supply-side estimation, as explained below). Most of those entrants offer either elementary or middle school grades. They enter in the whole city except for ward 3 (the most advantage area of D.C.) and ward 6 (which experienced substantial entry before 2004). Most entrants offer a specialized curriculum, with "other focus" being the most popular choice.

The three regions into which we can divide D.C. -West, Northeast and Southeast - are home to 16, 47 and 37 percent of all school-age children and have received 15, 61 and 24 percent of all charter entries during our sample period respectively (see Table 7d). In other words, the Northeast has received a disproportionately large amount of entry, and the Southeast has received disproportionately little.

When we consider (region, level, focus) combinations, the most popular among entrants is (Northeast, elementary, non-core), totalling more than 25 percent of all entries, followed by (Northeast, elementary, core), (Northeast, middle, non-core) and (Southeast, elementary, core),

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

[16] For instance, Friendship has two elementary school campuses (Southeast Academy and Chamberlain), one elementary/middle school campus (Woodridge), one middle school campus (Blow-Pierce), and one high school campus (College).

each one with about 12.5 percent of all entries. While 60 percent of entrants in the Northeast offer elementary school, 75 percent of entrants in the Southeast do so. Most entrants in the Northeast offer a non-core curriculum, yet most entrants in the Southeast offer a core curriculum, and all but one entrant in the West offer a non-core curriculum. The few entrants that high school or mixed-level grades are all located outside the Southeast and offer a non-core curriculum.

An interesting question is whether the charters that entered before our sample period ("early entrants") are different from those that entered during our sample period ("recent entrants"). As Table 7e 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. Relative to early entrants, recent entrants 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.

2.1.6 Variation across neighborhoods

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

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

3 Model

In this section we develop our model of charter schools, household school choice, regulator actions 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. The regulator in this model is the entity that authorizes charter school entry and decides on charter closings. As explained before, this role has been played by PCSB since 2007.

We use the term “entry point” to refer to a combination of location, grade level and focus. At each point in time, there is a prospective entrant per entry point who chooses whether to submit an application in order to open a charter school or not. In each period, the regulator decides whether incumbent charters can remain open or close. If they are not closed, incumbent charters might have a relocation opportunity. We assume that prospective entrants and the regulator take the locations, grades served, and focus of public and private schools as given. They also take private school tuitions as given. To decide on charters' entry and closings, the regulator forecasts charters' potential enrollment given the market structure by trying to anticipate households' choices.

The model thus has multiple stages: several stages of charter and regulator actions, 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 $\widetilde{D} = 3$ rows, each one storing a 0 or 1 depending on whether the household is White, Hispanic (default race is Black), and non-poor (this indicator equals 1 if the student does not qualify for free- or reduced lunch, and 0 otherwise).
- $\ell \in \{1, ..., L\}$ is the location of the household in one of the L possible neighborhoods of the school district. A student's location determines her geographic distance with respect to each school.[17]
- I is the income of the student's family.
- 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 do not equate a campus with a physical location; if a campus relocates we still treat it as the same campus. We treat multiple campus of the same organization as separate entities because in many cases they are run as such. In what follows, we use "school" and "campus" interchangeably. Our data includes $J = 281$ schools and $T = 5$ years (between 2003 and 2007). A household's choice depends on several variables that characterize a particular school and that are observed by the household at the time of making its choice:

- 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.
- y_j denotes time-invariant school characteristics such as type (public, charter, Catholic, other religious, nonsectarian) and focus (core, language, arts, vocational, other). For presentational clarity we will refer to y_j as "focus."
- p_{jgt} is tuition. Public and charter schools cannot charge tuition, but private schools can. Private school tuition can vary by grade.
- $\widehat{\widetilde{D}}_{jt}$represents households' beliefs about the composition of the school's student body, or peer composition. As we will see below, all households share the same beliefs; in equilibrium, households' beliefs are consistent with schools' peer composition. In our empirical application we use another variable, $\overline{D}_{jt}$, which stores actual percent of White, Hispanic and non-poor

[17] We assume that a student's location is given and does not depend on her choice of school. For models of joint residential and school choice, see Nechyba (1999, 2000) and Ferreyra (2007, 2009). In our empirical application, distance is measured as network distance and is expressed in miles.

students. These characteristics may change over time, as household choices change. Since $\overline{D}_{jt}$ averages over the vectors D of the school's students, it has $\widetilde{D}$ elements, and so does $\widehat{\overline{D}}_{jt}$.

- 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 expected peer characteristics as follows:

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

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:

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

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 $\widehat{\overline{D}}_{jt}$, which captures the potential variation in preferences for school peer characteristics across different demographic groups. In addition, it depends on the distance between the household's residence and the school and on school tuition.

Student achievement A_{ijgt} depends on a school-grade factor common to all students, Q_{jgt}, a student's demographic characteristics, the fit of the thematic focus to the student (captured by the interaction of student demographics and focus below), and a zero-mean idiosyncratic achievement shock 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. 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:[18]

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

Substituting (5) into (4), we obtain

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

At the time they choose a school, parents observe ξ^a_{jgt} but only have beliefs about the demographic composition of the student body, and ν_{ijgt} has not been realized yet. Hence, parents' expectation of (4) is:

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

Note that parents do not condition on their children's ability (which we do not observe). This modeling choice is driven by the absence of student-level data.

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

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

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}:

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

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 $\hat{\bar{D}}_{jt}$ 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:

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

[18] Since peer characteristic measures are available at the school but not the grade level, we do not place the subscript g on $\bar{D}$.

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, or simply school quality. The grade-specific component ξ_g captures elements that are common to a given grade across schools and over time. For instance, grade retention rates are highest in 9th grade, and dropout rates are highest in 12th grade. The time-specific component 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 higher than the school average.

The household-specific component of (9) is:

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

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:

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

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:

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

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

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

where the dot in ξ and p indicates the set of all grades in the corresponding school. The equilibrium demographic composition $\widehat{\widehat{D}}$ satisfies (17). For computational tractability, in the demand estimation we replace $\widehat{\widehat{D}}$ by the observed peer characteristics $\bar{D}$ in the right hand sides of equations (14)-(17), and calculate $\widehat{\widehat{D}}$ accordingly, and exploit the fact that the difference between $\bar{D}$ and $\widehat{\widehat{D}}$ is only due to sampling (and perhaps measurement) error.

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 shock and the mean grade productivity shock. The time fixed effect captures changes that affect proficiency rates in all schools and grades, such as modifications to the assessment instrument. The error term is a function of school idiosyncratic productivity shocks and the mean of the idiosyncratic components of performance of the school's students.

3.2 School Supply

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

In what follows we model a game between charter schools, the regulator and households. This game is inspired by the our understanding of the regulator's actual behavior based on conversations with individuals familiar with the regulatory process in D.C. We assume that each prospective entrant receives a random draw of the nonpecuniary benefit from operating a school - representing, for instance, the satisfaction of doing socially valuable work. Given this draw, the prospective entrant decides whether to submit an entry application or not. To make its decisions, the regulator forecasts *equilibrium* enrollment for applicants and incumbents by predicting households' choice of school. Only charters that are expected to be financially viable are allowed to operate. Below we describe the actual entry process and then provide details on 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 of its ability to secure a facility. The authorizer evaluates the enrollment projection by considering the enrollment in nearby public schools, similar incumbent charters, the size of the school's intended building, and how many students will guarantee financial viability for the school given the expected fixed costs.

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

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

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

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

3.2.2 Market structure

A market structure is fully described by the list of operating schools along with their focus and location. At a given point in time, the list of operating schools includes public and private schools, whose actions we take as given, the incumbent charter schools which remain open, and the new charter entrants. More specifically, there are C_t incumbent charters, each of which can operate in any of $L+1$ locations.[19] The locations are indexed by $l = 0, 1, ..., L$, where $l = 0$ corresponds to leaving the market and $l = 1, ..., L$ are the actual geographic locations. The action of incumbent charter j at time t is denoted as d^i_{jt}, with $d^i_{jt} = 0$ indicating that the charter closes and $d^i_{jt} = l, l = 1, ..., L$ indicating that the charter remains open and operates in location l. We assume there is one potential entrant for each entry point per period. An entry point combines one of the L

[19] We assume that while an incumbent charter can change locations, it cannot change grade level or focus.

potential locations, one of the Y potential focuses and one of the K grade levels, for a total of $E = L \times Y \times K$ entry points or potential entrants. Each potential entrant j may either enter the market (by submitting an application and obtaining the regulator's approval) or not. We use d^e_{jt} to denote the action of entrant j at time t, where $d^e_{jt} = 1$ stands for entering the market and $d^e_{jt} = 0$ for not entering.

Now we can formally define a market structure. Given the behavior of public and private schools, a market structure is the vector $\mathbf{M}_t$ of size $C_t + E$. The size of this vector is equal to the maximum possible number of charter schools which might operate at time t, equal to the incumbent charters from last period C_t plus the potential entrants from this period E. In this vector, the first C_t components (which take integer values from 0 to L) represent the actions of the corresponding incumbents. The other components (valued 0 or 1) indicate the actions of the corresponding potential entrants. Charters are indexed by j, with $j = 1 \ldots C_t$ representing incumbents and $j = C_t + 1 \ldots C_t + E$ representing potential entrants. Note that $\mathbf{M}_t$ with all zero components corresponds to a market with no charter schools at time t, and $\mathbf{M}_t$ with all positive components corresponds to a market in which all incumbents from last period remain open and every entry point has an entrant.

The following observations are in order. First, given the actions of public and private schools charters can form $(L+1)^{C_t} \times 2^E$ possible market structures at time t. Second, let $\{d^i_{jt}\}_{j=1}^{C_t}$ describe the actions of incumbents and $\{d^e_{jt}\}_{j=C_t+1}^{C_t+E}$ describe the actions of potential entrants. Define as $\mathbf{e}_{jt}$ the vector of size $C_t + E$ which has all zeroes except for the jth component, which is equal to 1. Then the market structure is related to charters' actions as follows:

$$\mathbf{M}_t = \sum_{j=1}^{C_t} d^i_{jt}\mathbf{e}_{jt} + \sum_{j=C_t+1}^{C_t+E} d^e_{jt}\mathbf{e}_{jt} \tag{19}$$

3.2.3 Payoffs of the agents

The agents that participate in the game described below receive the following payoffs:

Household's payoff: For a given market structure $\mathbf{M}_t$ households choose the schools that maximizes their utility as described in Section 3.1.

Charter operator's payoff: When a charter operates, its operator gets nonpecuniary benefit B, $B > 0$. If the charter does not operate, the operator gets zero nonpecuniary benefits. We assume that B is a random draw from a distribution with cdf function $F_B(\cdot)$. It is independent of the expected net revenues from operating the school[20] and of other entrants' B.

The regulator receives charter applications and decides whether to approve them. It also decides whether incumbent charters can remain open. Its decisions are based on charters' expected enrollment, which in turn determines their financial viability. Only charters whose expected profit is sufficiently high are allowed to enter or remain open.

3.2.4 Household beliefs

In order to forecast enrollment for incumbent and potential charters, the regulator needs to analyze market structures that may or may not be realized in the data. In Section 3.1 we derived expected

[20]Independence of the payoff from net revenues (profits) greatly simplifies the model and estimation. Otherwise in order to derive the optimal behavior of a prospective entrant, we would need to to calculate its expected profits, which would be a function of the distribution of future market structures. Without the independence assumption, this distribution would be a function of the behavior of other potential entrants. Given the number of potential entrants in our data, computing expected profits in this case would be computationally prohibitive.

enrollment expressions for the actual market structure. Here we derive enrollment for theoretically feasible market structures. We begin by describing *household beliefs* formally.

For a given market structure $\mathbf{M}_t$ and schools' qualities ξ, each household forms beliefs about schools demographic composition and chooses a school based on those beliefs. Let $\widehat{\overline{D}}(\mathbf{M}_t, \xi)$ be the collection of school expected demographic composition that form the beliefs of the households. Mostly we use short notation $\widehat{\overline{D}}$ for $\widehat{\overline{D}}(\mathbf{M}_t, \xi)$ to avoid cluttering. Below we describe the conditions under which these beliefs are consistent.

When choosing schools household i calculates the utility from school j as follows

$$U_{ijgt} = \delta_{jgt}(\widehat{\overline{D}}_{jt}) + \mu_{ijgt}(\widehat{\overline{D}}_{jt}) + \varepsilon_{ijgt} \tag{20}$$

where

$$\delta_{jgt}(\widehat{\overline{D}}_{jt}) = y_j\beta + \widehat{\overline{D}}_{jt}\alpha + \xi_{jgt}, \tag{21}$$

$$\mu_{ijgt}(\widehat{\overline{D}}_{jt}) = D_i\omega + y_j D_i\tilde{\beta} + D_i\widehat{\overline{D}}_{jt}\tilde{\alpha} + x_{ijt}\gamma + \varphi\log(I_i - p_{jgt}) \tag{22}$$

Given the above the probability of choosing school j by student i is

$$P_{ijgt}\left(\widehat{\overline{D}}\right) = \frac{\exp(\delta_{jgt}(\widehat{\overline{D}}_{jt}) + \mu_{ijgt}(\widehat{\overline{D}}_{jt}))}{\exp(\varphi\log(I_i)) + \sum_{k=1}^{J_{gt}^i}\exp(\delta_{kgt}(\widehat{\overline{D}}_{kt}) + \mu_{ikgt}(\widehat{\overline{D}}_{kt}))} \tag{23}$$

where J_{gt}^i is the number of schools available to student i. Hence , expected enrollment for grade g in school j is

$$\widehat{N}_{jgt}(\widehat{\overline{D}}) = \int_\ell\int_I\int_D P_{ijgt}(\widehat{\overline{D}})dh(D, I, \ell \mid g) \tag{24}$$

The total expected enrollment for school j is

$$\widehat{N}_{jt}(\widehat{\overline{D}}) = \sum_{g\in\kappa_{jt}}\widehat{N}_{jgt}(\widehat{\overline{D}}) \tag{25}$$

We say that $\widehat{\overline{D}}$ forms a *set of consistent beliefs of households* if it solves the following system of equations:

$$\widehat{\overline{D}}_{jt} = \frac{\sum_{g\in\kappa_{jt}}\widehat{N}_{jgt}(\widehat{\overline{D}})\int_\ell\int_I\int_D DP_{ijgt}(\widehat{\overline{D}}_{jt})dh(D, I, \ell \mid g)}{\widehat{N}_{jt}(\widehat{\overline{D}})} \quad \text{for all } j = 1, ..., J_t \tag{26}$$

Since $\widehat{\overline{D}}$ is in fact the function $\widehat{\overline{D}}(\mathbf{M}_t, \xi)$, in (24) the equilibrium expected enrollment is the function $\widehat{N}_{jgt}(\mathbf{M}_t, \xi)$.

Generally, (26) has multiple solutions and hence the model has multiple equilibria. For instance, White households may choose school A if they believe that other White households will attend A, yet they may choose school B if they believe that other White households will attend B. The disutility of traveling should in principle mitigate this issue: in our example, White households may not care about school B if it is located sufficiently far from their residences. Nonetheless, we cannot completely rule out the possibility of multiple equilibria. The issue does not affect the estimation of our demand-side parameters because we impose equilibrium and use observed student demographic composition, $\overline{D}$, to calculate the predicted market share in (23). However, the supply-side estimation (via the calculation of expected enrollment) and the counterfactuals might be affected. Hence, we use a *tatonnement*-type of algorithm as follows: We choose an initial value for $\widehat{\overline{D}}$, $\widehat{\overline{D}}^0$,for the right-hand side of (26), and get $\widehat{\overline{D}}^1$ for the left-hand side of (26). From $\widehat{\overline{D}}^1$ we similarly get $\widehat{\overline{D}}^2$ and so on until we converge.[21] In general, from $\widehat{\overline{D}}^k$ $(k = 0, 1, ...)$ we obtain $\widehat{\overline{D}}^{k+1}$ as follows

$$\widehat{\overline{D}}_{jt}^{k+1} = \frac{\sum_{g \in \kappa_{jt}} \widehat{N}_{jgt}(\widehat{\overline{D}}^k) \int_\ell \int_I \int_D DP_{ijgt}(\widehat{\overline{D}}_{jt}^k) dh(D, I, \ell \mid g)}{\widehat{N}_{jt}(\widehat{\overline{D}}^k)}. \tag{27}$$

Numerically an equilibrium can be found by performing iterations over (26).[22] To address multiplicity we choose the equilibrium attained by iterating from a specific starting point. For incumbent schools, the starting point is observed demographics; for the new entrants, the starting point is a linear function of neighborhood demographic characteristics and school characteristics.

3.2.5 Expected charter enrollment and profit

Recall that the regulator makes decisions on charter entry and exit based on charters' expected profits. At the beginning of t, the regulator observes ξ_{jgt} for all incumbents but does not observe ξ_j or $\Delta\xi_{jgt}$ for potential entrants. The regulator also observes ξ_g for each g and ξ_t. We assume that for potential entrants the shocks ξ_j and $\Delta\xi_{jgt}$ are independently distributed[23] with cdfs $F_{\xi_j}(.)$ and $F_{\Delta\xi}(.)$ respectively. These distributions are common knowledge. We use $F_j(.)$ to denote the joint distribution of demand shocks ξ_{jgt} for charter entrant j, and ξ_{-jgt} to denote incumbents' demand shocks.

Consider potential entrant j that intends to enter in location ℓ, specialize on focus y and offer grade level κ.The regulator calculates j's expected enrollment in grade g as follows

$$E_\xi \widehat{N}_{jgt}(\mathbf{M}_t; \theta^d) = \int \widehat{N}_{jgt}(\mathbf{M}_t, \{\xi_{jgt}, \xi_{-jgt}\}) dF_j(\xi_{jgt}) \tag{28}$$

where θ^d is the collection of demand-side model parameters. For the whole school, the regulator calculates expected profits as follows[24]

$$\bar{\pi}_{jt}^e \left(d_{jt}^e = 1, \mathbf{M}_t\right) = \sum_{g \in \kappa} E_\xi \hat{N}_{jgt}(\mathbf{M}_t; \theta^d) \left(R_{gt} - V_\kappa\right) - \zeta - F_\ell + \sigma_\nu \nu_{jt}^e \tag{29}$$

where ζ is entry costs, R_{gt} is the reimbursement per child in grade g, V_κ is the variable cost per child for grade level κ, F_ℓ is the fixed costs for operating in location ℓ, and ν_{jt}^e is an idiosyncratic shock unobserved to the econometrician. We assume that ν_{jt}^e follows an i.i.d. type I extreme value distribution with scale parameter σ_ν. This shock encompasses aspects of the school's performance that are observed to the regulator but not to the econometrician, such as the soundness of the

[21] Given that $\widehat{\overline{D}}$ is defined on a compact set (all values in $\widehat{\overline{D}}$ are between 0 and 1) and (26) describes a continuous mapping, such iterations always converge.

[22] In the iterations we only allow for changes in $\widehat{\overline{D}}$ that are within a specified range (± 6 percentage points, or 0.06). In the absence of capacity constraints, this type of restriction is necessary in order to prevent large, unrealistic changes in school enrollments and student body composition.

[23] It possible that $\Delta\xi_{jgt}$s might be correlated across grades or/and time. We do not model these correlations because we believe they only have a second-order effect on expected enrollment, and because our data does not allow for an accurate estimation of these correlations.

[24] Again $\mathbf{M}_t$ should be consistent with $d_{jt}^e = 1$.

business plan or the quality of the educational curriculum. Since the charter application in D.C. is a long form that requires extensive and detailed information on the part of the applicant, it is plausible to assume that the regulator observes ν^e_{jt}.

In order to monitor incumbent charters, the regulator calculates their profits. Consider incumbent j, located in ℓ_{jt} both in the previous period and the current one. The regulator calculates j's profits as follows[25]

$$\pi^i_{jt\ell_{jt}}\left(d^i_{jt} = \ell_{jt}, \mathbf{M}_t\right) = \sum_{g\in\kappa} N_{jgt}\left(R_{gt} - V_\kappa\right) - F_{\ell_{jt}} + \sigma_\nu \nu^i_{jt} \tag{30}$$

In this expression, N_{jgt} is actual enrollment of students and ν^i_{jt} is an idiosyncratic shock that is observed to the regulator but not to the econometrician. This shock follows an i.i.d. type I extreme value distribution with scale parameter σ_ν, and represents elements affecting the charter's performance such as the operator's managerial and financial ability, characteristics of the curriculum, etc. Since charters are subject to detailed financial supervision on the part of the regulator and are required to file multiple reports over the course of the year, it is plausible to assume that the regulator observes ν^i_{jt}. Note that our assumptions imply that the regulator observes every element in (29) and (30).

3.2.6 Timing of entry-exit-relocation events

Step 1 (*Submisison of applications by the potential entrants*). At the beginning of τ each potential entrant j privately learns the value of its nonpecuniary payoff B_j, which is drawn from the distribution $F_B(\cdot)$. All draws are independent. Based on the observed value of B_j the potential entrant decides whether to submit an entry application to start operating in $\tau+1$. Each entrant has a private type, ν^e, which captures the entrant's financial and managerial ability to run the charter and is distinct from the charter's quality, ξ_j, which affects households' utilities. Each entrant that submits an application learns its type $\nu^e_{j\tau}$. All other potential entrants do not learn their types.[26] In reality this step takes place in Spring t.

Step 2 *(Public and private schools)*. At the beginning of τ public and private schools make decisions regarding their own entry, exit and relocation. These actions become public knowledge. In reality, this step takes place in Spring t, and these decisions become effective in Fall t. Also at this point the $\xi_{jg\tau}$s of all the schools included in households' choice sets in Step 4 below become public knowledge. These choice sets include the charters authorized in Step 1 of period $\tau - 1$.

Step 3 *(Relocation opportunities for incumbent charters)*. For each charter incumbent j, located at $\ell_{j\tau-1}$ in $\tau - 1$ a new location ℓ, $\ell \neq \ell_{j\tau-1}$ and $\ell \neq 0$, might become available with probability[27]

$$\Pr(\ell) = \frac{\exp\{\breve{\alpha} - \breve{\beta} d_{\ell\ell_{j\tau-1}}\}}{1 + \sum_{\ell'\neq\ell_{j\tau-1},\ell'\neq 0}\exp\{\breve{\alpha} - \breve{\beta} d_{\ell'\ell_{j\tau-1}}\}}$$

[25] Recall that $\mathbf{M}_t$ should be consistent with the charter's presence in location ℓ^i_{jt}.

[26] Recall that if the prospective operator does not submit an application, entry does not take place and the operator obtains a zero payoff. When the prospective operator submits an application the probability of approval is p_a, and the payoff from operating the charter is equal to B. Hence, the operator's expected payoff from submitting an application is equal to $(1 - p_a) * 0 + p_a B = p_a B$. Note that p_a is always positive because $(v^e - v^e_0)$ has full support. Hence, this expected payoff has the same sign as B.

[27] With probability $\frac{1}{1+\sum_{\ell'\neq\ell_{j\tau-1},\ell'\neq 0}\exp\{\breve{\alpha}-\breve{\beta} d_{\ell'\ell_{j\tau-1}}\}}$ no new location becomes available.

where $d_{\ell' \ell_{j\tau-1}}$ is the distance between ℓ' and $\ell_{j\tau-1}$. Charters move if a new location becomes available for them, and inform the regulator about the move.[28] In reality, the regulator is informed of the move in Spring t, and the actual move usually takes place in Summer t.

Step 4 (*Households' school choice*). Recall that households observe the demand shocks $\xi_{jg\tau}$ of all the schools operating in the market in τ. Based on the available information, households choose a school for their children, and schools' enrollments are realized. In reality, parents choose a school in Spring t, and children attend the chosen school in Fall t and Spring $t+1$.

Step 5 *(Processing of entry applications).* The regulator decides whether to authorize the charter entry applications submitted in Step 1. If approved, the new charters will start operating in $\tau+1$. Nonetheless, the regulator makes its decision as if the charter applicant were to start operating right away in τ, based on the prevailing market structure $\mathbf{M}_\tau$. This market structure is equal to the one prevailing at the end $\tau-1$, adjusted to reflect Steps 2 and 3, and incorporating the new charters authorized in $\tau-1$. The regulator learns the types $\nu^e_{j\tau}$ of all entry applicants. Applicant τ is approved iff

$$\bar{\pi}^e_{j\tau}\left(d^e_{j\tau}=1,\mathbf{M}_\tau+\mathbf{e}_{j\tau}\right)\geq\sigma_\nu\nu^e_{j\tau 0}$$

where $\bar{\pi}^e_{j\tau}\left(\cdot,\cdot\right)$ is given by (29) and $\sigma_\nu\nu^e_{j\tau 0}$ is the entry threshold that the applicant must surpass to be authorized to open. Component $\nu^e_{j\tau 0}$ is random and follows an i.i.d. type I extreme value distribution.[29] Note that applications are in fact processed independently.

In reality, in Spring t the regulator authorizes entry for charters that will start operating in Fall $t+1$, and bases its decisions on the market structure that will prevail in Fall t.

Step 6 *(Detecting unprofitable incumbents).* By the end of τ the regulator learns the types $\nu^i_{j\tau}$ of all charters which operate on the market as well as their enrollment. Charter j, located in $\ell_{j\tau}$ is forced to leave the market in $\tau+1$ iff

$$\pi^i_{j\tau\ell_{j\tau}}\left(d^i_{j\tau}=\ell_{j\tau},\mathbf{M}_\tau\right)\leq\sigma_\nu\nu^i_{j\tau 0}.$$

where $\nu^i_{j\tau 0}$ is a type I extreme value i.i.d. random shock, and $\pi^i_{j\tau\ell_{j\tau}}\left(d^i_{j\tau}=\ell_{j\tau},\mathbf{M}_\tau\right)$ is charter j's actual profit in τ,based on the actual market structure and school enrollments in τ. Incumbent charters are evaluated independently. All closings become public knowledge by the end of period τ. In reality, this step takes place any time during Fall t (the school is usually allowed to finish the school year but not to start a new one).[30]

A new entrant authorized in Step 5 carries out the kinds of activities described in previous sections during the remainder of period τ and the beginning of period $\tau+1$. We assume that through these activities, all the parties learn the entrant's demand shocks $\xi_{jg\tau+1}$s.

3.2.7 Solution of the game

The solution of this game is a Perfect Bayesian Equilibrium. This type of equilibrium requires consistent beliefs by schools and households,[31] and expected payoff maximizing behavior based on these beliefs.

[28] We model relocation opportunities as exogenous to reflect the actual nature of relocations. When a charter wishes to move, it must inform PCSB of its plans but does not need PCSB's authorization to move. This institutional feature simplifies our analysis.

[29] The random threshold captures the possibility that the regulator may favor some applicants over others because they have socially desirable features, such as their focus or targeted student body.

[30] In reality, decisions to close charter schools may happen at any time during thes chool year. We simplify the analysis by assuming that such decisions take place in the Fall. This simplication is innocuous because exits are very infrequent during our sample period, and charters' financial situation in the Fall is very close to that in the Spring.

[31] An agent has consistent beliefs if it correctly calculates the probabilities of the equilibrium evolution of the game, given the available information and other players' equilibrium strategies.

In the game, agents have the ability to make choices only in steps 1 and 4. We analyze the equilibrium of the game backwards and start from the end. In Step 4, households exhibit the equilibrium behavior and formation of beliefs that we described in Section 3.2.4. In Step 1, the equilibrium strategy on the part of the applicant is to submit an application when $B > 0$ and not submit one otherwise. The probability of a positive B is equal to:

$$b = 1 - F_B(0).$$

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 the three estimation stages.

4.1 Data

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

Our data includes 65 markets (13 grades times 5 years) and J =281 campuses, for a total of J^D=1,269 school-year observations and J^X=8,112 school-grade-year observations. It also includes J^C=153 neigborhood-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 observe the following school characteristics: governance (public, charter, Catholic, other religious, private non-sectarian), location, grade span, focus, peer characteristics (percent of students of each ethnicity and low-income status), tuition for private schools, and proficiency rates for public and charter schools. Some school characteristics change over time while others remain constant. Location varies for schools that move during the sample period. Grade span varies for a number of schools that either add or drop grades over the period. Entry and exit of schools offering a given grade as well as changes in grade span of the existing schools affects the composition of households' choice sets. Thematic focus is constant over time and across grades within a school. Given the lack of time (and grade, for the most part) variation of tuition among private schools, tuition can also be viewed as a time-invariant school characteristic. For a given school, peer characteristics change over time. Proficiency rates also vary over time.

In the model, the economy is a collection of locations. For the sake of our demand estimation, a geographic 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.

Once we obtain this joint distribution, we randomly draw $ns = 100$ households for each market. 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. Given the low fraction of white and hispanic students in the population, we stratify our sample by year, grade and race.

At first we attempted to construct school choice sets for households in every location and grade that included all the charter and private schools offering that grade but only the public schools assigned to that location given attendance zone boundaries. Attendance zones are larger for middle and high schools than for elementary schools, and boundaries changed once during our sample period (in 2005). Appendix IV describes how we assigned each block group to an elementary, middle and high school attendance zone in each year. However, based on our resulting assignment 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 systematic across the District. For instance, Filardo et al (2008) document that approximately half of the children enrolled in public schools attend an out-of-boundary school. Thus, we opted for modeling the choice set available to a household interested in a given grade as the full set of schools offering that grade - namely, as though there were open enrollment in public schools.

4.2 Demand Estimation

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

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

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

$$\hat{N}_{jgt} = \frac{M_{gt}}{ns} \sum_{i=1}^{ns} \hat{P}_{jgt} \left(y_j, y_{-j}, \bar{D}_{jt}, \bar{D}_{-jt}, \xi_{jgt}, \xi_{-jgt}, p_{jgt}, p_{-jgt}, X_{ijt}; \theta^d \right). \tag{31}$$

where $\hat{P}_{jgt}(\cdot)$ is given by (14), where we have approximated $\widehat{\bar{D}}$ in the right-hand side of (14) by $\bar{D}$.

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

$\hat{N}_{jt} = \sum\limits_{g \in \kappa_{jt}} \hat{N}_{jgt}$, and predicted school peer characteristics are as follows:

$$\widehat{\widetilde{D}}_{jt} = \frac{\sum\limits_{g \in \kappa_{jt}} \left(\frac{M_{gt}}{ns}\right) \sum\limits_{i=1}^{ns} D_i \hat{P}_{jgt}(\cdot)}{\hat{N}_{jt}} \tag{32}$$

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

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

$$\bar{D}_{jt} = \widehat{\widetilde{D}}_{jt} + u_{jt}^{D}. \tag{33}$$

Similarly, we assume that $E\left(\overline{C}_{kt} \mid X_t\right) = \widehat{\widetilde{C}}_{kt}$, and that observed neighborhood cluster data are different from their expected value due to sampling or measurement error:

$$\overline{C}_{kt} = \widehat{\widetilde{C}}_{kt} + u_{kt}^{C}. \tag{34}$$

Since parents observe the unobserved (to us) school characteristics $\Delta\xi_{jgt}$ when choosing schools, the school demographic composition $\bar{D}_{jt}$ that results from household choices is correlated with $\Delta\xi_{jgt}$. Let Z_{jgt}^{X} be a row vector of L^X instruments, Z_{jt}^{D} be a row vector of L^D instruments and Z_{kt}^{C} be a row vector of L^C instruments. In our preferred specification, $L^X = 310$, $L^D = 102$, $L^C = 54$. Vertically stacking all observations yields matrices Z^X (dimension J^X by L^X), Z^D (dimension J^D by L^D) and Z^C (dimension J^C by L^C).

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

$$E\left[\Delta\xi_{jgt} \mid Z_{jgt}^{X}\right] = 0 \tag{35}$$

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

$$E\left[u_{jt}^{D} \mid Z_{jt}^{D}\right] = 0 \tag{36}$$

$$E\left[u_{kt}^{C} \mid Z_{kt}^{C}\right] = 0 \tag{37}$$

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

$$E\left[\left(Z_{jgt}^{X}\right)' \Delta\xi_{jgt}\right] = 0 \tag{38}$$

$$E\left[\left(Z_{jt}^{D}\right)' u_{jt}^{d}\right] = 0 \tag{39}$$

$$E\left[\left(Z_{kt}^{C}\right)' u_{kt}^{c}\right] = 0 \tag{40}$$

where u_{jt}^d and u_{jt}^c indicate the sampling error in a specific demographic characteristic d (for instance, in percent White students) or neighborhood-level variable c (for instance, percent of children in charter schools). Vertically stacking all observations yields vectors and rearranging elements yields vectors $\Delta\xi$, u^D and u^C with J^X, $\left(J^D * \widetilde{D}\right)$ and $\left(J^C * \widetilde{C}\right)$rows respectively. The first set of J^D rows in vector u^D correspond to the first demographic characteristic; the second set set to the second demographic characteristic, and so forth for the $\widetilde{D}$ demographics. Vector u^C has a similar structure for neighborhood-level variables.

In order to interact the sampling error for each demographic characteristic with every instrument in Z^D we introduce matrix $\widetilde{Z}^D$, which is block diagonal and repeats Z^D along the diagonal for a total of $\widetilde{D}$ times. Similarly, block-diagonal matrix $\widetilde{Z}^C$ repeats Z^C along the diagonal for a total of $\widetilde{C}$ times. We use the term "share moments" for (38), "demographic moments" for (39), and "neighborhood moments" for (40).

The sample analogs of (38), (39) and (40) are the following vectors:

$$\lambda_X(\Delta\xi) = \frac{1}{J^X} Z^{X\,\prime} * \Delta\xi \tag{41}$$

$$\lambda_D(\Delta\xi, \theta^d) = \frac{1}{J^D} \widetilde{Z}^{D\,\prime} * u^D \tag{42}$$

$$\lambda_C(\Delta\xi, \theta^d) = \frac{1}{J^C} \widetilde{Z}^{C\,\prime} * u^C \tag{43}$$

with L^X, $\left(L^D * \widetilde{D}\right)$ and $\left(L^C * \widetilde{C}\right)$ 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 with the demographic and neighborhood moments.

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

$$\begin{aligned} & \min_{\Delta\xi,\,\theta^d} \begin{bmatrix} \lambda_X(\Delta\xi) \\ \lambda_D(\Delta\xi,\theta^d) \\ \lambda_C(\Delta\xi,\theta^d) \end{bmatrix}' \begin{bmatrix} V_X & & \\ & V_D & \\ & & V_C \end{bmatrix} \begin{bmatrix} \lambda_X(\Delta\xi) \\ \lambda_D(\Delta\xi,\theta^d) \\ \lambda_C(\Delta\xi,\theta^d) \end{bmatrix} \\ & s.t. \\ S \quad = \quad & \hat{S}(\Delta\xi, \bar{D}; \theta^d) \end{aligned} \tag{44}$$

where the sample moments are defined as in (41-43) for some positive definite matrices V_X, V_D and V_C.[32] The MPEC algorithm simultaneously searches over values for $\Delta\xi$ and θ^d; given values for

[32] We use $V_X = \left(Z^{X\prime} Z^X\right)^{-1}$,$V_D = \left(\widetilde{Z}^{D\prime}\widetilde{Z}^D\right)^{-1}$ and $V_C = \left(\widetilde{Z}^{C\prime}\widetilde{Z}^C\right)^{-1}$.

these, it calculates the predicted market shares, peer characteristics and neighorhood-level variables. The constraints of the MPEC problem ensure that the observed enrollment shares S match the predicted enrollment shares $\hat{S}$ given values for the preference parameters, demand shocks and observed peer characteristics. Our standard errors are robust to arbitrary within-school correlation of $\Delta\xi$ (across grades and over time), arbitrary correlation of sampling errors u^d within a school-year, and arbitrary correlation of sampling errors u^c within a neighborhood-year.

Finally, the decomposition of the demand shock in (11) suggests the inclusion of school-, grade- and time-fixed effects in the utility function. Since the school-specific dummy variables capture both the value of school characteristics that do not vary over time, $y_j\beta$, and the school-specific mean of unobserved quality, 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 campuses in the data. Denote by Ξ 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: $\Xi = y\beta + \xi$. 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 $\hat{\beta} = \left(y'y\right)^{-1} y'\widehat{\Xi}$ and $\hat{\xi} = \hat{B} - y\hat{\beta}$ respectively, where $\widehat{\Xi}$ is the vector of school dummy coefficients contained in $\hat{\theta}^d$ and estimated through GMM. The standard errors of $\hat{\beta}$ are corrected to account for the estimation error of $\widehat{\Xi}$.

4.3 Supply estimation

To estimate the supply parameters $\theta^s = \left\{\mu_\xi,\ \sigma_\xi,\ \sigma_{\Delta\xi},\ b,\ \zeta,\ V,\ F,\ \sigma_\nu,\ \breve{\alpha},\ \breve{\beta}\right\}$, we first derive the likelihood function for the observed behavior of charter schools.[33] Recall that an entry point is a combination of geographic location, thematic focus and grade level. In our empirical application we have $L = 39$ locations; $Y = 5$ focuses and $K = 5$ grade levels (elementary, middle, high, elementary/middle and middle/high), for a total of $E = 975$ entry points.

Since our data pertain to school years, in what follows we use t to denote the Fall t / Spring $t+1$ school year. For each t we observe the set of schools operating in the market. We also observe the following: a) new charter entries, authorized in $t-2$ based on the market structure at $t-1$; b) charter closings, decided by the regulator in $t-1$ based on the market structure at $t-1$, which we assign to t because t is the first year we no longer observe a closing school in the data; c) charter relocations, which take place just before the beginning of t, and which we assign to t because t is the first year in the new location.

Let $E_\nu \bar{\pi}^e_{jt}\left(d^e_{jt}, \mathbf{M}_t\right)$ be the expected value of (29) with respect to ν. Let E be the number of potential applicants. Let C_t be number of charters operating in t, including the incumbents from $t-1$ that remained open in t as well as the new entrants. Let ℓ_{jt} be the location of charter j in t. We use $\hat{d}^e_{jt} \in \{0,1\}$ to describe whether entry point j has a new entrant in t and $\hat{d}^x_{jt} \in \{0,1\}$ to describe incumbent charter j closed at the end of $t-1$. The likelihood function is

$$\tilde{L}\left(\theta^s\right) = \prod_{t=2}^{T}\left[\left\{\prod_{j=1}^{E} \Pr\left(d^e_{jt} = \hat{d}^e_{jt} \mid \mathbf{M}_{t-1}\right)\right\} \times \left\{\prod_{j=1}^{C_{t-1}} \Pr\left(d^x_{jt} = \hat{d}^x_{jt} \mid \mathbf{M}_{t-1}\right)\right\} \times \left\{\prod_{j=1 \ldots C_{t-1}:\ \hat{d}^x_{jt}=0} \Pr\left(d^i_{jt} = \ell_{jt} | d^i_{jt-1} = \ell_{jt-1}\right)\right\}\right]$$

[33] Fixed costs F are assumed to be independent of the school's location, focus and time. The low frequency of entry and exit in our data precludes us from specifying a more flexible form for fixed (or variable) costs.

The *first product* inside the likelihood function stands for approved applications for school year t:

$$\Pr\left(d^e_{jt} = \hat{d}^e_{jt} \mid \mathbf{M}_{t-1}\right) = \begin{cases} b\frac{\exp\{E_\nu \bar{\pi}^e_{jt-1}(d^e_{jt-1}=1,\mathbf{M}_{t-1}+\mathbf{e}_{jt-1})/\sigma_\nu\}}{1+\exp\{E_\nu \bar{\pi}^e_{jt-1}(d^e_{jt-1}=1,\mathbf{M}_{t-1}+\mathbf{e}_{jt-1})/\sigma_\nu\}} & \text{if } \hat{d}^e_{jt} = 1 \\ 1 - b\frac{\exp\{E_\nu \bar{\pi}^e_{jt-1}(d^e_{jt-1}=1,\mathbf{M}_{t-1}+\mathbf{e}_{jt-1})/\sigma_\nu\}}{1+\exp\{E_\nu \bar{\pi}^e_{jt-1}(d^e_{jt-1}=1,\mathbf{M}_{t-1}+\mathbf{e}_{jt-1})/\sigma_\nu\}} & \text{if } \hat{d}^e_{jt} = 0 \end{cases}$$

where recall $\mathbf{e}_{jt-1}$ is the vector of size $C_{t-1} + E$ with all zero components except unity component $C_{t-1} + j$.

The *second product* corresponds to charter closings:

$$\Pr\left(d^x_{jt} = \hat{d}^x_{jt} \mid \mathbf{M}_{t-1}\right) = \begin{cases} \frac{1}{1+\exp\{E_\nu \pi^i_{jt-1\ell_{jt-1}}(d^i_{jt-1}=\ell_{jt-1},\mathbf{M}_{t-1})/\sigma_\nu\}} & \text{if } \hat{d}^x_{jt} = 1 \\ \frac{\exp\{E_\nu \pi^i_{jt-1\ell_{jt-1}}(d^i_{jt-1}=\ell_{jt-1},\mathbf{M}_{t-1})/\sigma_\nu\}}{1+\exp\{E_\nu \pi^i_{jt-1\ell_{jt-1}}(d^i_{jt-1}=\ell_{jt-1},\mathbf{M}_{t-1})/\sigma_\nu\}} & \text{if } \hat{d}^x_{jt} = 0 \end{cases}$$

notice that $E_\nu \pi^i_{jt\ell_{jt}}(d^i_{jt} = \ell_{jt}, \mathbf{M}_t)$ is the expected profit based on the actual enrollment and location of the charter at t.

The *third product* describes relocations:

$$\Pr\left(d^i_{jt} = \ell_{jt} | d^i_{jt-1} = \ell_{jt-1}\right) = \begin{cases} \frac{\exp\{\breve{\alpha}-\breve{\beta}d_{\ell_{jt}\ell_{jt-1}}\}}{1+\sum_{\ell' \neq \ell_{jt-1}, \ell' \neq 0}\exp\{\breve{\alpha}-\breve{\beta}d_{\ell'\ell_{jt-1}}\}} & \text{if } \ell_{jt} \neq \ell_{jt-1} \\ \frac{1}{1+\sum_{\ell' \neq \ell_{jt-1}, \ell' \neq 0}\exp\{\breve{\alpha}-\breve{\beta}d_{\ell'\ell_{jt-1}}\}} & \text{if } \ell_{jt} = \ell_{jt-1} \end{cases}$$

Note that the likelihood corresponding to the first year of our data (2003) cannot be calculated as we lack data on the previous year's market structure and charters' locations.

Recall our assumption that the regulator observes demand shocks ξ_{jgt}s for all schools in the market at t but not for potential entrants. Hence, in order to calculate entrants' expected profits we use Monte Carlo simulations based on our demand-side estimates of $\Delta\xi_{jgt}$s and ξ_js. To estimate θ^s,we first compute expected enrollment $E_\xi \widehat{N}_{jt}(\mathbf{M}_t)$ based on θ^s for each entry point and year, and then evaluate the likelihood function for alternative values of θ^s.

4.4 Proficiency Rate Estimation, and Summary

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

$$\bar{q}_{jt} = y_j \alpha^q + \bar{D}_{jt}\phi^q + y_j \bar{D}_{jt}\omega^q + \xi^q_j + \xi^q_t + \Delta\xi^q_{jt} + v^q_{jt} \tag{45}$$

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 as well as 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. Hence, to estimate the parameters of the proficiency rate function we first run an instrumental variables (IV) regression of passing rate on campus and year fixed effects, school demographic composition and interactions between school demographic compositions and time-invariant school characteristics. Then we regress the campus fixed effects estimates on time-invariant school characteristics. The residuals from this second regression are our estimates of ξ_j^q. We use the term "value added" to refer to these residuals.

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

4.5 Instruments

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

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

Matrix Z^D contains the instruments for the sampling error in school-year student demographics. These instruments include school type, focus, and interactions of school type with ward. Matrix Z^C contains the following instruments for sampling error in neighborhood-level variables: neighborhood-level number of public and charter schools, average family income, racial composition of school-age children, age distribution of school-age children, and ward dummies. Finally, matrix Z^Q used for the proficiency rate estimation contains local demographics for the schools' neighborhoods, similar to Z^X. It also includes campus and year 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 $(\alpha^a, \beta^a, \omega^a, \tilde{\beta}^a)$. Nonetheless, the parameters of the utility function are identified.

The parameters of the baseline component of utility, (α, β) in equation (10), are identified. All moments contributed to the identification of these parameters. 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, low-income students mix with other races and economic status in school, 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. The identification of these parameters comes from the demographic and neighborhood moments. 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 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. It is identified by the neighborhood-level variation in distance traveled to school and fraction of children enrolled in charters. In general, variation in school type, focus and location is critical to the identification of preference parameters. Parameter 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.

From a formal perspective, a condition for identification is that the matrix of derivatives of the sample moments with respect to the parameters have full rank. Evaluated at our parameter estimates, this matrix indeed has full rank.[34]

Proficiency rate parameters in (45) 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.

[34] 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.

On the supply side the likelihood function depends on the following set of parameters: $\left\{\mu_\xi,\ \sigma_\xi,\ \sigma_{\Delta\xi},\ b,\ \zeta,\ V,\ F,\ \sigma_\nu,\ \breve{\alpha},\ \breve{\beta}\right\}$. These parameters can be identified from the data in the following way. The expected value of the entrant's performance parameter μ_ξ and standard deviation parameter σ_ξ are estimated as a average and standard error from the empirical distribution of entrants' ξ_js[35]. Parameter $\sigma_{\Delta\xi}$ is the variance of the distribution of the estimated school-grade-year shocks $\Delta\xi_j$s. The probability of a positive charter operator payoff, b, is estimated as the ratio of annual average number of application to the number of entry points. Relocation parameters $\breve{\alpha}$ and $\breve{\beta}$ are identified by the patterns of charter moves. The larger the value of $\breve{\alpha}$, the larger the probability of moving, and the larger the value of $\breve{\beta}$, the lower the distance to the new location.

Since ζ and F enter additively in entrants' profits, they can only be identified by exits, given that incumbents' profits include F but not ζ. The larger the value of the entry cost ζ, the lower the likelihood of observing entries in the data. The larger value of the fixed cost F, the greater the likelihood of observing charter closings. The larger the value of variable cost V, the higher the likelihood that an incumbent will be closed, and the less likely that an entrant will be approved. Although F and V have similar roles, they differ in that V enters proportionally to enrollment but F does not. Finally, parameter σ_ν reflects the extent to which the regulator's decisions are based on $E_\nu \bar{\pi}^e_{jt}$ and $E_\nu \bar{\pi}^i_{jt\ell_{jt}}$ rather than ν^e_{jt} and ν^i_{jt} respectively.

4.7 Computational Considerations

The estimation of the academic proficiency function is straightforward, and Maximum Likelihood estimation of the supply side is straightforward once expected enrollments for potential entrants have been computed. However, estimation of the demand-side parameters is computationally involved because it requires solving the large-scale constrained optimization problem problem in (44). This MPEC problem has 8,452 unknowns – 340 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 order derivatives (which were computed by TomSym in our case). In contrast, Dube et al (2011) supplied second-order derivatives to the KNITRO solver and used the Interior/Direct algorithm. Avoiding the provision of analytical first- or second-order derivatives greatly facilitated our use of MPEC.

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

[35] In this distribution, we cannot include the ξ_js of incumbents that entered before 2003 (i.e., the early entrants) because those charters were closed at a higher rate than the entrants of our sample period.

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.[36] 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.[37] The computational time compares favorably with what Dube et al (2011) and Skrainka (2011) report for BLP problems, particularly taking into account that our problem has complicating features relative to straightforward BLP. The first is that our objective function includes demographic moments in addition to share moments. The second is that we have a relatively large number of products (schools) relative to the number of markets (grade-years). In a typical industrial organization context there are many markets relative to products. This gives rise to a sparser Jacobian, which in turn speeds up performance (see Dube et al 2011 for a discussion of how the speed advantage of MPEC declines as the sparsity of the Jacobian falls). The third complicating feature is the presence of some very small market shares, an issue related to the large number of schools relative to the number of students.

5 Estimation Results

5.1 Demand Side

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

Our estimates show that preferences over school types are quite heterogeneous across races and poverty status, and that they vary by school level. We interpret the estimates in terms of the choice differences that they would induce between two schools that are the same in everything except for a specific characteristic. In what follows, "middle and/or high schools" (MHS) denotes

[36] 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.

[37] 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.

the following levels: middle, middle/high, high, elementary/middle/high, and "EMS" denotes the elementary and elementary/middle levels. In the discussion regarding single- v. multi-campus charters, note that multi-campus charters tend to be newer and less likely to mix grade levels, and have higher math proficiency. They may also have more "brand recognition" as they have more establishments.

We begin by discussing preferences over school types among EMS. Most households prefer public over charter schools, yet not with the same intensity. Non-poor households are less likely to choose charters than low-income households. Faced with the choice between an otherwise identical public and single-campus charter school, low-income Blacks are 47 percent less likely to choose the single-campus charter school, but 5 percent more likely to choose a multi-campus charter than a public school. Hispanics have a stronger preference for charters than Blacks: although they are 8 percent less likely to attend a single-campus charter than a public school, they are 78 percent more likely to attend a multi-campus charter than a public school. Whites' preferences for charters are not significantly different than Blacks'. Both Blacks and Hispanics prefer a public over a Catholic school, although Hispanics are more likely than Blacks to choose the Catholic school. Whites, in contrast, are 40 percent more likely to choose a Catholic over a public school. All races are more likely to choose public over non-Catholic private schools, yet whites are less likely than others to do so.

We now discuss preferences over school types among MHS. The coefficient on MHS is positive, reflecting the fact that public MHS schools tend to be larger than public EMS. The negative coefficient on charter*MHS captures the fact that the size difference of MHS relative to elementary schools is smaller for charter than public schools. Similarly, the coefficient on private*MHS is also negative; given its magnitude, it indicates that blacks and hispanics are less likely to attend a private than a public school at the MHS level. The coefficient on private*MHS*white is positive (although not significant), indicating that at the MHS level, whites have a stronger preference than Blacks and Hispanics for private schools. Our estimated preferences over school types match school choices well (see Table 9), overall and by grade level.

Our estimates also reveal heterogeneity in focus preferences. Households prefer arts over core, probably reflecting the presence of some large arts schools (Arts and Technology Academy, Ellington, Hardy, William Doar). For Blacks and Whites, the preference for language relative to core is not significantly different from zero. In contrast, this relative preference is negative and significant for Hispanics. Given that 20.44 percent of Hispanic students attend a language-based school (see Table 10), this finding is somewhat surprising. Yet Hispanics exhibit a strong same-race preference, as described below, which suggests that their choice of language-focused schools may not be due to language per se but to the fact that those schools attract other Hispanics. Vocational and "other" focuses are less preferrable than core for blacks ad Hispanics, whereas whites have a positive and significant preference for "other focuses" over core. Our focus preference estimates capture the distribution of students over focuses, as Table 10 shows.

The coefficients on ward dummies capture preferences for each ward relative to wards 7 and 8, which is the most disadvantaged part of the city, located in the Southeast. Only the coefficients on wards 4 and 5 are significantly different from zero. They are also substantial in magnitude: a household is 175 percent more likely to choose a school in ward 4 than in wards 7 and 8, and 65 percent more likely to choose a school in ward 5 than in wards 7 and 8. These coefficients indicate that parents place high value on characteristics of the school's neighborhood. Ward 4, for instance has some desirable areas that are relatively safe, with parks and open spaces, etc.

Our estimates indicate an interesting pattern of preferences over peers' races. Students of all all races would like to attend a school with more white students (with a concomitant reduction in the number of black students). A black household is 109 percent more likely to choose a school that has an extra 10 percentage points of white students, yet is 30 percent less likely to choose a school with an extra 10 percentage points of Hispanic students. A white household is 283 percent more likely to choose a school with an extra 10 percentage point of white students, and a Hispanic household is 186 percent more likely. Although students of every race would like to have more white students in their school, whites have the strongest preference for white students and the highest ability to pay for them. Hispanics have strong same-race preferences as well, as they are 81 percent more likely to choose a school with an extra 10 percentage points Hispanic. Finally, poor households are 44 percent less likely to choose a school with an extra 10 percentage points of non-poor students. These estimates are consistent with the fact that while 74, 17, 9 and 43 percent of the students are black, white, hispanic and non-poor, respectively, the average black student attends a school that is 89 percent black, the average white student attends a school that is 69 percent white, the average Hispanic student attends a school that is 37 percent Hispanic, and the average poor student attends a school that is 73 percent poor. In other words, students are quite segregated by race and poverty status across schools.

We have allowed preferences for distance to vary depending on school type (public, charter or private). When choosing among public schools, the disutility of traveling an extra mile is quite large, as the additional mile makes a family 67 percent less likely to attend the more distant school. However, when choosing among charter schools, that extra mile only makes a family 2.5 percent less likely to choose the more distant school, and distance does not hinder the choice of the more distant school when choosing among private schools. These estimates are consistent with the fact that children travel longer to charter than public schools, and with the expectation that they would also travel longer to private than public schools. Nonetheless, these estimates must be interpreted with caution because approximately 50 percent of children in public schools attend their assigned neighborhood schools. Consequently, we expect the preference for distance to public school to be downward biased.

Coefficient φ in (39) captures sensitivity of private school enrollment to tuition. Our attempts to estimate this coefficient were not met with success, as the coefficient was poorly identified in the sample. After trying several specifications we settled for a linear specification in tuition, or φp_{jgt}. Since tuition does not vary over time and varies relatively little across grades, we quantified tuition using the school average, p_j, and treated it as another time-invariant school characteristic. Hence, we estimated φ via Minimum Distance Estimation, similarly to the coefficients on the other time-invariant school characteristics. The resulting coefficient on tuition is negative and significant and delivers reasonable estimates of willingness to pay. According to our estimates, a \$1,000 decline in tuition makes households 28 percent more likely to attend a (private) school. Families would be willing to pay about \$4,500 to attend a public school that is one mile closer. Blacks would be willing to pay approximately \$3,000 for an extra 10 percentage point white students, and whites would be willing to pay about \$5,500 for the same thing. Hispanics, in turn, would be willing to pay about \$2,400 for an extra 10 percentage points Hispanic.

Overall, our model fits the data well. The correlation between observed and predicted value is equal to 0.97, 0.96 and 0.94 for school percent of White, Hispanic and non-poor students respectively. It is equal to 0.81, 0.63 and 0.73 for neighborhood-level percent of students in charters, average distance traveled to public schools and average distance traveled to charter schools respectively. Distance traveled to public schools is quite difficult to fit given lack of data on the enforcement of in-boundary enrollment.

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

To disentangle the role of capacity, we need data on excess demand. Unfortunately these data are not available, and we can only speculate as to the possible biases induced in our coefficients. Lack of data on excess demand also prevents us from capturing a distinctive aspect of charter schools, namely that they must randomize access when oversubscribed.

Capacity issues arise in other markets as well. However, in ordinary markets price plays a rationing role, in the sense that excess demand leads to a higher price, which in turn clears the market. The absence of a price in the case of public and charter schools complicates matters. One might think that private schools are exempt of this problem because they charge a price, yet we believe this is true only to the extent that private schools behave like profit-maximizing firms. If they do not, then excess demand does not necessarily lead to a higher price. For instance, many Catholic schools face waiting lists yet they do not raise their price because they wish to remain affordable for families in the parish or the neighborhood, and hence ration access based on some other mechanism (first come, first served; sibling preference; parish preference, etc.). The capacity issue, then, is potentially a concern for a large number of schools in the sample. To the best of our knowledge this problem has not been examined before in a non-experimental setting for demand estimation.[38]

To the extent that capacity is a problem, it would mostly affect the parameters of the common utility (corresponding to 2 in the model, and to the "Baseline Utility" column in Table 8 except for the distance coefficients in this column). Since the baseline utility parameters include campus fixed effects, and we regress these on time-invariant school characteristics to estimate school quality ξ_j, our estimates of school quality would probably be biased as well. While these time-invariant characteristics explain 71 percent of the variation in campus fixed effects, the residuals capture a number of unmeasured school characteristics (insofar as they are constant over time) such as school culture, proximity to transportation, relations with the community, connections between the school and other organizations in D.C., existence of after-school and enrichment programs, features of the building site, characteristics of the school's neighborhood which are not captured by student demographics, etc. Building capacity might be another unmeasured characteristic captured by school quality. Most likely the schools facing excess demand have downward-biased estimates of school quality, and the schools absorbing that excess demand have upward-biased estimates of school quality. Hence, in the public-charter comparisons below we are likely underestimating the advantage of the best charter schools.

With these caveats in mind, Table 11a shows average public, private and charter school quality. Recall that, by construction, the average quality is zero for a given school type and in a given ward. The estimates show heterogeneity in the geographic distribution of school quality. In wards 1, 2 and 3, the highest school quality corresponds to charters; in wards 4 and 6, it corresponds to public schools; in wards 5, 7 and 8, it corresponds to private schools.

In Table 11b we focus on the comparison between public and charter schools located within two geographic areas: first, in the whole city except for the most advantaged ward (ward 3); second,

[38] Conlon and Mortimer (2012) study the effects of availability constraints on estimates using experimental data.

within the most disadvantaged wards (wards 7 and 8). Interestingly, the outcome of these comparisons depends on the school level. When focusing on all wards except 3, average quality is (slightly) higher for public than charter schools, yet charters are higher quality for elementary/middle and middle schools. Faced with the choice between a public and a charter school, the average quality difference is such that a family is 23 and 33 percent more likely to choose the charter school for the elementary/middle and middle school level, respectively, and willing to pay approximately \$900 and \$1,200 respectively to switch from public to charter school.

The differences are more dramatic for wards 7 and 8, the most disadvantaged in the city. Faced with the choice between a public and a charter school of average quality in wards 7 and 8, a household is 220 and 310 percent more likely to choose the charter for elementary/middle, and middle/high and high schools respectively, and is willing to pay \$4,700 and \$5,700 to go from the public to the charter school, respectively. These differences are substantive, particularly when considering that charter school quality is likely underestimated for the best schools. In other words, school quality varies substantially across schools and plays a quantitatively large role explaining households' choices of school. The higher school quality for charters among MHS is largely responsible for the higher market share for charters in those levels relative to EMS.

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

5.2 Academic Proficiency

Table 12 presents estimates of the passing rate function for math. Since our data consists of school-level passing rate in math tests for public and charter schools, we only have five school-year observations at most for each school. The change in the assessment instrument in 2005 led to large declines in passing rates. On average, passing rates were 52 and 51 percent in 2003 and 2004 respectively, and 29, 33 and 41 percent in 2005, 2006 and 2007 respectively. For some schools the swings in passing rates are particularly pronounced; since those schools have large enrollments the swings cannot be solely attributed to sampling error. Because of these data limitations, our achievement estimates should be taken with caution. We will only use these estimates to make predictions regarding achievement in our counterfactuals; in these predictions we will stress the direction of the change more than its magnitude.

Recall that in order to estimate the passing rate function, we regress the log odds of passing the math exam relative to not passing it, or log(pass rate / (100-pass rate)) on campus fixed effects, year fixed effects and school demographic characteristics. We instrument for the endogenous school demographic characteristics. We then regress school fixed effects on time invariant characteristics, and the residuals from this regression give us estimates of school value added (ξ_j^q in (45)). Table 12 reports the resulting set of parameter estimates.

We interpret our estimates in terms of how a particular school characteristic affects the relative odds of passing the math test, holding everything else constant. Among public schools, the relative odds of passing are 52 percent lower in MHS than in elementary school. When comparing a single-campus charter when a public school, the relative odds of passing are 79 percent lower for the charter at the elementary level, but 34 percent higher at the MHS level. Multi-campus charters fare better than single-campus charters. Although the relative odds of passing are 53 percent lower for multi-campus charters than for public schools at the elementary level, they are 205 percent higher at the MHS level.

Curricular focus seems to make a difference, as "other focus" schools (many of which teach a curriculum specialized in math) raise the relative odds of passing by 244 percent with respect to a core curriculum. Language and vocational curricula, in turn, lower the odds of passing relative to core. The coefficients on percent White and non-poor students are not significantly different from zero.

In the Minimum Distance Estimation regression, only 26 percent of the variation in school fixed effects is explained by time-invariant school characteristics. This means that 74 percent of the variation in school value added is explained by unmeasured school characteristics such as leadership and culture, instructional style, management of human resources, policies to foster parental engagement, length of school day and year, use of instructional time, etc. The residuals from this regression – our estimates of school value added – are reasonable in that they induce a ranking of charter schools by value added that largely agrees with PCSB's ranking (see, for instance, classification of schools by tier in http://www.dcpcsb.org/data/images/pcsb%20book_dec1.pdf). For example, at the top of our ranking are Elsie Whitlow Stokes, Paul, the KIPP campuses, Capital City, which also top PCSB's ranking.

School value added seems to play an important role in academic proficiency. Table 13 shows average value added for public and charter schools in all wards except for ward 3, and in wards 7 and 8. In all wards but 3, charters' premium in value added is large enough to raise the relative odds of passing by 213 and 85 percent at the elementary/middle and middle school levels. In wards 7 and 8, charters have higher value added than public schools at every level, and the advantage is particularly large for elementary/middle and middle schools, where charters raise the relative odds of passing by 555 and 127 percent respectively with respect to public schools.

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

To summarize, our academic proficiency estimates indicate substantial heterogeneity in school effectiveness due to school type, focus and value added. The fact that charters offer higher value added particularly in the most disadvanged areas of the city suggests that their elimination could be quite damaging to students in those areas, as we will see below.

5.3 Supply Side

Table 14 presents our supply-side estimates. We obtained these estimates using 975 entry points per year (39 clusters*5 levels*5 focuses, where levels are elementary, elementary/middle/, middle, middle/high and high and focuses are core, arts, language, vocational, other) and 4 years of data (2004 through 2007). The goal of the maximum-likelihood estimation is to find the parameter estimates that maximize the probability of the observed data. This task is complicated by the low frequency of entry, exit and relocation in our sample, which includes 33 entries, 3 exits and 20 relocations. Nonetheless, our setting allows for a careful calibration of some parameters as described below.[39]

Buckley and Schneider (2007) report that there were 71 applications for charter openings to

[39] The estimates presented below use entry and relocation episodes only, as we are currently revising the exit portion of the model. Entry and relocation episodes are sufficient to identify the parameters of the model.

take place between Fall 2004 and Fall 2007. This would result in b = probability of submitting an entry application = 71 / (975 entry points * 4 years) = 0.018. Assuming that the distribution of entries across grade levels is the same as the distribution of entry applications across grade levels, we arrive at a separate value of b for each grade level (see Table 14). This plausible assumption improves the computational performance of our estimator.

In order to calibrate V and F, we gathered data from charter schools' budgets for school year 2009-2010, the closest year to our sample period for which financial data are publicly available from PCSB. The data pertain to the charters in our data that were still open in 2009, including new campuses opened by the surviving charters (64 campuses in total). We classified salaries and other instructional expenditures as variable costs, and all remaining expenses as fixed costs. According to our data, on average 67.42 and 32 percent of revenues are devoted to covering variable and fixed costs respectively. As a percent of revenue, profit varies across charters between -14 and 10 percent, with an average and median of 0.6 percent.

Since both fixed and variable costs are highly sensitive to enrollment in our data, we regressed total costs on enrollment, location dummies and level dummies.[40]Table 15 shows the regression results. The coefficient on enrollment captures both a fixed and a variable cost component. According to our estimates, holding enrollment constant fixed costs are higher for high schools and mixed-level schools than for elementary or middle schools. They are also higher for schools located in the west (due to high real estate prices) or southeast (due to buildings' poor condition and high security and insurance costs) rather than the northeast. These estimates are consistent with the fact that most new entrants are located in the northeast and serve elementary or middle school.

Based on the predicted enrollment for each entrant, we used our cost function estimates to impute costs for each entrant, and used data on observed reimbursements per student by grade and year to impute revenues by entrant. On average, reimbursement per student grew from $8,300 in Fall 2004 to $9,600 in Fall 2007.

We then ran the MLE estimation. Our resulting MLE estimates have reasonable magnitudes. The estimated entry fee ζ is equal to $71,429. Recall that this represents the "financial cushion" required by the regulator in order to pay for set-up costs such as legal, accounting and realtor fees, student and teacher recruiting, etc. A reasonable estimate for ζ must be of the same order of magnitude as charters' average and median profits - intuitively, it the entry fee were much higher, the schools would have presumably incurred a loss at the opening stage and would not have been allowed to enter. Since the average and median profit for charters in the data are equal to $26,000 and $33,000 respectively, the estimated entry fee is reasonable. Not surprisingly, the estimate is not precise, as our cost function relies on several approximations and is time-invariant.

The estimated standard deviation of profits σ_ν is equal to $331,983, and is of the same order of magnitude as the standard deviation of charters' profits (approximately equal to $100,000). The magnitude of this estimate indicates that potential entrants are highly heterogeneous in aspects observed by the regulator but not by us, such as the quality of the business plan and intended educational program. The estimated relocation parameter $\breve{\alpha}$ indicates that a school is 74 times more likely to stay in a location than to move even within the same cluster, and estimated relocation parameter $\breve{\beta}$ indicates that given a choice between two alternative destinations, one of which is a mile farther than the other, charters are 37 percent more likely to take the closer destination.

Our estimates fit the data well. As Table 16 shows, our estimates capture the entry patterns observed in the data and described before. Moreover, our estimates match the number of relocations

[40] Before running the regression, we multiplied the dependent variable by (0.83)*(8.3/11) in order to incorporate two elements: 1) charter reimbursements for about 83 percent of total charter revenues (which also include federal grants for specific programs); 2) the average reimbursements in 2004 and 2009 were approximately equal to $8,300 and $11,000 respectively.

and the average relocation distance. As Figure 11 shows, they also match the distribution of relocation distance.

Our model includes 975 potential entrants per year; over 4 years, this amounts to 3,900 potential entrants. Nonetheless, the number of actual entries is much lower – 33 over the 4 years. To explain such low number, recall that only 71 applications were submitted; of these, only 33 were approved. In subsequent years, the annual number of applications and approvals has remained roughly constant. In other words, the determining factor of the low-frequency entry is the low-application rate b - which, in our model, means a low probability that a potential entrant would draw a positive value for his nonpecunary payoff B. This is not surprising, as the charter application form is a long, detailed document that requires a great deal of previous work on the part of the applicants, multiple iterations, and a significant investment of time and effort. It is plausible that very few individuals or organizations would be willing to embark themselves in this costly process. Lowering the charter application cost, however, may not be the recommendable, as it may attract a greater number of low-quality applicants.

At the same time, the fact that more than half of applicants are not approved is interpreted, in our model, as evidence that their expected profits is below the required threshold. This is consistent with charter schools' plight for additional funding and improved access to facilities (see, for instance, http://focusdc.org/advocacy). The plight seems quite relevant for charters that wish to locate in the southeast and/or serve middle and high school grades, where fixed costs are higher and yet charters seem to have a greater advantage in quality and value added over public schools.

6 Counterfactual Analysis

Our structural estimates can be used to study a number of alternative policy scenarios. For illustrative purposes, Table 17 depicts some results from a policy consisting of the elimination of charter schools. In particular, we study how students would have sorted across schools in 2007 if charter schools had been closed that year. The table shows observed patterns of student sorting across schools, the model's fit of the data, and the predicted sorting when charters are not allowed.

In 2007 charters attracted 22 percent of total student enrollment. In the counterfactual they attract zero percent. As the table shows, in the counterfactual most charter school students switch into public schools, and about 2% of all students switch from charters to Catholic schools. Most of these switches correspond to Black and low-income students, who would make up for most of the enrollment in charter schools. The fact that a good fraction of students switch into Catholic schools when charters are not available suggests that at least some Catholic schools must have been hurt by charter expansion. This is consistent with the fact that after our sample period, the Archdiocese of Washington, D.C. converted seven Catholic schools into charters, and pointed to the proximity of charter schools as one reason for their decision (Bowen McShane 2011).

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

We are currently developing the code to simulate entry-related counterfactuals. First, we will study the response of charter entry and student sorting to changes in per-student funding for charter schools. High schools are more costly to open and operate, and the relative lack of charter entry at the high school level might be related to poor funding. Since real estate is a prime concern for charters, we will also study the effect of greater access to facilities (represented as a lower fixed cost in some locations and/or higher funding). Although by law charter schools are the first claimant to vacant public school buildings, DCPS has not made those buildings available to charters on a regular basis. As public school enrollment continues to decline, the supply of facilities for charters should rise. Moreover, in recent years charters have had increasing access to "incubator facilities" where they are housed for a few years before moving to a permanent location.

While many states provide free transportation for children (even those attending private or charter schools), D.C. does not provide any busing at all. Thus, the provision of publicly-funded busing could alter household choices significantly. It could also alter the geographic pattern of charter entry and location.

As discussed above, the low entry rates of charters are mostly the consequence of low application rates. The regulator might be able to affect application rates by lowering the standards required for entry. The concern, of course, is that some of the additional applicants might perform poorly upon entering the market. Thus, we will study the effects of lowering entry standards and hence raising the probability that potential entrants would submit an application.

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

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

A persistent concern among policymakers and scholars is that charter schools do not promote racial integration (see Bifulco 2013 and the references therein). If promoting racial integration were an explicit goal of charters, one could ask how the regulator might be able to accomplish this goal. Our estimates indicate that whites have a preference for "other focuses" over core, and that all households prefer certain locations (i.e, ward 4) over others. Hence, charters that offer "other focuses" and are located close to where white households live have a reasonable chance of attracting white families. Moreover, the analysis of our data indicates that the most racially integrated charters from our sample have exactly these characteristics.

One might wonder to what extent the charter school landscape would be different if charter schools were centrally operated by the authorizer. Hence, we will explore how the market would differ if the charter sector were managed by an authorizer who acted as a central planner. A social planner might open either fewer or more charters, or target different entry points. This issue is similar to that study by Berry and Waldfogel (1999), who investigate whether there is excessive entry of radio stations. A related issue is how a central planner would manage the public system as a whole – a task that would require internalizing charters' effects on public schools with the goal of maximizing welfare and/or achievement.

7 Conclusion

In this paper we have developed a model of charter school entry and household choice of school and have devised an estimation strategy for the model. We estimate the model using a unique dataset for Washington, D.C., which incorporates information on all public, charter and private schools in D.C. between 2003 and 2007. Since we rely on an equilibrium framework, we model peer characteristics as an outcome of parental choices, with parents responding to those characteristics when making choices. We model the behavior of the charter school regulator, who makes decisions facing uncertainty on schools' demands.

Understanding the decisions made by the regulator, 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.

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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 1c

School Choice by Student Race and Poverty Status – All Grades

	Public	Charter	Catholic	Other Religious	Nonsectarian
All Students	61.57	16.93	9.81	5.40	6.28
White	27.31	2.75	23.23	20.97	25.72
Black	68.19	20.52	6.85	2.26	2.18
Hispanic	72.14	14.29	8.80	1.61	3.16
Non-Poor	50.60	11.64	14.57	10.42	12.75
Low-Income	69.83	20.92	6.23	1.61	1.40

School Choice by Student Race and Poverty Status – K through 6th grade

	Public	Charter	Catholic	Other Religious	Nonsectarian
All Students	65.72	15.48	7.51	5.70	5.59
White	36.84	4.09	13.38	22.50	23.18
Black	70.23	18.06	6.46	2.83	2.40
Hispanic	76.34	13.32	6.37	1.44	2.50
Non-Poor	55.18	11.46	9.78	11.54	12.03
Low-Income	72.16	17.94	6.12	2.13	1.65

School Choice by Student Race and Poverty Status – 7th through 12th grade

	Public	Charter	Catholic	Other Religious	Nonsectarian
All Students	56.22	18.81	12.79	5.00	7.18
White	17.62	1.41	33.23	19.43	28.31
Black	65.45	23.82	7.37	1.50	1.87
Hispanic	65.91	15.72	12.39	1.85	4.14
Non-Poor	46.07	11.82	19.31	9.32	13.48
Low-Income	66.15	25.65	6.42	0.78	1.01

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

TABLE 2
School Openings and Closings

	Public Schools				Charter Schools				Private Schools			
Year	**Total**	**Opened**	**Closed**	**Moved**	**Total**	**Opened**	**Closed**	**Moved**	**Total**	**Opened**	**Closed**	**Moved**
End 2002	142				27				70			
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
Total 03-07		2	8	8		36	3	20		3	8	5

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 6a

Student Demographics and Achievement by School Level and Program Focus

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

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

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 6b

Focus Choice by Student Race and Poverty Status

Students	Core	Arts	Language	Vocational	Other Focus
All	80.00	2.17	3.87	2.66	11.31
White	82.56	1.19	3.93	0.29	12.03
Black	82.05	2.47	1.87	3.22	10.40
Hispanic	58.14	1.53	20.44	2.48	17.40
Non Poor	79.27	2.16	3.00	2.01	13.56
Low Inc.	80.56	2.17	4.53	3.14	9.60

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

TABLE 7a

Charter School Entry Patterns, 2004-2007

a. By Grade Level

Level	Number of Entries
Elementary	19
Elementary/Middle	2
Middle	9
Middle/High	2
High	1
Elementary/Middle/High	0
Total	33

b. By Ward

Ward	Number of Entries	Number of Entries - Elementary	Number of Entries - Middle
1	4	2	2
2	5	3	2
3	1	0	1
4	5	3	1
5	6	2	1
6	2	2	0
7	6	4	1
8	4	3	1
Total	33	19	9

c. By Focus

Focus	Number of Entries	Number of Entries- Elementary	Number of Entries – Middle
Arts	4	2	0
Core	11	8	3
Language	3	2	1
Vocational	2	0	1
Other Focus	13	7	4
Total	33	19	9

d. Level and Focus, by Region

Region	Level	Core	Non-Core	Total
Northeast	**Elementary**	**4**	**8**	**12**
	Middle	**1**	**4**	**5**
	High	**0**	**1**	**1**
	Mixed	**0**	**2**	**2**
	Total Northeast	***5***	***15***	***20***
Southeast	**Elementary**	**4**	**2**	**6**
	Middle	**1**	**1**	**2**
	High	**0**	**0**	**0**
	Mixed	**0**	**0**	**0**
	Total Southeast	***5***	***3***	***8***
West	**Elementary**	**0**	**1**	**1**
	Middle	**1**	**1**	**2**
	High	**0**	**0**	**0**
	Mixed	**0**	**2**	**2**
	Total West	***1***	***4***	***5***
Total		**11**	**22**	**33**

TABLE 7e
Early versus Recent Charter Entrants

	Early Entrants	**Recent Entrants**
Number of campuses	27	36
Avg. Enrollment	432	169
Pct. Focused on Core	55.56	33.33
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 – Utility Function

Variable	**Baseline Utility**	**Interactions with Household Characteristics**		
		White	**Hispanic**	**Non-Poor**
Constant	*3.536** *(0.357)*			
Charter	*-0.625** *(0.090)*	-0.116 (0.248)	0.534* (0.149)	-0.382* (0.084)
Catholic	*-1.041** *(0.152)*	1.374* (0.221)	0.636* (0.150)	
Private Other Religious	*-0.931** *(0.392)*	0.552* (0.245)		
Private Nonsectarian	*-1.604** *(0.436)*	1.228* (0.299)		
Language	*-0.091* *(0.527)*	0.412 (0.422)	-0.967* (0.298)	
Arts	*0.328** *(0.153)*	0.232 (0.481)		
Vocational	*-0.684** *(0.150)*	0.750 (0.961)		0.213 (0.195)
Other focus	*-0.424** *(0.161)*	0.693* (0.258)	-1.112* (0.250)	-0.003 (0.137)
Tuition (in $1,000)	*-0.246** *(0.092)*			
Middle / high school	*1.417** *(0.197)*			
Charter * middle / high school	*-0.633** *(0.122)*			
Charter * multicampus	*0.672** *(0.114)*			
Private * middle / high school	*-1.204** *(0.165)*	0.488 (0.339)		
Ward 1	*0.278* *(0.570)*			
Ward 2	*0.316* *(0.401)*			
Ward 3	*-0.222* *(0.732)*			
Ward 4	*1.012** *(0.389)*			
Ward 5	*0.502** *(0.114)*			
Ward 6	*0.172* *(0.157)*			

TABLE 8
Parameter Estimates – Utility Function (cont.)

Variable	Baseline Utility	Interactions with Household Characteristics		
		White	Hispanic	Non-Poor
Fraction White	7.377* (2.635)	6.038* (0.449)	3.136* (0.272)	
Fraction Hispanic	-3.541** (2.018)	4.947* (1.066)	9.483* (0.760)	
Fraction Non-Poor	-5.866* (1.615)			4.474* (0.312)
Distance (miles)	-1.114* (0.034)			
Distance*charter (miles)	1.085* (0.066)			
Distance*private (miles)	1.229* (0.061)			

Notes: Based on 12,378 (=8,112+3,807+459) observations. Except where noted, parameters are GMM estimates including campus, grade and year fixed effects. Asymptotic standard errors are given in parentheses. "Baseline utility" corresponds to parameters from δ, except for the coefficients on distance, which correspond to μ. Coefficients marked with (*) are significant at the 5% significance level and (**) denotes significance at the 10% level. Estimates and standard errors in Italics were obtained through minimum-distance estimation of campus fixed effects on time-invariant school characteristics (number of observations in this regression = 281 campuses). Middle / high school =1 if school level is one of the following: middle, high, middle/high, elementary/middle/high. Multicampus = 1 if the charter school belongs to a multi-campus organization. The ward dummies indicate the ward where the school is located (in case the school has moved during the sample period, they indicate the ward of the last location during the period).

TABLE 9 – *Goodness of Fit: School Choice*

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

	Observed Values (%)					Predicted Values (%)				
Students	**Public**	**Charter**	**Catholic**	**Other Rel.**	**Non-Sect.**	**Public**	**Charter**	**Catholic**	**Other Rel.**	**Non-Sect.**
All	61.57	16.93	9.81	5.40	6.28	61.39	17.00	9.87	5.41	6.31
White	27.31	2.76	23.23	20.98	25.72	29.75	2.56	19.86	20.75	27.08
Black	68.19	20.52	6.85	2.26	2.18	67.54	20.93	7.36	2.21	1.97
Hispanic	72.14	14.29	8.80	1.61	3.16	70.28	12.86	11.33	2.76	2.76
Non Poor	50.60	11.64	14.57	10.43	12.76	52.22	10.69	14.51	10.18	12.39
Low Inc.	69.83	20.92	6.23	1.61	1.40	68.97	22.22	6.05	1.47	1.29

School Choice by Student Race and Poverty Status – Observed and Predicted Values, All Years – Grades K through 6th

	Observed Values (%)					Predicted Values (%)				
Students	**Public**	**Charter**	**Catholic**	**Other Rel.**	**Non-Sect.**	**Public**	**Charter**	**Catholic**	**Other Rel.**	**Non-Sect.**
All	65.72	15.48	7.51	5.70	5.59	65.54	15.66	7.51	5.70	5.59
White	36.84	4.09	13.38	22.50	23.18	37.60	3.25	13.09	22.05	24.03
Black	70.23	18.06	6.46	2.83	2.40	70.36	18.68	6.28	2.61	2.07
Hispanic	76.34	13.32	6.37	1.44	2.50	75.35	13.26	7.59	2.06	1.74
Non Poor	55.18	11.46	9.78	11.54	12.03	57.18	10.16	9.57	11.16	11.54
Low Inc.	72.16	17.94	6.12	2.13	1.65	71.00	19.43	6.10	1.96	1.51

School Choice by Student Race and Poverty Status – Observed and Predicted Values, All Years – Grades 7th through 12th

	Observed Values (%)					Predicted Values (%)				
Students	**Public**	**Charter**	**Catholic**	**Other Rel.**	**Non-Sect.**	**Public**	**Charter**	**Catholic**	**Other Rel.**	**Non-Sect**
All	56.22	18.81	12.79	5.00	7.18	56.05	18.75	12.92	5.04	7.24
White	17.62	1.41	33.23	19.43	28.31	20.68	1.76	27.69	19.26	30.61
Black	65.45	23.82	7.37	1.50	1.87	63.80	23.88	8.79	1.68	1.84
Hispanic	65.91	15.72	12.39	1.85	4.14	63.94	12.37	16.03	3.64	4.03
Non Poor	46.07	11.82	19.31	9.32	13.48	46.74	11.24	19.56	9.19	13.27
Low Inc.	66.15	25.65	6.42	0.78	1.01	65.79	26.59	5.98	0.71	0.94

Note: For each row, sum across columns equals 100. For a given group of students, a cell denotes the percent of students of that group that attend a particular kind of school.

TABLE 10
Goodness of Fit: Focus Choice

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

	Observed Values (%)					**Predicted Values (%)**				
Students	**Core**	**Arts**	**Language**	**Vocational**	**Other Focus**	**Core**	**Arts**	**Language**	**Vocational**	**Other Focus**
All	80.00	2.17	3.87	2.66	11.31	79.87	2.18	3.86	2.67	11.43
White	82.56	1.19	3.93	0.29	12.03	82.31	1.19	4.32	0.11	12.07
Black	82.05	2.47	1.87	3.22	10.40	81.81	2.45	1.73	3.25	10.76
Hispanic	58.14	1.53	20.44	2.48	17.40	61.30	1.82	18.84	2.79	15.26
Non Poor	79.27	2.16	3.00	2.01	13.56	79.74	1.99	3.64	1.68	12.96
Low Inc.	80.56	2.17	4.53	3.14	9.60	79.98	2.33	4.04	3.49	10.16

Note: For each row, sum across columns equals 100. For a given group of students, a cell denotes the percent of students of that group that attend a school with a particular focus.

TABLE 11a
School Quality, by School Type and Ward

	Public Schools	Charter Schools	Private Schools
Ward 1	0.051	0.250	-0.777
Ward 2	0.418	0.462	-1.205
Ward 3	-0.281	1.024	0.100
Ward 4	0.098	-0.112	-0.019
Ward 5	-0.120	-0.128	0.420
Ward 6	0.107	-0.139	-0.120
Ward 7	0.139	0.016	0.348
Ward 8	-0.274	-0.184	0.226

Note: school quality is the residual of the minimum-distance estimation regression of campus fixed effects on time-invariant school characteristics. Ward corresponds to the school's location; if the school has relocated, then ward corresponds to the last location in our sample period.

TABLE 11b
Public v. Charter School Quality

	All Wards Except Ward 3		Wards 7 and 8	
School Level	**Public**	**Charter**	**Public**	**Charter**
All	0.021	-0.017	-0.060	-0.066
Elementary	0.075	-0.114	0.062	-0.493
Elementary/Middle	0.076	0.284	0.126	1.289
Middle	-0.058	0.229	-0.141	-0.145
Middle/High and High	-0.189	-0.197	-1.242	0.169

Note: school quality is the residual of the minimum-distance estimation regression of campus fixed effects on time-invariant school characteristics. Ward corresponds to the school's location; if the school has relocated, then ward corresponds to the last location in our sample period.

TABLE 12

Parameter Estimates – Math Proficiency Rate

(Dependent Variable = log(PassRate / (100-PassRate))

Variable	Coefficient
Constant	*0.049* *(0.267)*
Charter	*-1.584** *(0.059)*
Language	*-0.971** *(0.195)*
Arts	*0.842** *(0.126)*
Vocational	*-0.584** *(0.040)*
Other focus	*1.237** *(0.161)*
Middle / high school	*-0.732** *(0.091)*
Charter * middle / high school	*1.874** *(0.034)*
Charter * multicampus	*0.826** *(0.053)*
Percent White	-0.002 (0.015)
Percent Hispanic	0.009* (0.004)
Percent Non-Poor	0.007 (0.009)
Year 2004	0.034 (0.078)
Year 2005	-1.255* (0.075)
Year 2006	-1.068* (0.079)
Year 2007	-0.648* (0.083)
Mean of Dependent Vble. Mean of Passing Rate (%) Std. Error of Regression Pseudo-R^2	-0.340 42.29 0.574 0.810

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

TABLE 13
Public v. Charter School Value Added – Achievement

	All Wards Except Ward 3		Wards 7 and 8	
School Level	**Public**	**Charter**	**Public**	**Charter**
All	-0.12	-0.01	-0.49	-0.03
Elementary	-0.12	-0.40	-0.44	-0.25
Elementary/Middle	-0.46	0.68	-0.51	1.37
Middle	-0.05	0.57	-0.55	0.27
Middle/High and High	-0.04	-0.60	-0.69	-0.56

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

TABLE 14
Parameter Estimates – Supply Side

Variable	**Coefficient**
Probability of Submitting an Application (b)	
Elementary	0.050
Middle	0.025
High	0.003
Mixed	0.006
Entry fee (ζ) (in \$1,000)	71.429 (137.00)
Std. dev. of profits (σ_v) (in \$1,000)	331.983** (188.774)
Relocation intensity parameter (A)	-4.292* (0.453)
Relocation sensitivity to distance (B) (distance in miles)	3.1824* (1.109)
Log-Likelihood	-360.169

Notes: Maximum Likelihood Estimates using entry and relocation observations. (*) denotes significant at the 5% level; (**) denotes significant at the 10% level.

TABLE 15

Charter School Costs

(costs in $1,000)

Independent Variable	Estimates
Enrollment	8.000 (0.253)
West (=1 if school is in West region)	461.496 (196.215)
Southeast (=1 if school is in Southeast region)	278.508 (90.309)
High (=1 if school serves grades 9-12)	267.654 (133.974)
Mixed levels (=1 if school serves mixed levels)	96.998 (91.330)
Constant	-54.251 (96.731)
Number of observations R^2 s.e. of regression Mean of dependent variable	64 0.953 323.8 2714.775

Unit of observation: charter school campus. OLS; standard errors in parentheses. Data: charter schools budgets for school year 2009-2010 from www.dcpcsb.org.

TABLE 16
Goodness of Fit: Number of Entries between 2004 and 2007

	Observed Values	Predicted Values
All Entries	33	35.06
Level		
Elementary	19	19.23
Middle	9	8.85
High	1	1.59
Mixed	4	5.38
Focus		
Core	11	7.78
Non-Core	22	27.27
Region		
Northeast	20	18.03
Southeast	8	10.57
West	5	6.45

	Observed Values		Predicted Values	
	Core	Non-Core	Core	Non-Core
Elementary	8	11	4.35	14.88
Middle	3	6	1.92	6.94
High	0	1	0.33	1.26
Mixed	0	4	1.19	4.19

	Observed Values			Predicted Values		
	Northeast	Southeast	West	Northeast	Southeast	West
Elementary	12	6	1	10.07	5.78	3.38
Middle	5	2	2	4.71	2.40	1.74
High	1	0	0	0.67	0.58	0.34
Mixed	2	0	2	2.58	1.8	0.99

	Observed Values			Predicted Values		
	Northeast	Southeast	West	Northeast	Southeast	West
Core	5	5	1	4.01	2.55	1.22
Non-Core	15	3	4	14.02	8.02	5.23

TABLE 17

Counterfactual Analysis: No Charter Schools in 2007

School Choice – By Student Demographic Group

	Observed School Choice (%)					**Predicted School Choice (%) With Charters**					**Predicted School Choice (%) Without Charters**				
Students	Public	Charter	Catholic	Other Religious	Non-Sectarian	Public	Charter	Catholic	Other Religious	Non-Sectarian	Public	Charter	Catholic	Other Religious	Non-Sectarian
All	56.59	21.55	9.96	5.54	6.35	56.56	21.61	9.90	5.58	6.34	76.62	0	11.76	4.36	7.26
White	28.00	3.83	23.23	20.70	24.23	30.03	4.34	19.14	20.80	25.68	36.71	0	21.74	13.74	27.81
Black	62.22	26.61	6.65	2.24	2.27	61.63	27.00	7.21	2.17	1.98	86.36	0	8.97	2.23	2.44
Hispanic	68.46	16.94	9.77	1.65	3.17	67.82	14.49	12.40	2.56	2.73	79.93	0	13.41	2.50	4.16
Non-Poor	48.84	14.65	14.25	10.00	12.26	49.28	12.86	14.67	10.48	12.70	62.63	0	15.66	7.57	14.14
Low Inc.	63.18	27.42	6.31	1.76	1.32	62.44	28.68	6.05	1.62	1.20	88.08	0	8.58	1.73	1.61

Note: For each row, sum across columns equals 100. For a given group of students, a cell denotes the percent of students of that group that attend a particular kind of school.

FIGURE 1
Number of Public, Charter and Private School Campuses

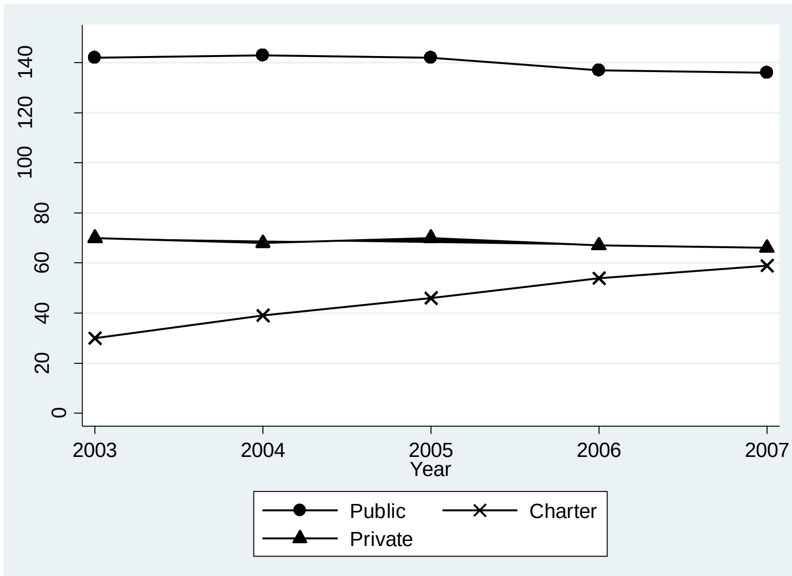


FIGURE 2
Enrollment in Public, Charter and Private School Campuses

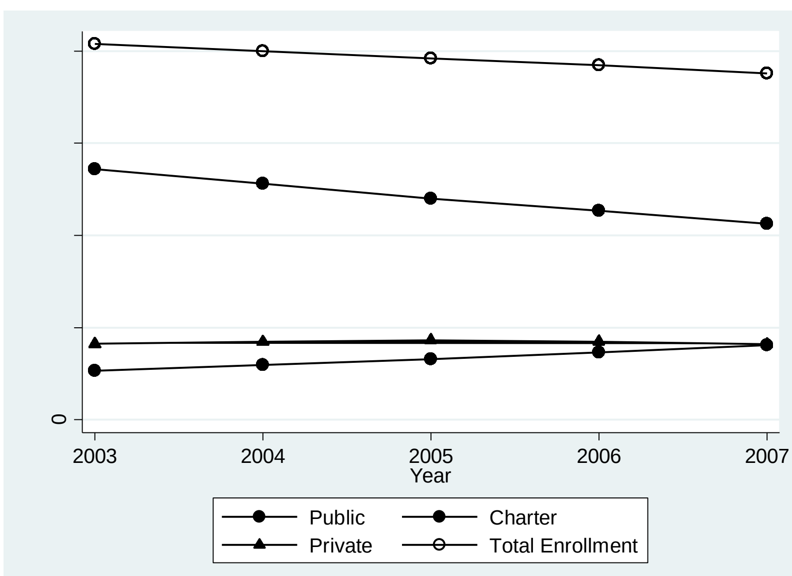
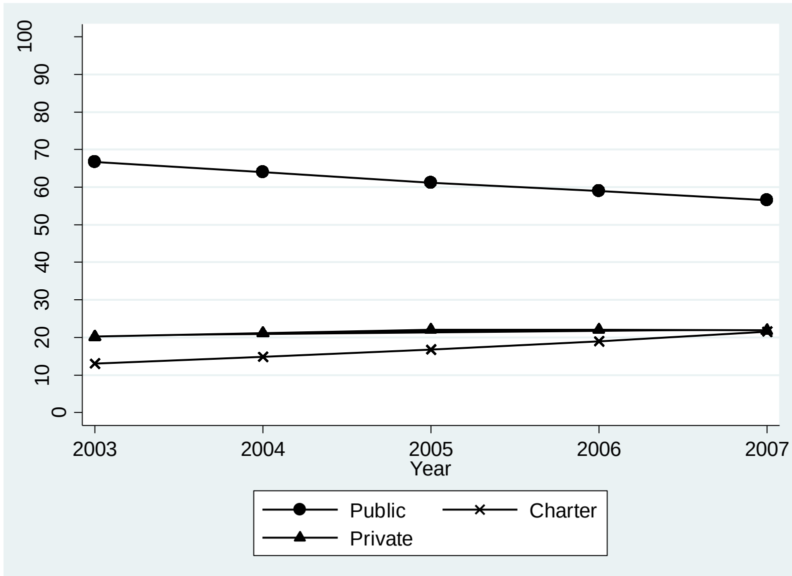
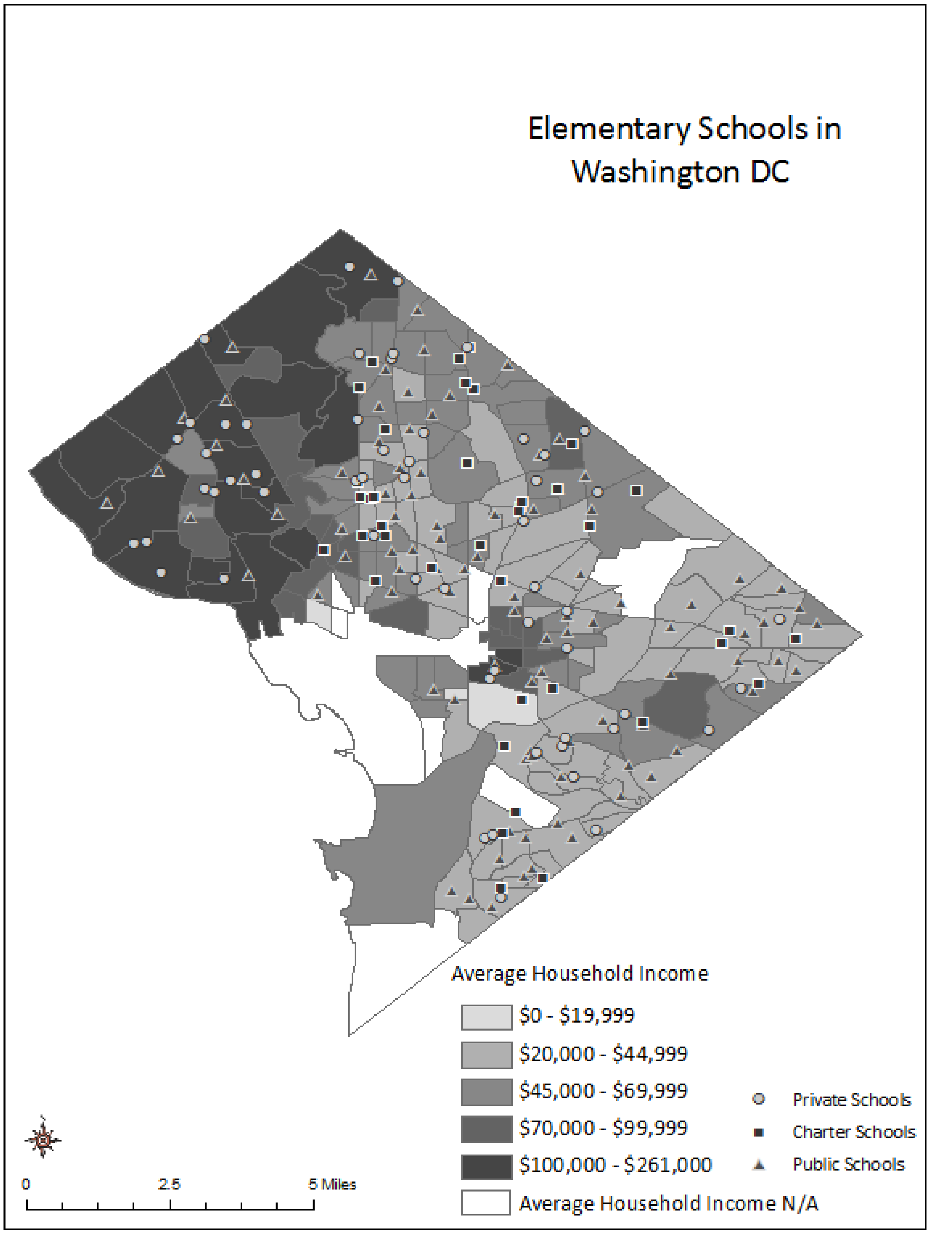


FIGURE 3
Enrollment Shares for Public, Charter and Private Schools



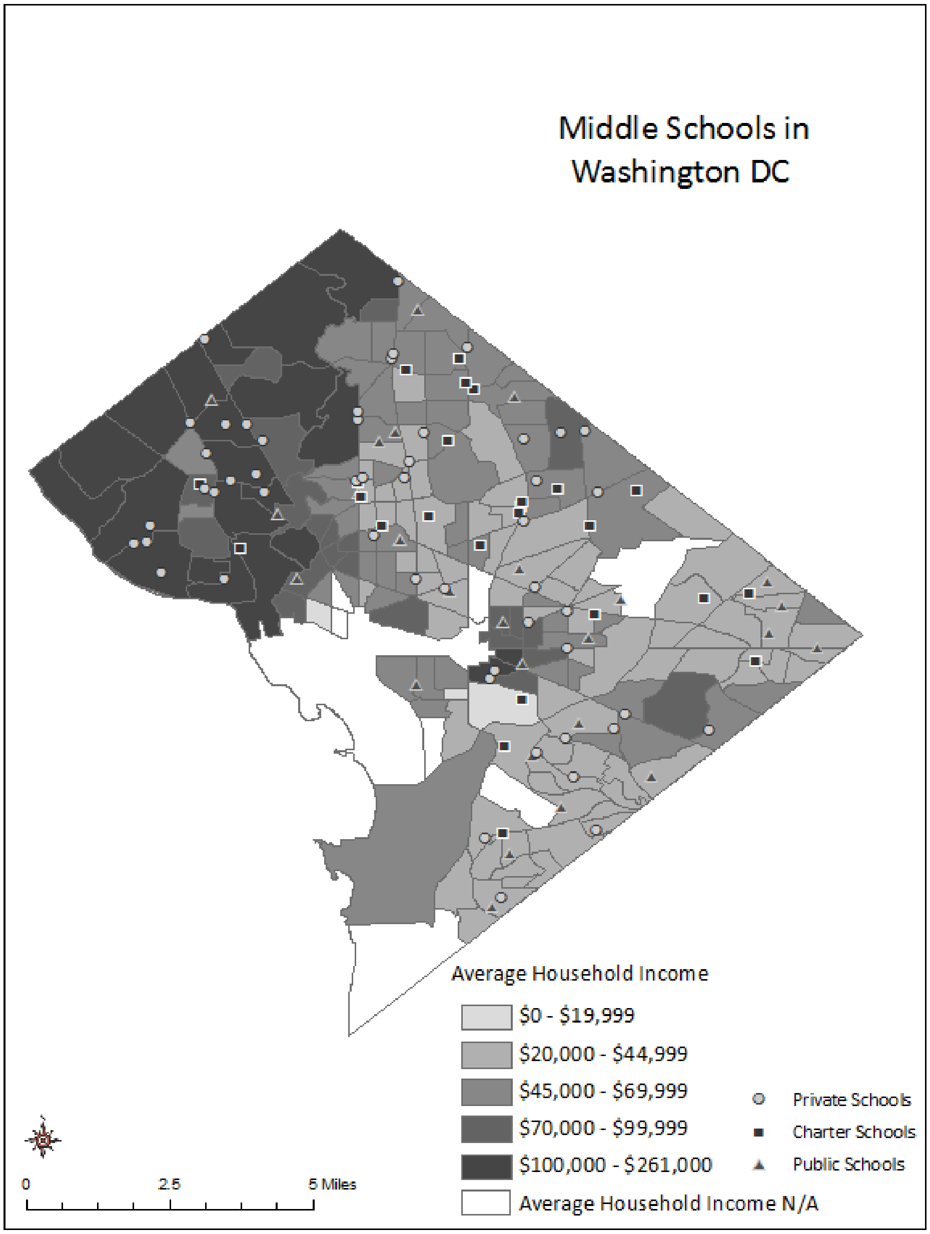
Notes: percentages calculated relative to total enrollment, aggregated over all schools and grades.

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



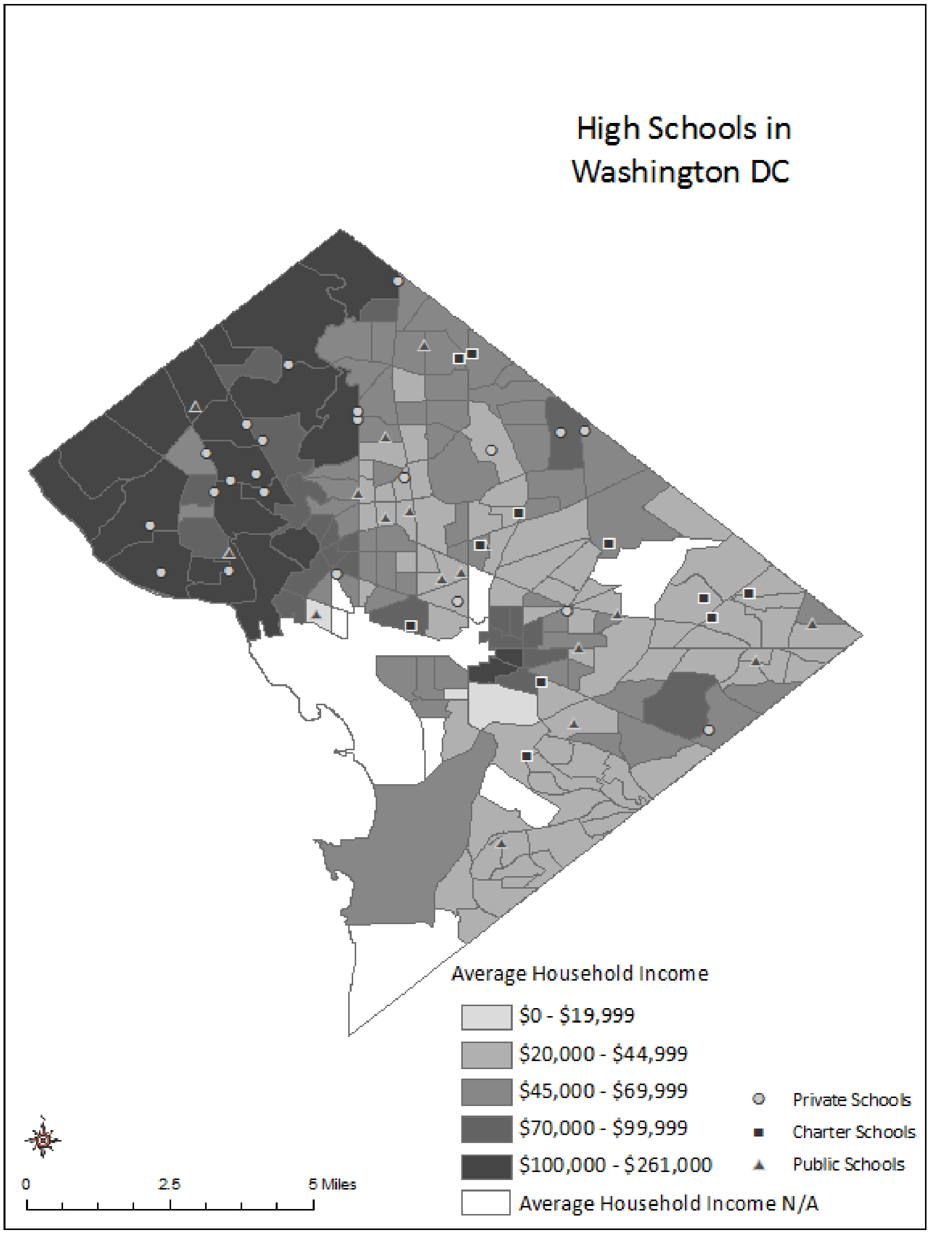
Note: Elementary schools include elementary, elementary/middle, and elementary/middle/high schools.

FIGURE 4b
Geographic Location of Middle Schools in DC in 2007



Note: Middle schools include midle, elementary/middle, middle/high and elementary/middle/high schools.

FIGURE 4c
Geographic Location of High Schools in DC in 2007



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

FIGURE 5a - ***Public Schools: Aggregate Enrollment Share by Grade***

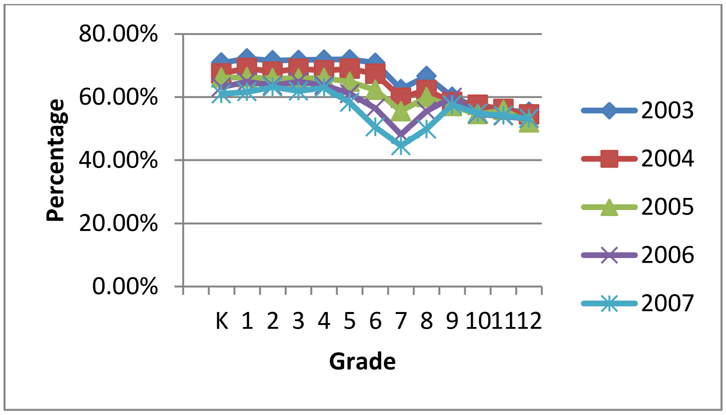


FIGURE 5b - ***Charter Schools: Aggregate Enrollment Share by Grade***

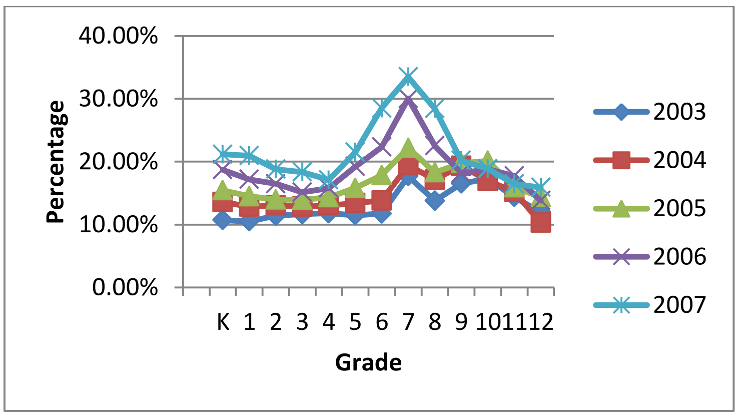
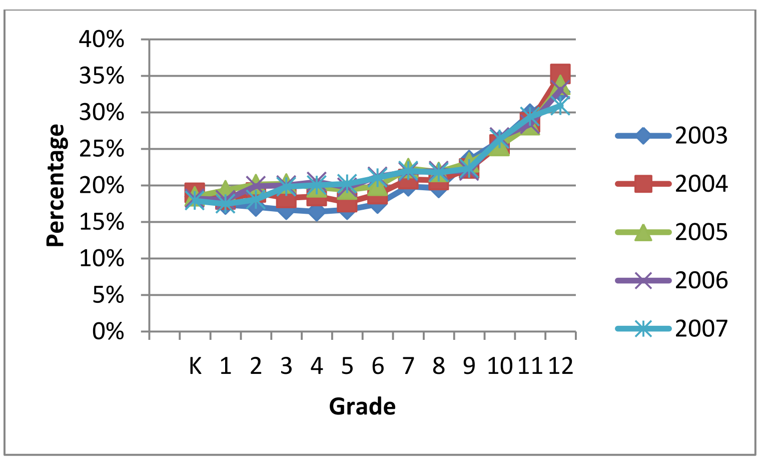


FIGURE 5c - ***Private Schools: Aggregate Enrollment Share by Grade***



Note: Shares are calculated relative to the total enrollment per grade, where total = aggregate enrollment over public, charter and private schools.

FIGURE 6
Number of Public, Charter and Private Schools by Grade in 2003 and 2007

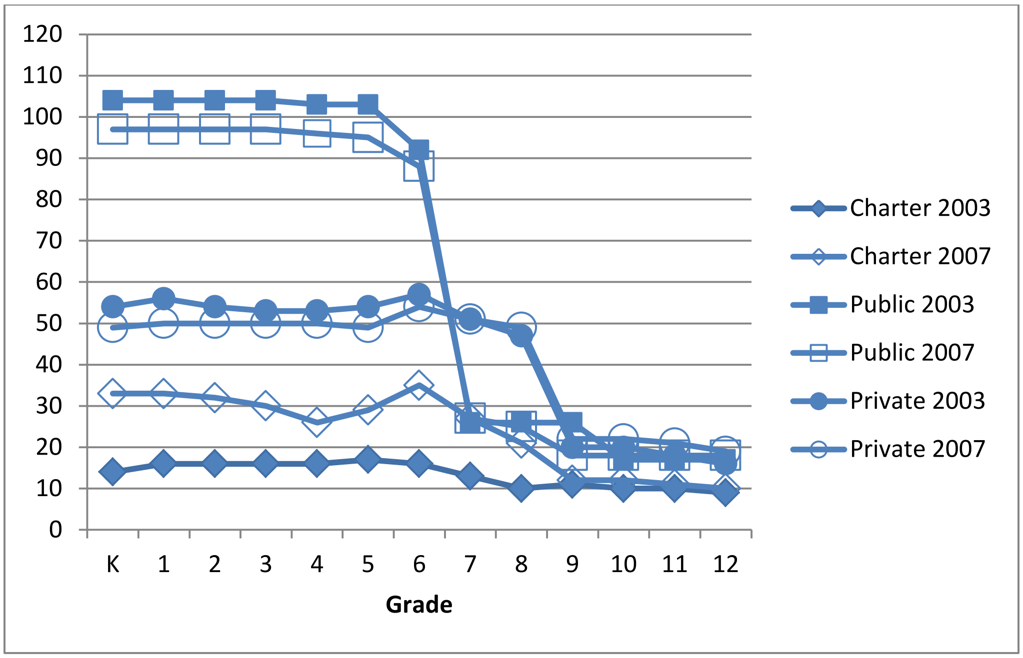


FIGURE 7
Average Grade Enrollment in Public, Private and Charter Schools in 2007

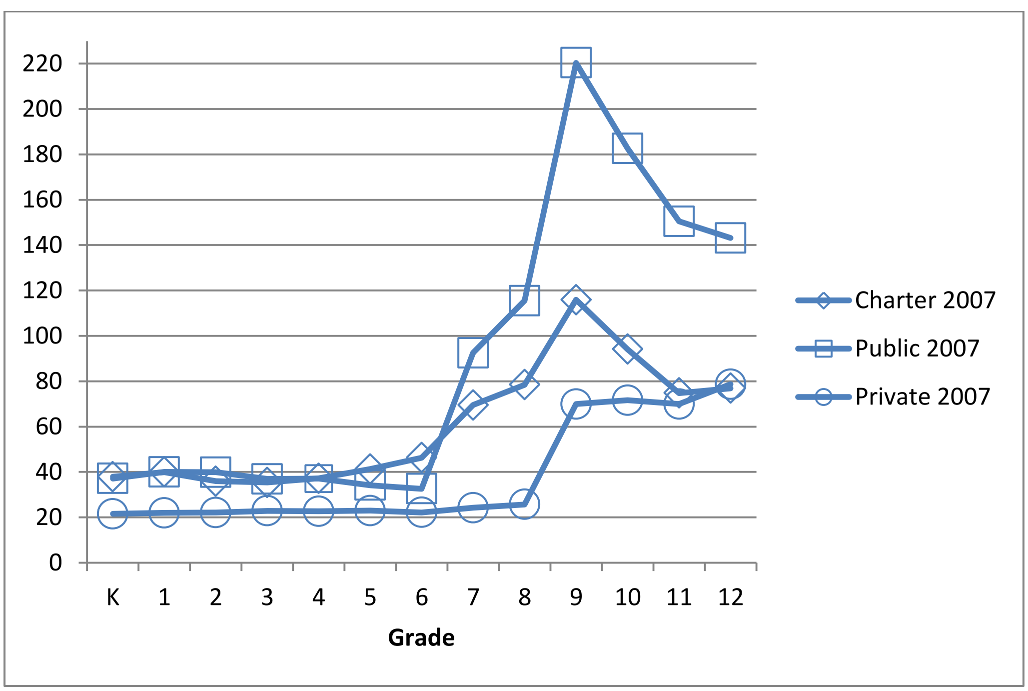
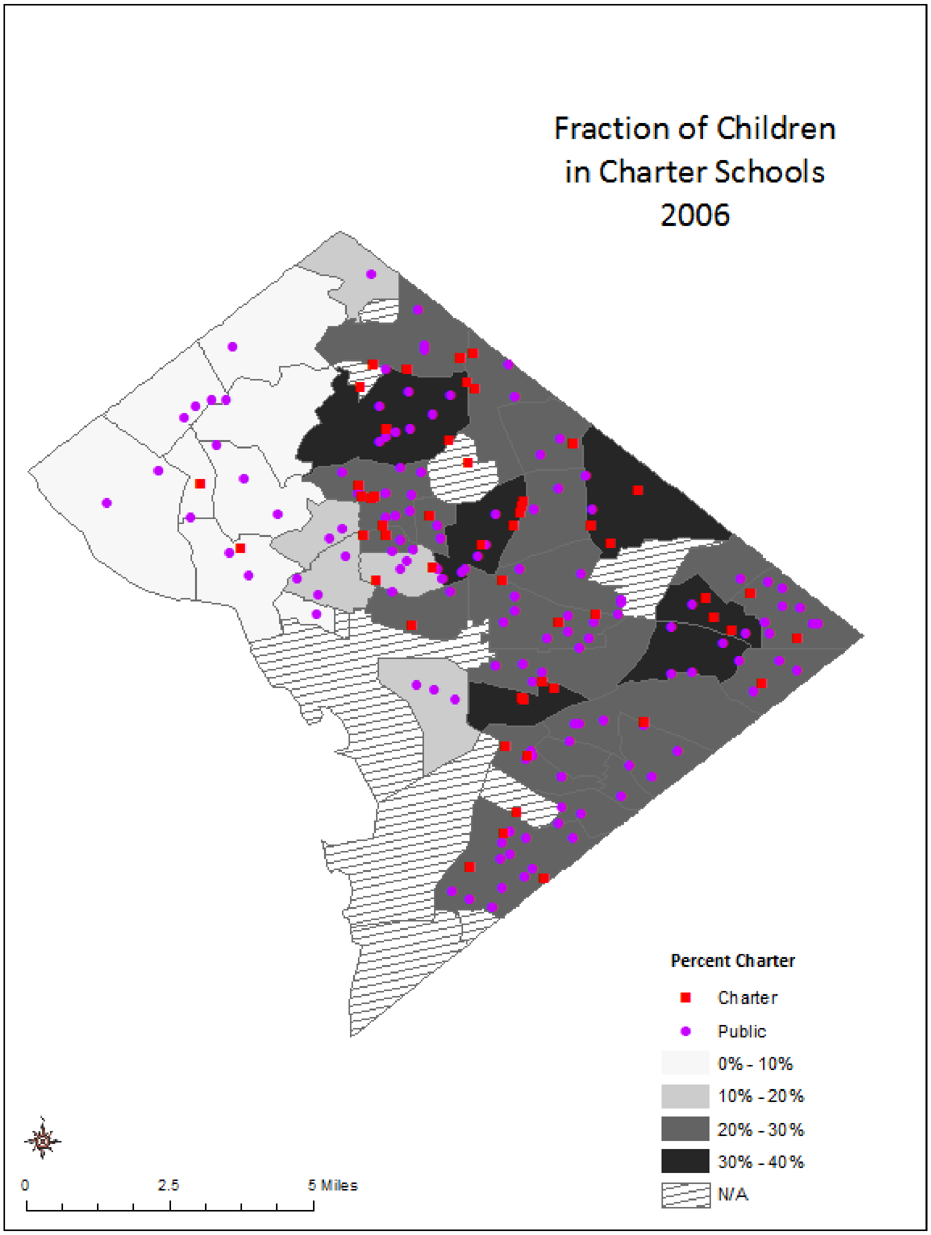
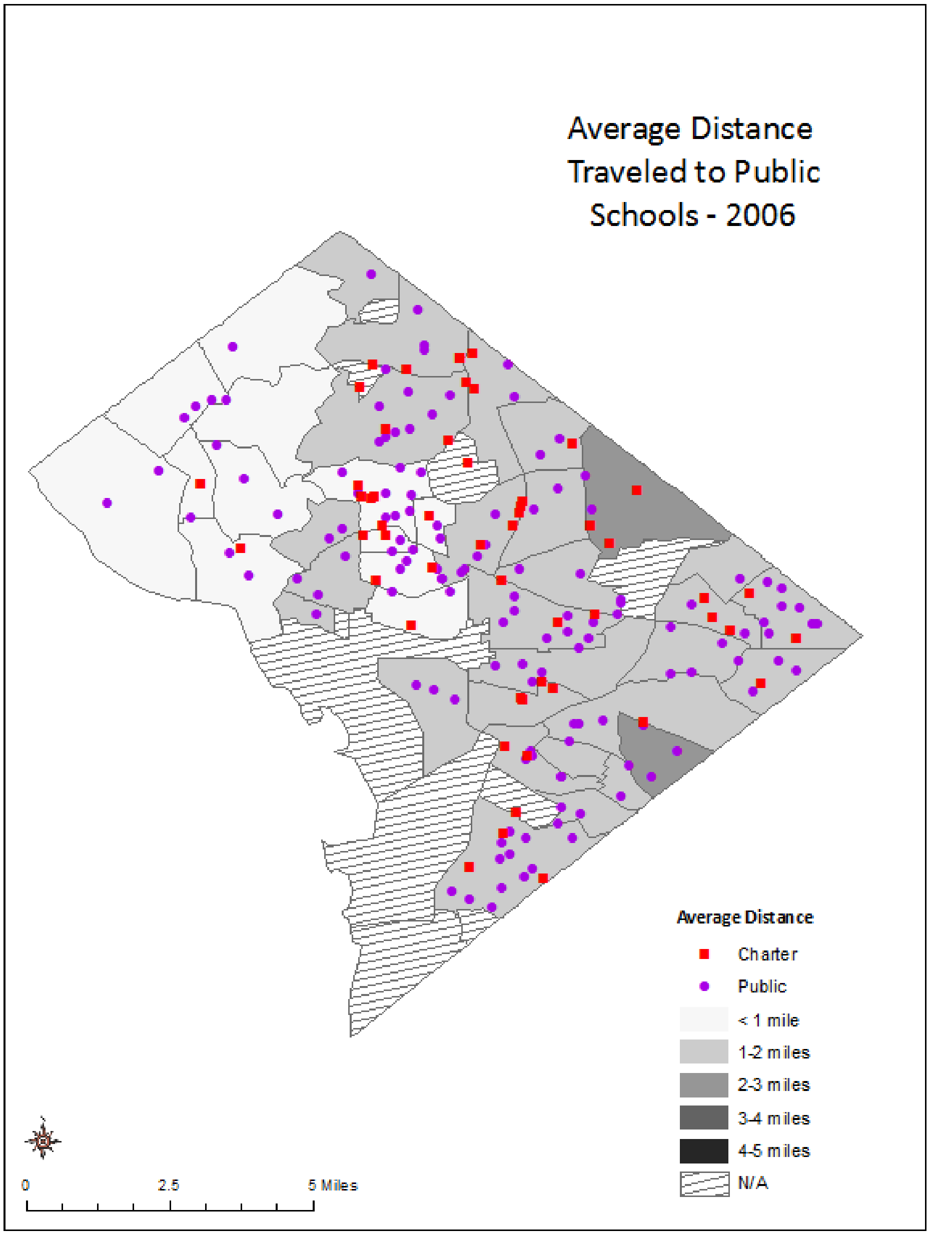


FIGURE 8
Neighborhood Percent of Children in Charter Schools in 2006



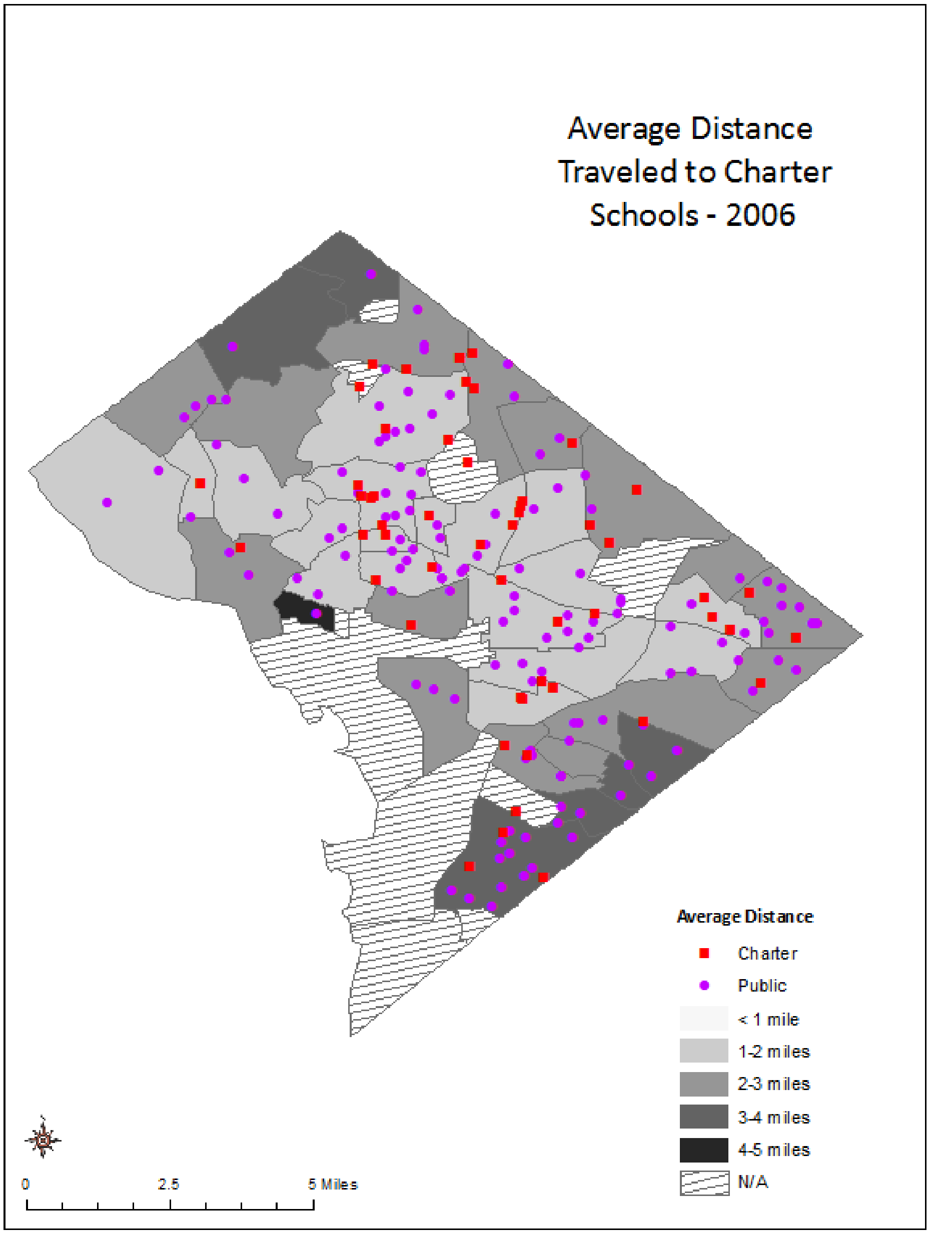
Note:The map depicts cluster-level data. Percent is calculated relative to all children in the public system (traditional public + charter schools).

FIGURE 9
Neighborhood Average Distance Traveled to Public Schools in 2006



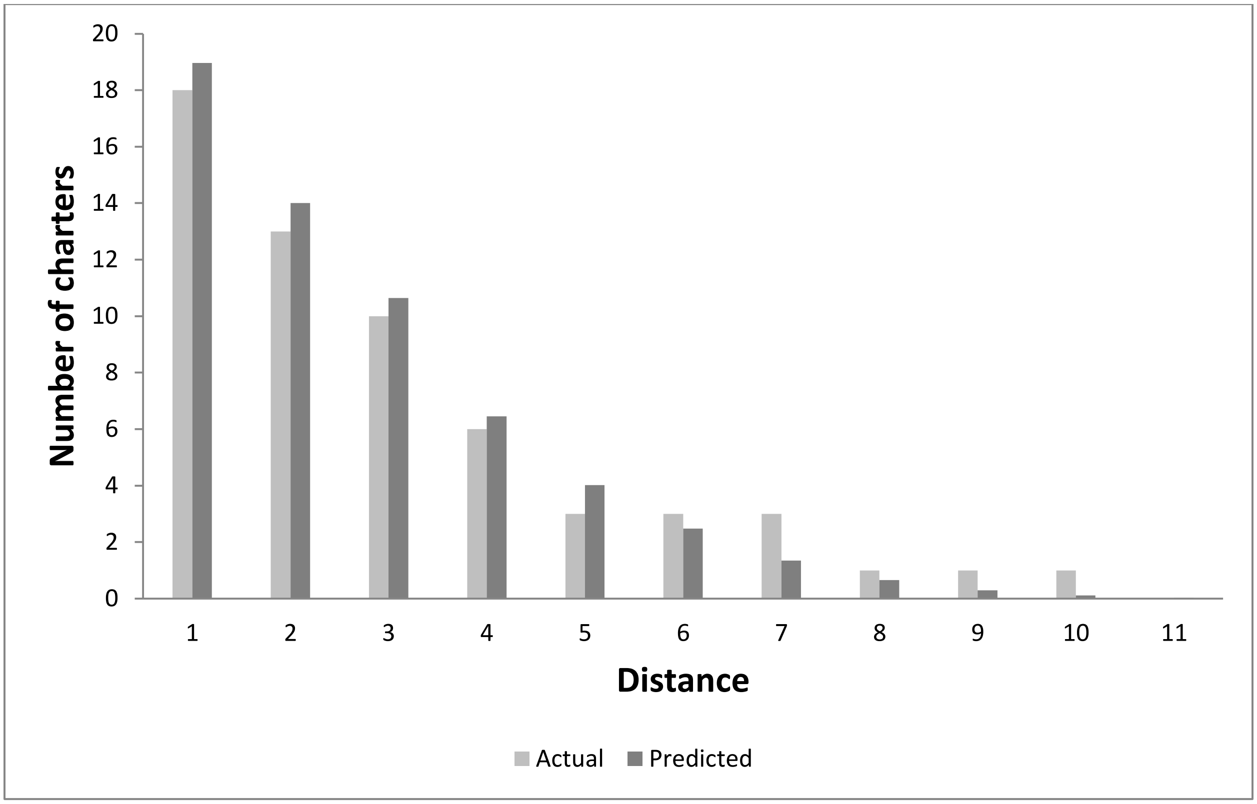
Note:The map depicts cluster-level data.

FIGURE 10
Neighborhood Average Distance Traveled to Charter Schools in 2006



Note:The map depicts cluster-level data.

FIGURE 11
Goodness of Fit – Relocations



Note: the horizontal axis depicts distance (in miles), and the vertical axis depicts number of charter schools. The blue line is the observed number of charters whose moving distance is greater than the distance on the horizontal axis. The black line is the predicted counterpart.