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

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Abstract

This paper develops and estimates an equilibrium model of charter school entry and school choice. In the model, households choose among public, private, and charter schools, and a regulator authorizes charter entry and mandates charter exit. The model is estimated for Washington, D.C. According to the estimates, charters generate net social gains by providing additional school options, and they benefit non-white, low-income, and middle-school students the most. Further, policies that raise the supply of prospective charter entrants in combination with high authorization standards enhance social welfare.

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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. They receive public funding in the form of a per-student stipend and do not have residence requirements; if oversubscribed, they determine admission by lottery. Charters are free from many regulations that apply to traditional public schools, but are subject to the same accountability requirements and are regulated by state laws. The first law passed in Minnesota in 1991 and has been followed by laws in 42 states and the District of Columbia, all of which differ widely in their permissiveness towards charters. Currently, the nation's 6,700 charters serve about 2.9 million students, or 5.1 percent of the primary and secondary market. While seemingly small, this market share conceals large variation across states and districts.

A prospective charter entrant presents a proposal to the chartering entity. The proposal, akin to a business proposal, specifies the school's mission, curricular focus (such as arts or language), grades served, teaching methods, anticipated enrollment, intended facilities, and financial plan. The decision to open a charter is similar to that of opening a firm in that both seek to exploit a perceived opportunity. For example, in a residence-based system, a low-income neighborhood with low-achieving public schools creates an opportunity for a charter entrant to serve households unsatisfied with the local public schools. Other example opportunities are middle-class families reasonably well served by local public schools but interested in different academic programs, or families attending private schools but willing to try charter schools to avoid tuition.

In this paper we investigate charter entry and household school choice for Washington, D.C. We document charter entry by geographic area, curricular focus and grade span to gain insight into the opportunities exploited by charters. We then explore how households sort among public, private and charter schools, and how the entry, exit or relocation of a school affects others. We also study the critical role of the chartering entity (henceforth, the regulator) in this market, quantify welfare gains from charters, and investigate how the educational landscape responds to regulatory changes.

Addressing these research questions is challenging. For example, when a student enrolls in a new charter school he affects the peer characteristics of both his new and former school. In other words, charter entry triggers equilibrium effects as students re-sort among schools. Although the entrant can specify some aspects of the school, like thematic focus and educational philosophy, the student body composition is largely beyond its control. The uncertainty about demand for charters poses an additional research challenge. The uncertainty is more severe for new entrants, whose ability to run the new enterprise may not be known. Further, the entry, exit or relocation of one school affects others and leads to student re-sorting.

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, a charter entry point is a combination of location (neighborhood), grade span and focus. For some entry points, prospective entrants submit entry applications to the regulator. Charter funding is connected to enrollment and prospective entrants must be financially viable. Hence, the regulator forecasts an applicant's enrollment and peer characteristics based on its entry point and approves applicants 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 contains information for all public, private and charter schools in the city including enrollment by grade, school demographics, focus and proficiency rates in standardized tests. We supplement these data with neighborhood-level information on charter school attendance and travel distance to charter and public schools. Lacking student-level data, we further augment the school-level data with the block-group level empirical distribution of child age, race, poverty status and family income, 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, we define a market as a grade-year combination. We estimate the model in three stages corresponding to student demand, school supply and school 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. We allow for a school-grade-year quality component (such as teacher quality) observable to households but not to the researcher. The ensuing correlation between school peer characteristics and the unobserved quality component is similar to the correlation between price and unobserved quality in BLP. Unlike price, which is determined by the firm under consideration, peer characteristics are determined by aggregate household choices and are similar to Bayer and Timmins's (2007) local spillovers. Following Nevo (2000, 2001), we exploit the panel structure of our data and include school, grade and year fixed effects to capture some variation in the unobserved quality component. The school fixed effects are our estimates of school quality; they capture unmeasured factors in household choices such as school climate and culture, length of school day and year and facility characteristics. When estimating parameters of the proficiency rate function we estimate a separate set of school fixed effects that capture the ability of schools to raise passing rates in standardized math tests, and these constitute our measure of school productivity.

To study the behavior of charters facing the same institutional structure, we focus on a single, large urban district. We chose Washington, D.C. because it has a permissive, well-established 1996 charter law under which the charter school sector has grown to 44 percent of total public school enrollment as of 2015-2016.¹ It has a single public school district, the District of Columbia Public Schools (DCPS), which facilitates research design and data collection. Finally, it is relatively large with substantial variation in household demographics, which provides scope for charter entry.

The majority of charter entrants in D.C. have located in the disadvantaged areas of the city, namely the Northeast and Southeast, which are home to most of the poor, non-white students, and to the lowest-proficiency public schools. Most charter entrants offer elementary and middle school grades and a specialized curriculum. Poor, nonwhite students have access to fewer school options than their more advantaged counterparts at all grade levels, but particularly at middle and high school.

Our estimates show that poor, non-white students have the strongest preference for charters. They also show that many students have a preference for specialized curricula, of which public and private schools offer little. Based on our estimates, in the Northeast and Southeast charters have, on average, higher school quality than public schools, particularly for middle and high school, and higher school productivity, particularly in elementary and middle schools. Such quality and productivity differences are largest in the most disadvantaged area, namely the Southeast.

The ensuing combination of household preferences, characteristics, and choice sets, along with the geographic distribution of school options, quality, and productivity is closely associated with the observed charter entry patterns. These patterns are also associated to charter fixed costs, which are highest in the most affluent parts of the city (due to high real estate costs) and in the most disadvantaged (due to facilities' condition and to high security and insurance costs). Further, fixed costs are higher for high school than for lower grades.

From a social standpoint, the existence of charter schools yields net benefits based on our estimates. Welfare gains from charters are highest for middle-school students, for whom charters contribute the most in quantity and quality of options, and for poor, black students in all grades.

Given these benefits, in our counterfactuals we investigate alternative avenues for charter expansion in D.C., namely, a funding increase, a relaxation of approval (authorization) standards, and policies aimed at raising the supply of prospective entrants. Our results indicate that raising the supply of prospective entrants while maintaining strict approval standards is welfare-enhancing. Policies that facilitate the application process by aiding entrants in obtaining building facilities, developing business and instructional plans, learning from other charters and navigating bureaucratic processes can raise the supply of prospective entrants.

¹As of 2014-2015, 11 districts had more than a 30 percent charter share. The five largest shares were in New Orleans (93 percent), Detroit (53 percent), Flint (47 percent), D.C. (44 percent), and Kansas (41 percent). Source: http://www.publiccharters.org.

Throughout we make several contributions. First, we develop and estimate a rich yet tractable model of charter entry. While most charter school literature studies achievement effects,² relatively little research has focused on entry. In a reduced form fashion, Glomm et al (2005), Rincke (2007), Bifulco and Buerger (2015) and Imberman (2011) study charter entry while Henig and MacDonald (2002) study early charter location in Washington, D.C. Cardon (2003) models entrant quality choice when facing an existing public school. Closest to our approach is Mehta's (2012) structural study of charter entry in North Carolina. We differ from Mehta in several ways: we model student heterogeneity in race, income and poverty status; we endogenize student body composition in these characteristics; and we include private schools in the student choice set. While we model charters as responsive to public schools, we do not model public school strategic response to charters given the lack of evidence for it - as explained below. In our model, as in reality, all charters in the economy are available to households regardless of their residential location, and this means that each public school competes against potentially many charters, and vice versa. Finally, we model charter heterogeneity in curricular focus, grade coverage and costs.³

Second, we contribute to the empirical literature on school choice. While others have estimated school choice models with endogenous peer characteristics (Ferreyra 2007, Altonji et al 2015), we rely on the full choice set of private and charter schools, and model unobserved school quality. In addition to market shares, we match school peer characteristics, neighborhood fraction of children enrolled in charter schools and neighborhood average travel distance to public and charter schools.

Using the full school choice set in addition to modeling school unobserved quality poses severe computational challenges. Hence, we recast our demand-side estimation as a mathematical programming with equilibrium constraints (MPEC) problem following Dube et al (2012) and Skrainka (2012). While these authors supply analytical gradients and Hessians to optimization software, we combine two software solvers in such a way that requires only first-order derivatives, and for these we use a symbolic differentiation tool. We can therefore experiment with different model specifications without recoding derivatives, thus making novel use of state-of-the-art computational tools.

Third, we contribute to the literature on firm entry in industrial organization, reviewed by Berry and Reiss (2007) and Draganska et al (2008). We develop a supplyside model of charters featuring the regulator's key role. The model is realistic as well as tractable, and could be applied to other regulated industries such as child care provi-

²For a comprehensive review of the charter achievement literature, see Betts and Tang (2011). For recent studies, see Angrist et al (2013), Clark et al (2011) and references therein.

³Other related work includes Walters (2012) and Neilson (2013). Using data on charter school lotteries and individual-level school choice and achievement, Walters estimates preference and achievement parameters. Neilson (2013) uses Chilean student-level data to estimate achievement and BLP-style preference parameters. Neither Walters nor Neilson model school entry or endogenous peer characteristics.

sion and for-profit tertiary education. The entry literature typically uses reduced-form demand specifications, yet we specify a structural model of school choice and allow for unobserved school quality, as in Carranza et al (2011). A major focus of the entry literature is the strategic interaction between entrants and/or incumbents. We do not, however, model public or private school decisions because there is limited school entry and exit activity during our sample period, and this precludes the identification of a strategic decision-making model for them. Moreover, the six superintendents DCPS has had between 1998 and 2007, coupled with its financial instability, suggests that it may not have been able to react strategically to charters during our sample period.

The rest of the paper proceeds as follows. Section 2 describes the institutional framework and data sources. Section 3 describes basic data patterns. Section 4 presents the model. Section 5 describes the estimation strategy, and Section 6 presents estimation results. In Section 7 we discuss counterfactual results, and Section 8 concludes.

2 Institutional Framework and Data Sources

In 1995, Congress passed the DC School Reform Act allowing for the creation of charter schools in the District and instituting the DC Board of Education (BOE) as a charter authorizer. The Public Charter School Board (PCSB), created in 1996 as an additional, independent authorizer, has been the sole authorizing and supervising entity since 2006. Charters in D.C. are autonomous, non-profit institutions. They receive the same operational per-pupil funding as public schools. In addition, they receive a per-pupil facilities allowance. Since funding is fungible, henceforth "reimbursement" refers to total (operational plus facilities-related) per-student funding.

The Office of the Mayor has had direct authority over DCPS since 2007. DCPS includes multiple attendance zones for each grade span; middle- and high-school attendance zones are much larger than elementary school zones. At the "state" level, the overarching institution for public and charter schools is the Office of State Superintendent of Education (OSSE). In what follows, "total enrollment" refers to the aggregate over public, private and charter schools, and "total public enrollment" to the aggregate over traditional public and charter schools.

We focus on the 2003-2007 period in order to maximize data quality and comparability over time and across schools. In addition, 2007 marked the beginning of important changes in DCPS and hence constitutes a good endpoint for us.⁴ Our data include school-level information on every public, charter and private school in Washington, D.C. for 2003-2007, neighorhood level information on school choice and distance traveled to school for 2003-2006, and block group-level information on child age, race, poverty

⁴In 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. The first such reforms took effect in Fall 2008.

status, and family income. Appendix A provides further details on the data.

While public and private schools have one campus each, many charters have multiple campuses. Hence, our unit of observation is a campus-year; "campus" is the same as "school" for single-campus schools.⁵ We have 700, 228 and 341 campus-year observations for public, charter and private schools respectively. Our dataset includes regular schools; it excludes special education and alternative schools, schools with residential programs and early childhood centers. For each observation we have address, grade enrollment for kindergarten through 12th grade, percent of students of each ethnicity (black, white and Hispanic),⁶ and percent of low-income (or "poor") students, who qualify for free or reduced lunch. We also have the school's thematic focus, which we classify into Core, Language, Arts, Vocational and Other (math and science, civics, etc.). In addition, for public and charter schools we have reading and math proficiency rates (i.e., the fraction of students who pass D.C.'s reading and math tests); for charter schools we have school type (Catholic, other religious and non-sectarian) and tuition.

Enrollment and proficiency for public and charter schools come from OSSE. Public school addresses and student demographics come from the Common Core of Data (CCD) from the National Center for Education Statistics (NCES) and OSSE. Curricular focus (henceforth, focus) for public schools come from Filardo et al (2008). Charters' student body composition and proficiency rates come from OSSE and the School Performance Reports (SPRs). Charters' focus comes from schools' own statements, SPRs and Filardo et al (2008). Charter reimbursement rates come from D.C.'s Office of the Chief Financial Officer. Further information comes from past Internet archives and from Friends of Choice in Urban Schools (FOCUS). A complicating factor in charter data collection is the dispersion and inconsistencies of data sources, and their non-uniform treatment of multi-campus charters.

NCES's Private School Survey (PSS) is our main source of private school data. Since PSS is biennial, we use the 2003, 2005 and 2007 waves. We impute 2004 data by linear interpolation of 2003 and 2005, and similarly for 2006. Average school tuition for the school year 2002-2003 comes from Salisbury (2003). All dollar amounts are expressed in dollars of year 2000.

We follow DCPS's criteria and classify schools into the following grade spans: elementary (covering grades in the K-6 range, which was the typical range for public elementary schools in 2003-2007), middle (covering grades 7th and/or 8th), high (covering grades in the 9th-12th grade range), and elementary/middle, middle/high, and el-

⁵A 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.

⁶Since students of other races (mostly Asian) constitute only 2.26 percent of the total K-12 enrollment, for computational reasons we folded them into the white category.

ementary/middle/high. Mixed-level categories (such as middle/high) are quite common among charters. Note that a grade span is a *set* of grades rather than a single grade.

Our neighborhood-level data comes from Filardo et al (2008)'s data appendices. Local urban planning agencies use the concept of "neighborhood cluster" to proxy for a neighborhood, and group D.C.'s Census tracts into 39 clusters. We observe each neighborhood's fraction of children enrolled in charter schools relative to total public enrollment, and average distance traveled to public or charter schools. An alternative (but larger) measure of neighborhood is given by wards. The District has eight wards; Ward 3, in the Northwest, is the most advantaged, and Wards 7 and 8, in the Southeast, are the most disadvantaged. For convenience we split the city into three regions: West (Ward 3 and some parts of Ward 2), Southeast (Wards 7 and 8) and Northeast.

For the sake of demand estimation, ideally we would observe the joint distribution of child grade, race, poverty status and parental income at the block group level (there are 433 block groups in D.C.) for every year between 2003 and 2007. Since this is not the case, we use 2000 Census data and other sources to estimate the joint distribution. Appendix A.3 provides further details.

3 Descriptive Statistics

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. Between 2003 and 2007 it grew from 577,000 up to 586,000, although school-age population declined from 82,000 to 76,000 according to the Population Division of the U.S. Census Bureau and American Fact Finder. The city's racial breakdown has changed as well, 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. As Figures 1a, 1b and 1c show, whites reside mostly in the West; blacks reside mostly in the Northeast and Southeast; and Hispanics reside mostly in a central corridor between the West and the Northeast. Income varies greatly among races. For instance, in 2013 median household income was \$112,000 for whites, but only \$38,000 for blacks and \$51,000 for Hispanics. As a result, households are also segregated by income, as Figure 1d shows. This residential segregation has important implications for school markets and for charter schools' demand.

3.1 Basic trends in school choice

As Figure 2A shows, total enrollment declined by about 6,000 students over our sample period, yet charter enrollment grew by that amount. Since private school enrollment remained steady at about 21 percent of total enrollment, market share for public schools fell from 66 to 56 percent yet rose from 13 to 22 percent for charters. The number



Figure 1: Race and Income Spation Distribution, Washington, D.C. 2000.

of charter school campuses more than doubled, from 27 to 59, whereas the number of public and private school campuses declined slightly due to a few closings and mergers (Figure 2B and Table 1). Over the sample period, 43 percent of private schools were Catholic, 24 percent belonged to other religions and 32 percent were nonsectarian. Average charter reimbursement grew from \$7,900 in Fall 2003 to \$9,600 in Fall 2007.

Public schools are widely heterogeneous. Table 2 shows that student demographic vary greatly among public schools, as do proficiency rates. Nonetheless, on average public and charter schools have demographically similar students; more than 90 percent of them are non-white and about two-thirds are low-income. In contrast, about 60 percent of students in private schools are white and less than a quarter are low-income.

Public and charter schools have similar average reading and math proficiency (about 41 percent). This similarity, however, masks an important variation by grade span, as described below.

Private schools tend to be located in more affluent neighborhoods than public or charter schools. Nonetheless, Catholic schools are located in less affluent neighborhoods than other private schools and enroll higher fractions of black and Hispanic students. At \$6,300, their average tuition is lower than that at other religious or non-sectarian schools, whose average tuition equals \$15,000 and \$15,500, respectively.



Figure 2: Enrollment and Schools in Washington D.C.

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

Figure 3 shows the geographic distribution of public, private and charter schools. For each grade span, public schools are spread throughout the city. As for private

Public Schools				Charter Schools				Private Schools				
Year	Total	Opened	Closed	Moved	Total	Opened	Closed	Moved	Total	Opened	Closed	Moved
End 2002	142	- St. 1			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	59	6	1	5	68	0	2	3
Total 03-07		2	8	8		36	4	20		3	8	5

Table 1: School Openings and Closings

Notes: Each cell indicates number of campuses. "Total" corresponds to the Fall of the corresponding year. 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 2: Demographics and Achievement in 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	17.2	0	78.71	7.61	0	30.6	2.8	0	5	56.12	0	85.1
Pct Black	73.84	15.67	100	81.89	37.47	100	89.69	68	100	38.16	7.27	99.21
Pct. Hispanic	8.96	0.24	26	10.49	0	34.47	7.51	0	26	5.72	0	10.92
Pct. Low Income	56.88	3.24	87.63	64.68	27.44	88.56	70.47	50.3	95	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	12.8	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." and "Math Prof." are Reading and Math proficiency rates, respectively. "Tract income" is average household income in the school's Census tract. Pct. Low Income for private schools is imputed as described in Appendix A.1.3. Proficiency data is not available for private schools. Weighted statistics; weight = Fall enrollment.

schools, their market consists of two segments that differ in student body, tuition and location. The first one includes schools serving non-white, low-income students. These schools, which charge a relatively low tuition (between \$4,000 and \$6,000), are predominantly located in the Northeast or Southeast and are mostly Catholic. The second segment includes schools serving mostly white, non-poor students. These schools, which charge higher tuition (between \$6,500 and \$25,000), are predominantly located in the West and are mostly non-sectarian. Importantly, charter schools are concentrated in the Northeast and Southeast, home to most of the non-white, lower-income population.

Panel a in Table 3 shows stark differences in school choice by student race.⁷ About 70 percent of black and Hispanic children attend public schools, compared to only 27 percent of whites. Between 15 and 20 percent of blacks and Hispanics attend charters, relative to 3 percent of whites. Nearly three quarters of whites attend private schools, compared to less than 15 percent of blacks and Hispanics.

As Figure 4 shows, children who live in the eastern portion of the city are more likely to attend charters. This is consistent with the fact that most black, poor children reside in that area, and that charter schools are concentrated there. In contrast, children who live in the western, affluent portion of the city are more likely to attend private schools (see Appendix Figure 1 with 2000 Census data; data not available for 2003-2007). Regardless of their residential location, children travel longer to charter than

⁷In the absence of individual-level data, we use school-level data to approximate the distribution of school (and later focus) choice across students.



Figure 3: Geographic Location of Schools in 2007

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	Public	Charter	Catholic	Other Religious	Nonsectarian
a. All Grades					
All Students	61.57	16.93	9.81	5.4	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	8.8	1.61	3.16
b. K through 6 th grade					
All Students	65.72	15.48	7.51	5.7	5.59
White	36.84	4.09	13.38	22.5	23.18
Black	70.23	18.06	6.46	2.83	2.4
Hispanic	76.34	13.32	6.37	1.44	2.5
c. 7 th through 12 th grade					
All Students	56.22	18.81	12.79	5	7.18
White	17.62	1.41	33.23	19.43	28.31
Black	65.45	23.82	7.37	1.5	1.87
Hispanic	65.91	15.72	12.39	1.85	4.14

Table 3: School Choice by Student Race

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

to public schools. Median distance traveled to public schools is equal to 0.33, 0.64 and 1.47 miles for elementary, middle and high school respectively, whereas median distance traveled to charter schools is equal to 1.42, 1.66 and 2.37 miles respectively (Filardo et al 2008).

3.2 Variation by grade span and focus

As Table 4 shows, most public schools are elementary. While the average public elementary school has about 280 students, the average public middle and high school has almost 400 and 640 students, respectively. Charters tend to be smaller than public schools, and private schools tend to be smaller than charters. Although public schools rarely mix grade spans, charters and private schools often do.

	Public Schools			Charter Schools			Private Schools		
	%	% Stud.	Avg. Enr.	%	% Stud.	Avg. Enr.	%	% Stud.	Avg. Enr.
Elementary	68.57	55.02	277	42.11	27.69	192	17.3	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

 Table 4: Grade Levels in Public, Charter and Private Schools

Notes: Avg. Enr. is average enrolment and % Stud. is percentage of students. 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. "n/a" indicates there are no public schools of this grade level.

Figures 5A-5C show that market share for each school type varies across grade



Figure 4: Neighborhood Percent of Children in Charter School in 2006

Note: Percent relative to all students in the public system (in public and charter schools).

spans. Public school shares peak for elementary school grades; charter school shares peak for middle school grades and private school shares peak for high school grades. Consistent with this, panels b and c of Table 3 show that students from all races are less likely to choose public schools after 6th grade - 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 Catholic and charter schools.⁸

Figure 5 also shows that during the sample period public schools lose market share in all grades but particularly in middle school. Charters, in contrast, gain market share in all grades, particularly in grades 6-8. This gain might partly relate to the fact that 6th and 7th grades are natural entry points into charters, since students must change schools when finishing elementary school. But the gain might also relate to the fact that charter seats appear to have expanded the most at the middle school level. As Figure 6A shows, during the sample period the number of charters is well below that of public schools for grades K-6, but by the end of the period the number of public and charter schools is almost the same for grades 7 and 8. While average grade enrollment (a proxy for the number of per-grade seats offered by the school) is lower for charters than public schools for grades 7 and higher (Figure 6B), the difference is relatively small for grades 7 and 8. Thus, by opening new campuses and endowing them with relatively large capacities, charters seem to have expanded middle school students' choice sets the

⁸It is possible that white parents would leave the District once their children finish elementary school. As a simple test of this conjecture we calculate the fraction of white children per age. The fraction declines from 19 to 13 percent as age rises from 0 to 4, but stabilizes around 10 percent between ages 5 and 18. Thus, white parents appear to leave the District *before* their children start school.

most.





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 Schools and Average Enrollment by School Type and Grade

Moreover, proficiency rates vary across school types, grade spans and neighborhoods (see Table 5).⁹ As the table shows, there is a large proficiency gap in the public schools available to different students. Proficiency rates in the public schools available to non-white, poor students outside Ward 3 are only half as high as those in Ward 3, and are particularly low in Wards 7 and 8 (the Southeast). At the elementary level, on average charters have slightly lower proficiency than public schools, which is not surprising given that public elementary schools include Ward 3's high-proficiency schools. Nonetheless, in the upper (particularly middle-school) grades, on average charters surpass public schools, particularly in middle school and in the Southeast.

Curricular focus is another important difference between charter and non-charter schools. 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 6). Overall, 80, 11, 4, 3 and 2 percent of students attend a Core-curriculum, Other, Language, Vocational or Arts school respectively (see Table 7). Blacks are more likely

⁹Since reading shows similar patterns, we focus on math from now on.

	Public Schools	Charter Schools
Overall		15 15
Elementary	46.20	39.85
Middle	36.35	50.02
High	34.05	37.00
Ward 3		5. N
Elementary	81.73	n/a
Middle	77.50	73.77
High	55.94	n/a
Outside Ward 3		24 A 4 6 7 1 9 0
Elementary	42.78	39.85
Middle	32.45	49.55
High	30.91	37.00
Wards 7 and 8		
Elementary	35.66	32.81
Middle	23.99	45.62
High	15.50	39.69

Table 5: Average Math Proficiency Rates in Public and Charter Schools

Notes: the unit of observation is a campus-year. Observations weighted by Fall enrollment. Ward corresponds to the school's last location during the sample period. "Elementary" encompasses elementary, elementary/middle and elementary/middle/high levels; "Middle" refers to middle; "High" encompasses "middle/high" and "high" levels.

than other students to choose Arts or Vocational; whites and non-poor students are more likely than black or low-income students to choose Other, and Hispanics are more likely than whites or blacks to choose Language. In other words, charters offer a curricular variety that seems to appeal to the variety of students in the District.

	0	v	• •
Focus	Public Schools	Charter Schools	Private Schools
Core	83	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 6: Program Focus by School Type

Notes: the unit of observation is a campus-year. For instance, among charter campuses, on average 47.37 percent offer a core curriculum, 9.65 percent offer an arts curriculum, etc.

3.3 Entries, relocations and closings

Public and private schools experienced relatively few openings, closings and relocations during the sample period (see Table 1), particularly when measured against the number of schools of each type that existed by the end of 2002.¹⁰ In contrast, openings and relocations were quite frequent among charters. Charters often open with a subset of

¹⁰DCPS has closed schools since 1976 due to declining enrollment, school mergers, or demolition of housing projects. Since 2000 DCPS has engaged in further efforts to "rightsize" the public school system. Declining student population and enrollment have been the main driver of closings (Filardo et al 2008). Most public school relocations were temporary (to "swing space") as the schools underwent renovation. Regarding private school closings, they were mostly idiosyncratic and affected schools with fewer than 50 students.

Students	Core	Arts	Language	Vocational	Other Focus
All	80	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	10.4
Hispanic	58.14	1.53	20.44	2.48	17.4
Non Poor	79.27	2.16	3	2.01	13.56
Low Inc.	80.56	2.17	4.53	3.14	9.6

 Table 7: Focus Choice by Student Race and Poverty Status

Note: Each row indicate 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.

their intended grades and add grades over time, moving from small, temporary facilities to larger, permanent facilities.

Our charter sample includes 63 campuses and 45 schools. Ten schools run multiple campuses, mostly to serve different grade spans. Appendix Table 1 displays charter school entry patterns between 2004 and 2007 (the years used for supply-side estimation, as explained below). Of the 33 entrants, 19 offer elementary grades, 9 middle grades, 4 elementary/middle or middle/high, and one high school. Two-thirds of entrants offer a specialized curriculum; Other is the most popular focus choice. The West, Northeast and Southeast of the District 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 Figure 7). In other words, the Northeast has received disproportionately large entry, and the Southeast disproportionately little.

Further, Southeast entrants are more likely than others to offer elementary grades. They are also more likely to offer a Core curriculum, perhaps indicating that in this area, where public school proficiency is the lowest, parents are relatively less interested in curricular variety.

Of the four charter closings in our sample, two were due to academic reasons and one to mismanagement.¹¹ The average charter relocation distance is 3.47 miles (median = 3.09 miles), and 5 of the 20 moves happened within the same cluster.

To summarize, there is much disparity in the educational options available to different students in Washington, D.C. Students living in the West, who are mostly white and high-income, have access to high-proficiency public schools and also to private schools, including the high-tuition private schools located in their own neighborhoods. In contrast, students living in the Northeast and Southeast, who are mostly non-white and low-income, have access to lower-proficiency public schools and, depending on their willingness and ability to pay, to some low-tuition private schools. It is precisely in the Northeast and Southeast where most charter schools have opened, and where most charter school students live. Further, charters have expanded middle school students'

¹¹The fourth closing involved a campus from a multi-campus organization. The campus existed only for a year and then re-assigned students to the two other campuses in the organization.



Figure 7: Location of Charter School Entrants in Washington D.C., 2004-2007

choice sets the most, and they have substantially increased the variety of curricular offerings in the market.

4 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. Public, private and charter schools exist in the economy and serve various grade spans. The economy is populated by households that live in different locations within the city and have children who are eligible for different grades. Given its budget constraint, each household chooses among the schools offering its required grade.

Although the model includes public, private and charter schools, we only model charter behavior. Since entry, exit and relocation are less common among public and private schools than among charters, we would not be able to identify a strategic decision-making model for public or private schools. In addition, DCPS was probably not acting strategically at the time given its internal disarray. Moreover, we lack time-varying tuition data. Thus, we assume that in any given period public and private schools make decisions first, and the regulator and charters take these decisions as given. Since public and private schools might react to changes in the environment at some point, in our counterfactuals we implement a simple rule whereby they close if their enrollment falls below a specific threshold, and remain open otherwise.

A charter entry point is a combination of location, grade span and focus. At a given time, in each entry point there is a prospective entrant deciding whether to apply for opening a charter school or not. The prospective entrant receives a random draw of the nonpecuniary net benefit from operating a charter, based on which it decides whether to submit an entry application to the regulator. To decide whether to authorize the entry, the regulator forecasts the prospective entrant's enrollment by predicting household equilibrium choice of school. In addition, the regulator decides whether incumbent charters can remain open based on their financial and academic viability.

Thus, our model has multiple stages of charter, regulator and household actions. We start with the household choice stage.

4.1 Household Choice of School

We use *J* to denote total number of schools in the economy. Households in the economy have one child each. In what follows, we use "household", "parent", "family", "child" and "student" interchangeably. Student *i* is described by variables $(D, \ell, I, g, \varepsilon)$, where:

• D_i is a row vector describing student *i* demographics. In our data this vector contains $\tilde{D} = 3$ binary elements indicating whether the household is white, Hispanic (omitted category is black) and non-poor, respectively.

- $\ell, \ell \in \{1, ..., L\}$ is household location in one of the economy's L neighborhoods.¹²
- *I* is annual income of the student's family *i*.
- g is the child's grade, ranging from g = 0 (kindergarten) to g = 12 (12th grade).
- ε is a vector that describes the student's idiosyncratic preference for each school.

Subscript j denotes a school campus, and subscript t denotes a school year. We treat multiple campuses of the same school as separate units because they are often run as such. In what follows, we use "school" and "campus" interchangeably as well as "school year" and "year". When making its choice for year t, household i takes into account the following characteristics of school j:

- G_{jt} is the set of grades served by the school, or "grade span."
- x_{ijt} is the geographic distance from the household's residence to the school.

• y_j is a row vector with time-invariant school characteristics such as type (public, charter, Catholic, other religious, nonsectarian) and focus (Core, Language, Arts, Vocational, Other). For brevity we refer to y_j as "focus."

- p_{jgt} is tuition. It is always equal to zero for public and charter schools.
- \overline{D}_{jt} is the row vector of households' beliefs about the school's peer (or student

¹²A child's location determines her travel distance to each school. We take student location as given and do not model household residential choice. For models of joint residential and school choice, see Nechyba (2000) and Ferreyra (2007). In estimation we measure distance as network distance, expressed in miles. We use Census block groups as household locations for demand estimation, and neighborhood clusters as the locations used to define entry points for supply estimation.

body) composition at *t*. As explained below, in equilibrium these beliefs are consistent with the expectation of the realized schools' peer composition. Empirically we use another variable, \overline{D}_{jt} , which is the school's actual percent of white, Hispanic and non-poor students, calculated by averaging the D_i vectors for all students in *j*.

• ξ_{jgt} is a demand shock that captures unobserved (to us) characteristics of the school and grade at time *t*.

We define a market as a (grade g, year t) pair. Market size M_{gt} is the number of students who are eligible to enroll in grade g in year t.

Below we describe the derivation of the utility function, which encompasses both elements of preference and achievement. Superindexes p and a denotes "preference" and "achievement," respectively.

The household indirect utility function is:

$$U_{ijgt} = \delta_{jgt}^{\nu} + \mu_{ijgt}^{\nu} + \varepsilon_{ijgt}$$
(1)

where δ_{jgt}^{p} is the baseline utility enjoyed by the children enrolled in grade g at school j in school year t, μ_{ijgt}^{p} is a student-specific deviation from δ_{jgt}^{p} , and ε_{ijgt} is an idio-syncratic preference. Baseline utility depends on school characteristics, expected peer characteristics and tuition as follows:

$$\delta_{jgt}^{p} = y_{j}\beta^{p} + \widehat{\overline{D}}_{jt}\alpha^{p} - p_{jgt}\varphi^{\delta} + \xi_{jgt}^{p}.$$
(2)

Here, α^p and β^p are parameter vectors and ξ_{jgt}^p is an unobserved (to us) characteristic of the school and grade that affects household utility, such as the teacher's responsiveness to parents and her enthusiasm in the classroom. The household-specific component of utility is given by:

$$\mu_{ijgt}^{p} = E\left(A_{ijgt}\right)\phi^{p} + [y_{j}\otimes D_{i}]\tilde{\beta}^{p} + [D_{i}\otimes\widehat{\overline{D}}_{jt}]\alpha^{\mu} + x_{ijt}\gamma^{\mu}.$$
(3)

This component depends on the student's expected achievement at this school, $E(A_{ijgt})$, which we explain below. It also depends on the interaction of student demographics D_i with y_j and \overline{D}_{jt} , which captures the variation in utility from focus and expected peer characteristics across students of different demographic groups. In addition, this utility component depends on the distance between the household's residence and the school, x_{ijt} .

Student achievement A_{ijgt} depends on a school-grade factor common to all students, Q_{jgt} , student characteristics D_i , the interaction $[y_j \otimes D_i]$, and a zero-mean idio-syncratic achievement shock w_{ijgt} , which parents do not observe when choosing the school:

$$A_{ijgt} = Q_{jgt} + D_i \omega^a + [y_j \otimes D_i] \tilde{\beta}^a + w_{ijgt}.$$
(4)

The school-grade factor Q_{jgt} , depends on the school's focus y_j , peer characteristics \overline{D}_{jt} , and productivity shock ξ^a_{igt} :

$$Q_{jgt} = y_j \beta^a + \overline{D}_{jt} \alpha^a + \xi^a_{jgt}$$
⁽⁵⁾

where ξ^{a}_{igt} is unobserved (to the econometrician) characteristics of the school and grade

that affect children's achievement. This captures, for instance, teachers' effectiveness at raising achievement. Note that while the productivity shock ξ_{jgt}^a affects achievement, the preference shock ξ_{jgt}^p in (2) affects household satisfaction for reasons other than achievement.

Substituting (5) into (4), and taking parents' expectation of (4) we obtain:

$$E\left(A_{ijgt}\right) = y_{j}\beta^{a} + \overline{D}_{jt}\alpha^{a} + D_{i}\omega^{a} + [y_{j}\otimes D_{i}]\tilde{\beta}^{a} + \xi^{a}_{jgt}.$$
(6)
ting (6) into (3) we obtain:

Substituting (6) into (3), we obtain: $\mu_{ijgt}^{p} = y_{j}\beta^{a}\phi^{p} + \widehat{\overline{D}}_{jt}\alpha^{a}\phi^{p} + D_{i}\omega^{\mu} + [y_{j}\otimes D_{i}]\beta^{\mu} + [D_{i}\otimes\widehat{\overline{D}}_{jt}]\alpha^{\mu} + x_{ijt}\gamma^{\mu} + \phi^{p}\xi_{jgt}^{a}$ (7)

where $\omega^{\mu} = \omega^{a} \phi^{p}$ and $\beta^{\mu} = \tilde{\beta}^{p} + \phi \tilde{\beta}^{a}$.

Next, we substitute (2) and (7) into (1) and regroup terms to obtain expressions (8), (9) and (10). Thus, household utility is:

$$U_{ijgt} = \delta_{jgt} + \mu_{ijgt} + \varepsilon_{ijgt} \tag{8}$$

where δ_{jgt} and μ_{ijgt} are defined below in (9) and (10).

The baseline utility component δ_{jgt} is equal to:

$$\delta_{jgt} = y_j \beta^{\delta} + \widehat{\overline{D}}_{jt} \alpha^{\delta} - p_{jgt} \varphi^{\delta} + \xi_{jgt}$$
⁽⁹⁾

where vector $\beta^{\delta} = \beta^p + \beta^a \phi^p$ captures the total utility from focus that arises directly from pure preferences over focus, and indirectly from focus impact over achievement. Similarly, vector $\alpha^{\delta} = \alpha^p + \alpha^a \phi^p$ captures household preferences over peer characteristics as well as the impact of these on expected achievement. Thus, the model captures the potential tension between enhancing achievement and appealing to students. For example, an Arts curriculum may not enhance achievement, but it may appeal to parents. The demand shock $\xi_{jgt} = \xi_{jgt}^p + \xi_{jgt}^a \phi^p$ captures elements such as teacher characteristics that may reflect a similar tension. For instance, parents may not like a teacher's strict policies even though they raise achievement.

The student-specific component of (8) is:

$$\mu_{ijgt} = D_i \omega^{\mu} + [y_j \otimes D_i] \beta^{\mu} + [D_i \otimes \overline{D}_{jt}] \alpha^{\mu} + x_{ijt} \gamma^{\mu}.$$
(10)

This utility component is a function of the student's characteristics, D_i , as well as the interaction of these with school focus y_j and expected peer composition $\widehat{\overline{D}}_{jt}$. It is also a function of the student's distance to school. Coefficients β^{μ} reflects both preferences and expected achievement.

As in Nevo (2000, 2001), we decompose the demand shock as follows: $\xi_{jgt} = \xi_j + \xi_g + \xi_t + \Delta \xi_{jgt}$. Component ξ_j captures school-specific elements such as culture, educational philosophy, and length of school day and year; we refer to ξ_j as "school quality." Component ξ_g captures grade-specific elements, while ξ_t captures time-varying elements common to all schools and grades. We normalize as follows: $E(\Delta \xi_{jgt}) = 0$.

Hence, $\xi_j + \xi_g + \xi_t$ is the mean of ξ_{jgt} , and $\Delta \xi_{jgt}$ is a deviation from it.¹³

To summarize, the utility function (8) incorporates both household preferences over school characteristics as well as the contribution of these characteristics to expected student achievement. Since lack of achievement data at the student level prevents us from separately identifying those two aspects, we estimate the demand-side parameter vector $\theta^d = (\beta^{\delta}, \alpha^{\delta}, \varphi^{\delta}, \omega^{\mu}, \beta^{\mu}, \alpha^{\mu}, \gamma^{\mu})$. While we refer to these as "preference parameters," it should be kept in mind that some of these parameters reflect total utility arising both from preferences and achievement.

Instead of choosing a specific school, the household may choose the outside good (j = 0) with normalized utility $U_{i0gt} = \varepsilon_{i0gt}$. The outside good may represent options such as home schooling, attending a private school outside the city, or dropping out of school.

Among schools offering grade g in year t, the school choice set for child i encompasses all public schools (as if they had open enrollment),¹⁴ all charter schools, and all private schools affordable to the household. We assume that i can afford private school j if tuition p_{jgt} does not exceed a certain share of the household's annual income I_i . Let J_{igt} be the number of schools in i's choice set. Student i chooses a school in order to maximize utility. Assuming that the error terms in (8) are i.i.d. type I extreme value, the probability that household i chooses school j for year t is:

$$P_{ijgt}\left(y_{gt}, \widehat{\overline{D}}_{gt}, \Xi_{gt}, p_{gt}, X_{igt}; \theta^d\right) = \frac{\exp(\delta_{jgt} + \mu_{ijgt})}{1 + \sum_{k=1}^{J_{igt}} \exp(\delta_{kgt} + \mu_{ikgt})}$$
(11)

where we have introduced some compact vector notation: vector y_{gt} describes the focuses of the schools offering g at t, and vectors \widehat{D}_{gt} , Ξ_{gt} and p_{gt} describe the expected peer characteristics, demand shocks ξ_{jgt} , and tuitions respectively of the schools offering g at t. In addition, X_{igt} denotes the observable variables that are either specific to i or to its match with the schools: D_i , I_i , and x_{ijt} .

Since a market is a grade-year combination, a school that offers multiple grades

¹³We can apply a Nevo-type decomposition to ξ_{jgt}^p and ξ_{jgt}^a to obtain $\xi_{jgt}^p = \xi_j^p + \xi_g^p + \xi_t^p + \Delta \xi_{jgt}^p$ and $\xi_{jgt}^a = \xi_j^a + \xi_g^a + \xi_t^a + \Delta \xi_{jgt}^a$. Since $\xi_{jgt} = \xi_{jgt}^p + \xi_{jgt}^a \phi^p$, these decompositions yield $\xi_{jgt} = \left(\xi_j^p + \phi^p \xi_j^a\right) + \left(\xi_g^p + \phi^p \xi_g^a\right) + \left(\xi_t^p + \phi^p \xi_t^a\right) + \left(\Delta \xi_{jgt}^p + \phi^p \Delta \xi_{jgt}^a\right) = \xi_j + \xi_g + \xi_t + \Delta \xi_{jgt}$. Hence, the school-specific component ξ_j (or "school quality") captures both school characteristics that affect utility (ξ_j^p) , and school characteristics that affect achievement (ξ_j^a) . A similar reasoning applies to ξ_g and ξ_t .

¹⁴Data limitations motivate this "open enrollment" assumption, innocuous for the development of the model. Using GIS software we established the public schools assigned to children in each block group depending on their grade level. However, based on the 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. during the sample period was based on residential location only to a limited extent. For instance, Filardo et al document that approximately half of the children enrolled in public schools attend an out-of-boundary shool. Moreover, the mechanism was seemingly not systematically applied across the District. Hence, we simplified by assuming public school open enrollment.

participates in multiple markets. Let $h(D, I, \ell | g)$ be the joint distribution of student demographics, income and locations conditional on grade. Given (11), school *j*'s expected market share for grade *g* in *t* is the addition, over all students in grade *g*, of their probabilities of choosing school *j* at time *t*:

$$\widehat{S}_{jgt}\left(y_{gt}, \overline{\overline{D}}_{gt}, \Xi_{gt}, p_{gt}; \theta^d\right) = \int_{D} \int_{I} \int_{\ell} P_{ijgt}(\cdot) dh(D, I, \ell \mid g)$$
(12)

The expected number of students choosing school j for grade g at t is equal to the number of students in that market times the school's expected market share:

$$\widehat{N}_{jgt}\left(y_{gt}, \widehat{\overline{D}}_{gt}, \Xi_{gt}, p_{gt}; \theta^d\right) = M_{gt} \,\widehat{S}_{jgt}\left(\cdot\right). \tag{13}$$

Adding over grades, the total expected number of students in school j at year t is hence equal to

$$\widehat{N}_{jt}\left(y_t, \overline{\overline{D}}_t, \Xi_t, p_t; \theta^d\right) = \sum_{g \in G_{jt}} \widehat{N}_{jgt}(\cdot)$$
(14)

where we introduce additional vector notation for compactness: y_t , \overline{D}_t , and p_t are vectors that describes focuses, household beliefs on expected peer characteristics and prices respectively of all operating schools in t, and Ξ_t is the vector that stores the demand shocks ξ_{jgt} of all operating schools in t.

The resulting expected demographic composition for school j is thus equal to

$$\tilde{D}_{jt}(y_t, \widehat{\overline{D}}_t, \Xi_t, p_t; \theta^d) = \sum_{g \in G_{jt}} \left\{ \frac{\widehat{N}_{jgt}(\cdot)}{\widehat{N}_{jt}(\cdot)} \int_{D} \int_{I} \int_{\ell} DP_{ijgt}(\cdot) dh(D, I, \ell | g) \right\}.$$
(15)

In this expression, the triple integral calculates the grade-level average student body composition for each school. This grade-level average is then multiplied by a ratio that represents the school's share of students enrolled in the grade. For computational tractability, in the demand estimation we replace $\widehat{\overline{D}}$ by the observed peer characteristics \overline{D} in the right hand side of equations (11)-(15).¹⁵

From the above it follows that demand for school *j* could vary from t - 1 to *t* due to multiple reasons. These include changes in the school's expected demographic composition; changes in *j*'s grade offerings (for instance, through the addition or removal of grades) or location; the opening, closing or relocation of other schools; changes in other schools' grade offerings; changes in the overall number of students in the city, or in the geographic distribution of their residential locations; changes in the year-specific demand shock ξ_t ; and changes in the demand shock residual $\Delta \xi_{jgt}$ (for instance, if a school replaced its grade *g* teacher with a better one).

Recall that lack of individual-level data on achievement precludes the identification of the achievement function (4). Nonetheless, we can derive the following equation

¹⁵This exploits the fact that the difference between \overline{D} and $\widehat{\overline{D}}$ is due to sampling (or measurement) error.

for a school's expected proficiency rate q_{jt} (see Appendix D.2 for details):

$$q_{jt} = y_j \alpha^q + \overline{D}_{jt} \phi^q + [y_j \otimes \overline{D}_{jt}] \omega^q + \xi_j^q + \xi_t^q + \Delta \xi_{jt}^q$$
(16)

where ξ_j^q is the school's productivity shock (later referred to as "productivity") while ξ_t^q captures shocks that affect proficiency rates in all schools and grades in t.¹⁶ The error term $\Delta \xi_{jt}^q$ is a function both of *j*'s idiosyncratic productivity shocks and the mean of the idiosyncratic components of students' performance. Given our lack of individual-level data, we emphasize that neither achievement nor proficiency are essential aspects of this paper. Instead, the goal of our proficiency estimates is to provide counterfactual predictions.

4.2 School Supply

Below we present a game among charter schools, the regulator and households. The game reflects the institutional aspects of regulator behavior and charter entry, exit and relocation in Washington, D.C. The model is based on our exchanges with PCSB staff, charter-advocacy organizations, and charter founders. Appendix D.1 provides further information on the institutional details associated with charter entry. Note, for now, that in order to enter in the Fall of calendar year t, potential entrants must submit their application in January or February of calendar year t - 1. For example, in order to open in the Fall of 2018, a potential entrant must submit her application in January or February of school year t, potential entrants must submit their application in the Spring of school year t - 2.

Some additional notation is in order. Let \mathbf{M}_t be a market structure in t. For the operating schools in t, the market structure describes all the school characteristics (type, focus, location, grades served and tuition) observed by students when making their choices, with the exception of school demand shocks Ξ_t . Taken together, \mathbf{M}_t and Ξ_t constitute the information set used by households when computing the utility from their various school options.

In what follows, first we present the payoffs of the agents. Next we define household consistent beliefs, and potential entrants' entry point, expected enrollment and expected profits. The we present the timing of the entry-exit-relocation events, followed by the solution of the game.

Payoffs of the agents.

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

Household's payoff: For any (\mathbf{M}_t, Ξ_t) households obtain utility as described in Section 4.1.

¹⁶Since (16) is derived from the aggregation of individual-level expected proficiencies within a school, ϕ^q is the sum of the impact of a student's own demographic characteristics on her expected proficiency, and that of her peers. See further details in Appendix D.2.

Entrant's payoff: When a charter operates, the corresponding entrant receives nonpecuniary net benefit *B*, and receives 0 otherwise.¹⁷ We assume that *B* is a random draw from a distribution with cdf $F_B(\cdot)$. It is independent of the charter's expected profit and of other prospective entrants' *B*.

The *regulator* receives charter applications and decides whether to approve them based on charters' expected profit, as explained below. It also decides whether incumbent charters can remain open based on their profits and proficiency.¹⁸

Consistent household beliefs.

For a given market structure \mathbf{M}_t and set of schools' demand shocks Ξ_t , each household forms beliefs $\tilde{D}(\mathbf{M}_t, \Xi_t)$ about schools' demographic composition and chooses a school accordingly. From now on, we use $\widehat{\overline{D}}$ to denote a *set of consistent household beliefs* which satisfy the following system of equations:

$$\widehat{\overline{D}}_{jt} = \sum_{g \in G_{jt}} \frac{\widehat{N}_{jgt}(\overline{D})}{\widehat{N}_{jt}(\widehat{\overline{D}})} \int_{\ell} \int_{I} \int_{D} DP_{ijgt}(y_{gt}, \widehat{\overline{D}}_{gt}, \Xi_{gt}, p_{gt}, X_{igt}; \theta^d) dh(D, I, \ell \mid g), \ j = 1, \dots, J_t.$$
(17)

where (17) is the evaluation of equation (15) at a student body composition equal to the fixed point $\widehat{\overline{D}}_{jt}$, and $P_{ijgt}(\widehat{\overline{D}})$, $\widehat{N}_{jgt}(\widehat{\overline{D}})$ and $\widehat{N}_{jt}(\widehat{\overline{D}})$ are calculated as in (11), (13) and (14) correspondingly. In other words, when households have consistent beliefs about schools' demographic composition (represented as $\widehat{\overline{D}}$ in the RHS of (17)), the choices they make result in schools' demographic compositions (represented as $\widehat{\overline{D}}$ in the LHS of (17)) that are consistent with those beliefs.

Generally, (17) has multiple solutions and hence the model has multiple equilibria.¹⁹ The issue does not affect demand-side estimation because we use observed values, \overline{D} , to calculate predicted market shares in demand estimation. However, supplyside estimation and counterfactuals might be affected. Hence, based on (17) we use a *tatonnement*-type of algorithm. We choose an initial value for $\hat{\overline{D}}$, $\hat{\overline{D}}^0$, and calculate the sequence $\hat{\overline{D}}^k$ (k = 0, 1, ...). We obtain $\hat{\overline{D}}^k$ from $\hat{\overline{D}}^{k-1}$ by substituting the latter into right hand side of (17) for $\hat{\overline{D}}$ until convergence.²⁰ To address multiplicity we choose the equilibrium attained by iterating from a specific starting point. The starting point is

¹⁷These benefits represent the net present value of the founder's satisfaction from contributing to society through the charter school, net of the effort and time cost of submitting the charter entry application.

¹⁸According to Buckley and Schneider (2007), 40 percent of charter entry applications were approved during our sample period.

¹⁹For 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.

²⁰Given that \widehat{D} is defined on a compact set (all values in \widehat{D} are between 0 and 1) and (17) describes a continuous mapping, such iterations always converge. In addition, in the iterations we only allow for changes in \widehat{D} within a specified range (±0.06). Since we do not model capacity constraints, this restriction prevents unrealistically large changes in enrollments and student body compositions.

observed school demographics for incumbents, and a linear function of neighborhood demographic and school characteristics for new entrants.²¹

Entry points, expected charter entrant enrollment and profit.

We assume there is one potential charter entrant for each entry point in each year. Entry points result from all possible combinations of *L* locations, *Y* focuses and *K* grade spans, for a total of $E = L \times Y \times K$ entry points or potential entrants. Each potential entrant may enter the market or not. Entering the market requires the submission of an entry application as well as the regulator's approval of the application. Indicator d_{jt}^e denotes whether potential entrant in entry *j* enters in *t*.²²

In order to decide on approval, the regulator calculates the entrant's expected profit. This calculation depends on the regulator's information at the time of making its decision. Thus, consider potential entrant j for entry point (ℓ, y, G) . When receiving applications in school year t - 1 for school year t + 1, the regulator does not know the knows the set of schools that will operate in t + 1, but knows the set of schools that will operate in t.²³ The regulator also observes the time-invariant, grade-specific demand shocks ξ_g , the year-specific demand shock for t, ξ_t , the demand shocks of all operating schools in t, Ξ_t , and the per-child reimbursements prevailing in t for each grade, R_{gt} . However, the regulator does not observe the potential entrant's school quality ξ_j or its deviations $\Delta \xi_{jgt}$ from the mean. We assume that ξ_j and $\Delta \xi_{jgt}$ for potential entrants are independently distributed with cdfs $F_{\xi}(.)$ and $F_{\Delta\xi}(.)$, respectively, and that these distributions are common knowledge. These distributions can be used to obtain the distribution of demand shocks ξ_{jgt} for potential entrants, F(.).

The regulator decides on j's application based on the expected profit that j would obtain, in equilibrium, if it were to enter the market at t. Since the regulator does not know the potential entrant's quality ξ_j or deviations $\Delta \xi_{jgt}$, the regulator calculates equilibrium enrollment for each possible value of the entrant's demand shock, and integrates over the distribution of the shocks. Formally, the regulator predicts equilibrium house-

²¹More specifically, for actual entrants we regress school demographic characteristics (percent white, percent hispanic and percent non-poor) on indicator variables for school level, focus, cluster and year. Then we use the estimated coefficients to predict school demographic characteristics for new entrants given their school level, focus and cluster, and the entry year. Note that fitted values for actual entrants match actual values very well.

²²We do not model the behavior of multi-campus charters. Given the sample low number of entries, identifying a separate entry model for them would not be possible. In addition, the computational burden of such a model would be substantially higher than the current model's. Nonetheless, when estimating utility function parameters we include an indicator for multi-campus charters (see Table 8). This purges the estimates of school quality ξ_j of possible multi-campus biases. Since these estimates are used to form the empirical distribution of entrants' quality $F_{\xi}(.)$, eliminating such biases is consistent with modeling entry of single-campus charters.

²³Since the regulator receives entry applications in early Spring, it is reasonable to assume that it knows the set of operating schools and the year-specific shock for the coming school year.

hold choices for a market structure \mathbf{M}_t that is augmented in order to include *j*, which we denote \mathbf{M}_t^j . In this equilibrium, *j*'s expected enrollment for *g* is:

$$E_{\xi}\widehat{N}_{jgt}(\mathbf{M}_{t}^{j};\boldsymbol{\theta}^{d}) = \int \widehat{N}_{jgt}(y_{gt},\widehat{\overline{D}}_{gt},\{\xi_{jgt},\Xi_{t}\},p_{gt};\boldsymbol{\theta}^{d})dF(\xi_{jgt})$$
(18)

where $\widehat{N}_{jgt}(\cdot)$ is given by (13); y_{gt} and p_{gt} correspond to the schools in \mathbf{M}_t^j , and \overline{D}_{gt} are consistent beliefs on peer characteristics given \mathbf{M}_t^j and $\{\xi_{jgt}, \Xi_t\}$ for schools that offer g. As suggested by (18), expected enrollment varies across entry points and over time.

For the whole school,²⁴ the regulator calculates j's expected profits as follows

$$\bar{\pi}_{jt}^{e}\left(d_{jt}^{e}=1,\mathbf{M}_{t}^{j};\boldsymbol{\theta}^{d}\right)=\sum_{g\in G_{jt}}E_{\xi}\hat{N}_{jgt}(\mathbf{M}_{t}^{j};\boldsymbol{\theta}^{d})\left(R_{gt}-V\right)-\zeta-F_{G_{jt}\ell}+\sigma_{v}v_{jt}^{e} \quad (19)$$

where ζ is entry cost, R_{gt} is per-child reimbursement, V is per-child variable cost, $F_{G_{jt}\ell}$ is the fixed cost of operating in location ℓ and grade span G, and v_{jt}^e is the entrant's financial type,²⁵ unobserved to us. We assume that v_{jt}^e follows an i.i.d. type I extreme value distribution, and σ_v is a scale parameter. Given the extensive information submitted by charter applicants, we assume that the regulator observes $\sigma_v v_{it}^e$.

Timing of entry-exit-relocation events.

In this game we model market activity as a multiperiod interaction. The game period encompasses the Spring semester and summer of school year t - 1, and Fall semester of school year t (i.e., the game period is a calendar year). We continue to use t to denote a school year rather than a calendar year. During the game period market participants interact in the sequence of actions of the following stage game:

Step 1 (Submission of applications by the potential entrants). For each entry point, prospective entrant *j* privately learns the value of its non-pecuniary benefit from running a charter school, B_j . Draws of B_j are independent across potential entrants. Based on its draw, *j* decides whether to submit an application in order to start operating in the next game period. Prospective entrants that submit an application learn their type v_{jt}^e while others do not. In reality this step takes place in Spring t - 1, in order to start operating in Fall t + 1.

Step 2 (*Relocation opportunities for incumbent charters*). For each incumbent charter *j*, located in ℓ_{jt-1} in t-1, a new location ℓ , $\ell \neq \ell_{jt-1}$, may become available for *t* with probability $Pr(\ell) = \exp\{\breve{\alpha} - \breve{\beta}d_{\ell\ell_{jt-1}}\}/(1 + \sum_{\ell'=1:\ell'\neq\ell_{jt-1}}^{L}\exp\{\breve{\alpha} - \breve{\beta}d_{\ell'\ell_{jt-1}}\})$, where $d_{\ell'\ell_{jt-1}}$ is the distance between the current location ℓ' and the new location ℓ_{jt-1} .

²⁴We assume for simplicity that the entrant offers its full set of grades since entering. Although in reality charters add grades over time until reaching their full grade coverage, the regulator considers expected profits for the full grade coverage when deciding on authorization. Also for simplicity we do not model capacity choice, although the model naturally precludes the entry of very small charters that would not be able to cover fixed costs.

²⁵The entrant type is a shock encompassing aspects of the entrant's financial condition that are observed to the regulator but not to the econometrician, such as the availability of revenue sources besides student reimbursement, and how its expected costs differ from similar charters.

If a new location becomes available, the charter moves and reports the move to the regulator. Relocations become public knowledge. In reality, the regulator is informed of the move in Spring t - 1, and the actual move usually takes place in Summer t - 1.

Step 3 (*Public and private schools*). Public and private schools make their entry, exit and relocation decisions, and these become public knowledge. In reality this step takes place in Spring t - 1 and the decisions become effective in Fall t.

Step 4 (*Households' school choice*). The set of operating schools in Fall *t* constitutes the market structure \mathbf{M}_t . This includes all incumbent public, private and charter schools that remain open in Fall *t*, and the new charters authorized in Spring t - 2 that start operating in Fall *t*. Demand shocks ξ_{jgt} of all the schools in \mathbf{M}_t are realized and become public knowledge. Thus, in Spring t - 1 households choose a school for Fall *t* based on the set of operating schools in *t* and their observed characteristics, including their demand shocks.

Step 5 (*Processing of entry applications*). The regulator decides whether to authorize the entry applications submitted in Step 1. If approved, a new charter starts operating in Fall t + 1. The regulator makes its decision based on market structure \mathbf{M}_{t}^{j} , since this augments \mathbf{M}_{t} with new charter j, as if j were to open in Fall t. The regulator learns the financial type \mathbf{v}_{jt}^{e} of each applicant. Applicant j is approved iff $\bar{\pi}_{jt}^{e} \left(d_{jt}^{e} = 1, \mathbf{M}_{t}^{j}; \theta^{d} \right) \geq \sigma_{v} \mathbf{v}_{jt0}^{e}$, where $\bar{\pi}_{jt}^{e} (\cdot, \cdot)$ is given by (19), and $\sigma_{v} \mathbf{v}_{jt0}^{e}$ is an entry threshold. Component \mathbf{v}_{jt0}^{e} follows an i.i.d. type I extreme value distribution. Applications are processed independently. Authorized charters carry out several activities, such as student and teacher recruiting and building renovations, during the remainder of the current game period and the beginning of the next one. We assume that all parties learn entrants' demand shocks ξ_{jgt+1} through these activities. In reality this step takes place in Spring t - 1.

Step 6 (*Closing of charter incumbents*). The regulator determines whether incumbent charters can continue operating. For public and charter schools, academic performance is measured as proficiency in the tests taken at the beginning of the current game period; test results become public information at the end of Step 4. Let \overline{q}_{jt} stand for charter *j*'s proficiency rate in the tests. Charter *j* must close by the end of *t* if either its financial mis-performance index $a^{\pi} + b^{\pi} \left[\sum_{g \in G_{jt}} N_{jgt} (R_{gt} - V) - F_{G_{jt}\ell} \right]$ or its proficiency mis-performance index $a^q + b^q \overline{q}_{jt}$ (adjusted for school tenure) exceed a certain threshold. In these indices, a^{π} and b^{π} are parameters related to charters' financial standing while a^q and b^q are related to academic performance. Hence, *j* is closed iff $\max \left\{ a^{\pi} + b^{\pi} \left[\sum_{g \in G_{jt}} N_{jgt} (R_{gt} - V) - F_{G_{jt}\ell} \right], a^q + b^q \overline{q}_{jt} + c^q e_{jt} \right\} + \varepsilon_{jt1} \ge \varepsilon_{jt0}$ (20) where e_{jt} is a closing eligibility variable, equal to 1 if the charter has operated for at least five years and 0 otherwise.²⁶ Shock ε_{it1} captures elements of the charter's performance

²⁶This dummy is included for empirical purposes, as closings due to academic reasons rarely happen

observed to the regulator (not to us), and ε_{jt0} is the threshold that, when surpassed, determines closing. Shocks follow i.i.d. type I extreme value distributions. Charters are evaluated independently. All closings become public knowledge. In reality closings are decided during Fall *t*, and take place at the end of school year *t*.

Solution of the game.

The solution of the game is a Perfect Bayesian Equilibrium. It requires consistent beliefs by agents and expected payoff maximizing behavior based on the beliefs.

Agents make choices only in steps 1 and 4 of the game. We analyze the equilibrium of the stage game backwards. In Step 4, households exhibit the equilibrium behavior and formation of beliefs that we described previously. In Step 1, the equilibrium strategy on the part of the applicant is to submit an application only when its non-pecuniary net benefit from running a charter school, *B*, is positive. The probability of a positive *B* is equal to $\gamma^{B_+} = 1 - F_B(0)$. An increase in γ^{B_+} raises the supply of prospective entrants. Such increase could be due to an influx of socially motivated individuals in the economy, or to an increase in social appreciation for charters' contribution. It could also be due to a reduction in the cost of the activities necessary for an entry application, such as preparing the application, locating facilities, developing a business and instructional plan, learning about successful charters, etc. For brevity we refer to an increase in γ^{B_+} as a reduction in entrants' application costs.

5 Data and Estimation

Estimation proceeds in three stages, in which we estimate demand-side parameters θ^d , supply-side parameters θ^s and proficiency rate parameters θ^q respectively. We describe the data and estimation below.

5.1 Data

Our data include 65 markets (13 grades times 5 years) and J^S =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. Recall that we observe the following school characteristics: type (public, charter, Catholic, other religious, private non-sectarian), location, grades covered, focus, student body composition by race and poverty status, tuition (for private schools) and proficiency rates (for public and charter schools). In the data some characteristics (such as student body composition and grades covered) change over time. Similarly, household choice sets change as well as some schools enter, exit or change grade coverage. Since we have tuition only for school year 2002, we impute the same value to all years. Lacking direct information on the number of children eligible for each grade, we estimate the market sizes M_{gt} as described in

before the school's fifth year.

Appendix A.2. Then, for each market we make ns=100 draws (each one corresponding to a hypothetical child) from the joint distribution of child race, poverty status, income and location.²⁷

5.2 Demand Estimation

To estimate θ^d we use Generalized Method of Moments (GMM) and match market shares at the school-grade-year level ("share moments"), student demographic composition at the school-year level ("demographic moments"), and average fraction of students attending charter schools, average distance traveled to public schools, and average distance traveled to charter schools at the neighborhood-year level ("neighborhood moments"). While typical BLP consists of share moments, we augment the GMM objective function with the other two sets of moments.

Let C_{kt} be the $\widetilde{C} \times 1$ vector of average values for neighborhood k in year t, with the following $\widetilde{C} = 3$ elements: (i) percent of children enrolled in charter schools, (ii) average travel distance for children enrolled in public schools, and (iii) average travel distance for children enrolled in charter schools. Let \overline{C}_{kt} denote this vector's observed counterpart.

Recall that X_{igt} denotes the observable variables that are either specific to household *i* or to its match with the schools (such as *i*'s distance to the schools). Denote by X_t the set that contains the following: the union of the X_{igt} sets over all households, market structure \mathbf{M}_t (which includes the charcteristics of all schools operating at *t*), and the set of schools' demand shocks Ξ_t . In other words, X_t is the set of all household and school characteristics at *t*. We assume that $E(\overline{D}_{jt}|X_t) = \widehat{D}_{jt}$, where \widehat{D}_{jt} is the set of consistent beliefs given by (17) and $E(\overline{C}_{kt}|X_t) = \widehat{\overline{C}}_{kt}$, where $\widehat{\overline{C}}_{kt}$ are expected values for neighborhood variables given the set of consistent beliefs. Observed values \overline{D}_{jt} and \overline{C}_{kt} are different from their expected values due to sampling (or measurement) error: $u_{jt}^D = \overline{D}_{jt} - \widehat{\overline{D}}_{jt}$ and $u_{kt}^C = \overline{C}_{kt} - \widehat{\overline{C}}_{kt}$. Following BLP and Nevo (2000, 2001), we assume that $\Delta \xi_{jgt}$ is mean-independent of the corresponding instruments: $E(\Delta \xi_{jgt}|Z_{jgt}^X) = 0$. In addition, we assume $E(u_{it}^D|Z_{it}^D) = 0$ and $E(u_{kt}^C|Z_{kt}^C) = 0$.

To implement the GMM estimator, we first calculate moments' predicted values. We abuse notation and use the symbol "~" for predicted values. Consider the *ns* draws for children eligible to attend grade *g* in year *t*. Predicted enrollment for (j,g,t) is $\hat{N}_{jgt} = \frac{M_{gt}}{ns} \sum_{i=1}^{ns} P_{ijgt} (y_{gt}, \overline{D}_{gt}, \xi_{gt}, p_{gt}, X_{igt}; \theta^d)$, where the enrollment probability $P_{ijgt}(\cdot)$

²⁷Given the distribution of households by location, demographic type and age for each year, we draw 100 children for each grade and year, 50 for each of the grade's two most frequent ages. We assume two ages per grade (for instance, ages 5 and 6 in kindergarten), and 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. The sample is probability-weighted, with the weights being equal to the measure of the household type and age in the corresponding year.

is given by (11) and we use \overline{D} to approximate $\widehat{\overline{D}}$ in the RHS of (11). Predicted enrollment share for (j, g, t) is

$$\widehat{S}_{jgt} = \frac{\widehat{N}_{jgt}}{M_{gt}} \tag{21}$$

and S_{jgt} denotes its observed counterpart. Predicted school characteristics are equal to $\widehat{\overline{D}}_{jt} = \frac{\sum_{g \in G_{jt}} \left(\frac{\hat{N}_{jgt}}{ns}\right) \sum_{i=1}^{ns} D_i P_{ijgt} \left(y_{gt}, \overline{D}_{gt}, \Xi_{gt}, p_{gt}, X_{igt}; \theta^d\right)}{\sum_{g \in G_{jt}} \hat{N}_{jgt}}$. Predicted neighborhood-level mo-

ments, $\widehat{\overline{C}}_{kt}$, are calculated similarly. We use these predicted values to estimate the shocks $\Delta \xi_{jgt}$, u_{jt}^D and u_{kt}^C .

To estimate the BLP model, researchers typically rely on a nested-fixed point algorithm. This finds the baseline utilities δ that equate predicted and observed market shares for each value of θ^d . Since this algorithm is slow and potentially inaccurate, we follow Dube et al (2012) and formulate our estimation as a mathematical programming with equilibrium constraints (MPEC). Our MPEC problem, more complex than Dube et al's given the inclusion of demographic and neighborhood moments, is as follows:

$$\min_{\Delta\xi, \theta^d} \begin{bmatrix} \lambda_X(\Delta\xi) \\ \lambda_D(\Delta\xi, \theta^d) \\ \lambda_C(\Delta\xi, \theta^d) \end{bmatrix}' \begin{bmatrix} V_X & O & O \\ O & V_D & O \\ O & O & V_C \end{bmatrix} \begin{bmatrix} \lambda_X(\Delta\xi) \\ \lambda_D(\Delta\xi, \theta^d) \\ \lambda_C(\Delta\xi, \theta^d) \end{bmatrix} \quad s.t. \ S = \hat{S}(\Delta\xi; \theta^d) \quad (22)$$

where λ_X , λ_D and λ_C are sample interactions of the shocks $\Delta \xi$, u^D and u^C with the corresponding instruments (see details in Appendix E.1); $\hat{S}(\cdot)$ is given by (21); and V_X , V_D and V_C are positive definite matrices. The MPEC algorithm simultaneously searches over values of $\Delta \xi$ (and hence δ) and θ^d ; given values for these, it calculates moments' predicted values. The constraints of the MPEC problem ensure that observed enrollment shares *S* match predicted shares \hat{S} .

Given the decomposition of the demand shock ξ_{jgt} , we include school-, gradeand time-fixed effects in the utility function. Since the school fixed effects capture both the value of time-invariant school characteristics, $y_j\beta$, and of school quality ξ_j in (9), we apply a minimum-distance procedure as in Nevo (2000, 2001) to estimate β and ξ_j separately (see Appendix E.1 for details). Finally, we use our estimates of $\Delta \xi_{jgt}$ for all schools and of ξ_j for all entrants to obtain the empirical counterparts of the distributions F_{ξ} and $F_{\Delta\xi}$.

5.3 Supply estimation

Supply-side parameters are $\theta^s = \{\gamma^{B_+}, \zeta, V, F, \sigma_v, \check{\alpha}, \check{\beta}, a^{\pi}, b^{\pi}, a^q, b^q, c^q\}$. In our application, the economy includes L = 39 locations (neighborhood clusters), Y = 5 focuses (Core curriculum, Arts, Language, Vocational, Other) and K = 5 grade spans (elementary, middle, high, elementary/middle, middle/high), for a total of E = 975 potential entrants per year. For each school year *t* we observe the schools operating in the

market. We also observe the following: a) new charter entries, authorized in t - 2 based on \mathbf{M}_{t-1} as described in the game's Step 4; b) charter closings; c) charter relocations.²⁸

Let C_t be the total number of charters operating in t, including incumbents from t-1 that remain open in t as well as new entrants. Let \tilde{C}_t be the number of incumbent charters that remain in the same location as in t-1. Let ℓ_{jt} be j's location in t, and let $\overline{\ell}_{jt}$ be its observed counterpart. Variable $d_{jt}^e \in \{0,1\}$ indicates whether there is a new entrant in entry point j in year t; variable $d_{jt}^x \in \{0,1\}$ indicates whether incumbent j closes at the end of t-1 and is hence closed in t; and variables \overline{d}_{jt}^e and \overline{d}_{jt}^x are the observed counterparts of d_{jt}^e and d_{jt}^x respectively. The likelihood function is:²⁹

$$\tilde{L}(\boldsymbol{\theta}^{s}) = \prod_{t=2}^{T} \left\{ \prod_{j=1}^{E} \Pr\left(d_{jt}^{e} = \overline{d}_{jt}^{e} | \mathbf{M}_{t-1}\right) \prod_{j=1}^{\tilde{C}_{t-1}} \Pr\left(d_{jt}^{x} = \overline{d}_{jt}^{x}\right) \prod_{j=1:\ \overline{d}_{jt}^{x}=0}^{C_{t-1}} \Pr\left(\ell_{jt} = \overline{\ell}_{jt} | \overline{\ell}_{jt-1}\right) \right\}$$

where the first product inside $L(\cdot)$ stands for new entries in school year t, the second product corresponds to charter closings, and the third product corresponds to relocations.

In the likelihood function the probabilities for new charter entries in school year *t* are:

$$\Pr\left(d_{jt}^{e} = \overline{d}_{jt}^{e} \mid \mathbf{M}_{t-1}\right) = \begin{cases} \gamma^{B_{+}} \frac{\exp\{E_{v}\overline{\pi}_{jt-1}^{e}(d_{jt-1}^{e} = 1, \mathbf{M}_{t-1}^{j}; \theta^{d})/\sigma_{v}\}}{1 + \exp\{E_{v}\overline{\pi}_{jt-1}^{e}(d_{jt-1}^{e} = 1, \mathbf{M}_{t-1}^{j}; \theta^{d})/\sigma_{v}\}} & \text{if } \overline{d}_{jt}^{e} = 1 \\ 1 - \gamma^{B_{+}} \frac{\exp\{E_{v}\overline{\pi}_{jt-1}^{e}(d_{jt-1}^{e} = 1, \mathbf{M}_{t-1}^{j}; \theta^{d})/\sigma_{v}\}}{1 + \exp\{E_{v}\overline{\pi}_{jt-1}^{e}(d_{jt-1}^{e} = 1, \mathbf{M}_{t-1}^{j}; \theta^{d})/\sigma_{v}\}} & \text{if } \overline{d}_{jt}^{e} = 0 \end{cases}$$

where \mathbf{M}_{t-1}^{J} is the market structure of year t-1 adjusted to include entrant j. Expected profit $E_{v}\bar{\pi}_{jt-1}^{e}$ is given by formula (19) and is calculated using the estimates of θ^{d} , F_{ξ} and $F_{\Delta\xi}$ from the demand-side estimation.

The probabilities for charter closings are:

$$\Pr\left(d_{jt}^{x} = \overline{d}_{jt}^{x}\right) = \begin{cases} \frac{\exp\{a^{q} + b^{q}\overline{q}_{jt-1} + c^{q}e_{jt}\}}{1 + \exp\{a^{q} + b^{q}\overline{q}_{jt-1} + c^{q}e_{jt}\}} & \text{if } \overline{d}_{jt}^{x} = 1\\ \frac{1}{1 + \exp\{a^{q} + b^{q}\overline{q}_{jt-1} + c^{q}e_{jt}\}} & \text{if } \overline{d}_{jt}^{x} = 0 \end{cases}$$

where \overline{q}_{jt-1} is the proficiency rate of charter *j* in year t-1 and e_{jt} is a closing eligibility variable, equal to 1 if the charter has completed at least five years of operation and 0 otherwise.

The probabilities for charter relocations are given by:

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

²⁸The closing year is the first year that the school is not in the data. Relocation year is the first year that the school appears in its new location.

²⁹Note that the likelihood for 2003 cannot be calculated as we lack data on market structure, charter locations and charter proficiency in 2002.

Infrequent entry and exit in our sample complicate the estimation of θ^s . Nonetheless, we can calibrate some parameters. According to Buckley and Schneider (2007), there were 71 charter entry applications between Fall 2004 and Fall 2007, which results in an estimated charter application probability, $\widehat{\gamma^{B_+}}$, equal to 0.018 (=71 / (975 entry points * 4 years)).³⁰

In order to calibrate varible and fixed costs, V and F respectively, we use budget data for school year 2009-2010, which is the closest to our sample period with publicly available financial data. We use data for the charters in our sample that were still open in 2009, including the campuses they had added by then. We run the following regression:

 $\widehat{TC} = F_0 + V_e \cdot Enr + F_W \cdot W + F_{SE} \cdot SE + F_H \cdot H + F_M \cdot M$ (23) where *TC* is school total cost; *Enr* is enrollment; *W* and *SE* indicate whether the school is located in the West or Southeast respectively; *H* is a high school indicator, and *M* is an indicator for whether the school offers mixed levels (such as middle/high). The estimate of V_e is our calibrated value for *V*, and we use the appropriate combination of F_0 , F_W , F_{SE} , F_H and F_M estimates to calibrate *F* by charter location and grade span. These estimates, along with predicted enrollment, enable us to impute expected costs to each entrant. We impute expected revenues based on actual per-student reimbursements and predicted enrollment, and obtain expected profits per entrant. We then use Maximum Likelihood Estimation (MLE) to estimate the remaining parameters $\{\zeta, \sigma_V, \check{\alpha}, \check{\beta}, a^q, b^q, c^q\}$.³¹

5.4 Proficiency Rate Estimation, and Summary

According to (16), school j's observed proficiency rate \overline{q}_{jt} is given by:

$$\bar{q}_{jt} = y_j \alpha^q + \overline{D}_{jt} \phi^q + [y_j \otimes \overline{D}_{jt}] \omega^q + \xi_j^q + \xi_t^q + \Delta \xi_{jt}^q + v_{jt}^q$$
(24)

where the error term is the addition of the a school-year unobserved shock on proficiency $\Delta \xi_{jt}^q$ and sampling or measurement error v_{jt}^q . Since values of $\Delta \xi_{jt}^q$ may be correlated with values of $\Delta \xi_{jgt}$ for school j, \overline{D}_{jt} may be correlated with $\Delta \xi_{jt}^q$, thus requiring the use of instrumental variables.

To estimate the coefficient on time-invariant school characteristics α^q separately from the school fixed effects ξ_j^q , we use a similar procedure to that used in demandside estimation. We first run a 2SLS regression of passing rate on campus and year fixed effects, \overline{D}_{jt} and $[y_j \otimes \overline{D}_{jt}]$. Then we regress the campus fixed effects estimates on time-invariant school characteristics; the residuals from this regression are our estimates of ξ_j^q , or "school productivity". We use our estimates of ξ_j^q for entrants to obtain the empirical distribution of school productivity.

³⁰In practice we use a different value of γ^{B_+} for each grade level in order to improve the performance of our Maximum Likelihood estimator.

³¹We cannot estimate a^{π} and b^{π} as the sample lacks closings due to financial reasons.

The estimation of proficiency rate parameters is straightforward, and so is the Maximum Likelihood estimation of supply side parameters once expected enrollments for potential entrants have been computed.³² However, GMM estimation of the demandside parameters is computationally involved as it requires solving the large-scale constrained optimization problem in (22). This problem has 8,436 unknowns – 324 parameters in θ^d (including 281 campus fixed effects) and 8,112 elements in the $\Delta\xi$ vector – and 8,112 equality constraints. Through a creative use of solvers, we avoid coding first- or second-order derivatives and attain great speed, despite our problems' complicating features relative to the typical BLP problem. See Appendix E.2 for computational details.

5.5 Instruments

For the identification of the demand-side parameters, the main concern is the endogeneity of peer characteristics in (8). Since families observe $\Delta \xi_{jgt}$ when making enrollment decisions, \overline{D}_{jt} is likely correlated with $\Delta \xi_{jgt}$. Thus, we instrument for \overline{D}_{jt} using the following variables Z_{jgt}^X for school *j*'s Census tract: number of public, charter and private schools that offer grade *g* in year *t*, and local demographics as of year 2000. Local demographics include percent of children of each race and the relevant age for the corresponding grade span (elementary, middle or high school), percent of low-income children, average family income, average house value, percent of owner-occupied housing units, average number of children per family, percent of families in each income bracket, and ward indicators. We also include interactions of local demographics as of year 2000 with charter and private indicators; interactions of local demographics as of year 2000 with grade span indicators; campus fixed effects; grade fixed effects, and year fixed effects.

The number of public, charter and private schools constitute a relevant instrument because a school's student body characteristics are expected to be correlated with the availability of other, substitute schools in the local neighborhood. It is a valid instrument because $\Delta \xi_{jgt}$ is realized in Step 4 of the entry-exit-relocation game, *after* all schools have made the entry, exit or relocation decisions that determine the number of schools of each type by Census tract. Note that this instrument varies at the school, grade, and year level. Local demographics as of year 2000 constitute a relevant instrument as schools draw students from their local neighborhood, and we expect local

³²In order to calculate entrants' expected profits for the entry probabilities in the likelihood function, we first compute expected enrollment in (18) for each entry point and year given our estimates of θ^d . Recall our assumption that the regulator observes the demand shocks ξ_{jgt} for all schools in the market at *t* but not for the potential entrants. Hence, in order to calculate entrants' expected enrollments we integrate over the distribution of ξ_{jgt} for potential entrants by using Monte Carlo simulations based on our estimates of F_{ξ} and $F_{\Delta\xi}$. Although this calculation takes multiple days given our number of entry points, for a given set of demand estimates it takes place only once, before the likelihood estimation.

demographics to be relatively stable between year 2000 and our sample period. It is a valid instrument because $\Delta \xi_{jgt}$ is realized after year 2000. For a given school, local demographics vary over time for schools that move. In addition, for schools that span multiple grade levels, local percent of children of each race and poverty status varies by grade span, and varies within school over time if grade span changes.

The instruments for the sampling error in school-year student demographics, Z_{jt}^D , are the following: school type, focus, and level; interactions of school type with ward; interactions of school type with level; interactions of tuition with private school type (Catholic, Other Religious, Non-Sectarian); and year indicators.

The instruments for sampling error in neighborhood-level variables, Z_{kt}^C , are the following: neighborhood-level number of public and charter schools in the corresponding year, and the following cluster-level demographics as of year 2000: average family income, racial and poverty composition of school-age children, percent of children of elementary and middle school age, and ward indicators.

As with the demand-side parameters, the main concern for the identification of the proficiency rate parameters is the endogeneity of peer characteristics in (24). Since our proficiency data is at school-year level, we use the same instruments as for the demand-side estimation (which are at the school-grade-year level), but averaged at the school level (weighting each grade by enrollment).

5.6 Identification

On the demand side, variation in school type, focus, grade span, location, tuition and peer characteristics vis-a-vis variation in household demographics and location helps identify preference parameters. A sufficient condition for identification is that the matrix of derivatives of sample moments with respect to the parameters have full column rank. Evaluated at our parameter estimates, this matrix indeed has full column rank. Although most parameters affect the predicted value of multiple moments, parameters (α^{δ} , β^{δ} , φ^{δ}) in the baseline utility component mainly affect predicted enrollment shares, and parameters (ω^{μ} , α^{μ} , β^{μ} , γ^{μ}) in the student-specific utility component mainly affect predicted demographic and neighborhood moments. Proficiency rate parameters in (24) are identified by variation in school type, focus, grade span and peer characteristics.

On the supply side, conditional on the calibrated charter application probability γ^{B_+} , variable costs *V* and fixed cost parameters *F*, parameters' main effects on model predictions are as follows. Increasing entry fee ζ lowers overall predicted entry, and increasing the standard deviation of applicants' financial types σ_v changes the predicted distribution of entry across entry points, making it less sensitive to predicted enrollment and costs. Increasing relocation intensity $\check{\alpha}$ raises predicted relocations' frequency, and increasing relocation sensitivity to distance $\check{\beta}$ lowers average predicted distance, respectively. An increase in closing intensity a^q , in closing sensitivity to math proficiency

 b^q , or in closing sensitivity to eligibility c^q raises the number of predicted closings, closings' sensitivity to proficiency rates, and closings' likelihood after the first five years, respectively.

6 Estimation Results

6.1 Demand Side

Table 8 presents our preference parameter estimates. Most of them are statistically significant and of the expected sign. The "baseline utility" column displays the parameter estimates for (9), and represents the preferences of black, low-income households. Remaining columns present parameter estimates for (10), with differences in the preferences of white, Hispanic and non-poor households with respect to those of black, lowincome households. We interpret the estimates in terms of the choice probability difference they would induce between two schools that only differ in a given characteristic. In the empirical application, time-invariant school characteristics include school type, focus, tuition, grade span, interactions between school type and grade span, an indicator for multi-campus charters, and ward.³³ In what follows, "middle and/or high schools" (MHS) refers to schools offering middle, middle/high, high, elementary/middle/high levels, and "non-MHS" to schools offering the remaining levels.

Our estimates show heterogeneity in school type preferences across races and poverty status, and by school level. Among non-MHS, most households prefer public over charter schools yet not with the same intensity. Non-poor students are less likely to choose charters than poor students. Low-income blacks are less likely to choose a single-campus charter than a public school, but slightly more likely to choose a multicampus charter than a public school. Hispanics have a stronger preference for charters than blacks. Although non-whites are more likely to choose a public than a Catholic school, Hispanics have a stronger Catholic school preference than blacks. Whites are more likely to choose a Catholic over a public school. In addition, whites have a stronger preference than non-whites for private MHS. Our estimated preferences match school choices well (see Appendix Table 3), overall and by grade span.

Estimates of focus preferences show that some households prefer non-Core over Core curricula. According to these estimates, households prefer Arts over Core, and non-whites prefer Core over Vocational. Whites and blacks seem indifferent between Language and Core, yet Hispanics prefer Core over Language. While the latter seems inconsistent with Hispanics' relatively high attendance of Language-focused schools

³³Recall that our estimates of school qualities ξ_j are obtained via Minimum Distance Estimation, by regressing campus fixed effects on time-invariant school characteristics. We have included all such available characteristics to avoid biasing the school quality estimates, particularly since these are used to estimate the empirical distribution of new entrants' quality, F_{ξ} .
Variable	Baseline	Interactions with Household			
· uninote	Utility	Characteristics			
	c unity	White	Hispanic	Non-Poor	
Constant	3.536*				
2.2	(0.357)				
Charter	-0.625*	-0.116	0.534*	-0.382*	
	(0.090)	(0.248)	(0.149)	(0.084)	
Catholic	-1.041*	1.374*	0.636*		
	(0.152)	(0.221)	(0.150)		
Private Other Religious	-0.931*	0.552*			
	(0.392)	(0.245)			
Private Nonsectarian	-1.604*	1.228*			
	(0.436)	(0.299)			
Language	-0.091	0.412	-0.967*		
	(0.527)	(0.422)	(0.298)		
Arts	0.328*	0.232			
	(0.153)	(0.481)		-	
Vocational	-0.684*	0.75			
	(0.150)	(0.961)			
Other focus	-0.424*	0.693*	-1.112*	-0.003	
	(0.161)	(0.258)	(0.250)	(0.137)	
Tuition (in \$1,000)	-0.246*				
	(0.092)				
Middle / high school	1.417*				
	(0.197)				
Charter * middle / high school	-0.633*				
5	(0.122)				
Charter * multicampus	0.672*				
	(0.114)				
Private * middle / high school	-1.204*	0.488			
	(0.165)	(0.339)			
Fraction White	7.377*	6.038*	3.136*	-	
	(2.635)	(0.449)	(0.272)		
Fraction Hispanic	-3.541**	4.947*	9.483*		
The first this paint	(2.018)	(1.066)	(0.760)		
Fraction Non-Poor	-5.866*	(11000)	(01/00)	4.474*	
	(1.615)			(0.312)	
Distance (miles)	-1.114*			(0.012)	
Distance (miles)	(0.034)				
Distance*charter (miles)	1.085*				
Distance charter (miles)	(0.066)				
Distance*nrivate (miles)	1 229*			· · · · · · · · · · · · · · · · · · ·	
Distance private (miles)	(0.061)				

Table 8: Parameters Estimates: Utility Function

Notes: Based on 8,112 observations for share moments; 1,269 observations for demographic moments and 153 observations for neighborhood moments. 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 error in Italics were obtained through Minimum-Distance Estimation (MDE) of campus fixed effects on time-invariant school characteristics, including dummies identifying each school's last ward in the sample. Number of observations in the MDE regression = 281 campuses.

(see Table 6), below we describe that Hispanics exhibit a strong same-race preference, and might choose Language schools because these attract other Hispanics and not necessarily because of the language curriculum. Blacks and Hispanics prefer Core over Other, yet the reverse is true for whites. As Appendix Table 4 shows, our focus preference estimates capture students' focus choices.

Coefficients on ward dummies (see Appendix Table 2) indicate that parents place a high value on characteristics of the school's neighborhood. Distance coefficients indicate that travel disutility is high when attending a public school but not otherwise. Since approximately 50 percent of children in public schools attend their assigned neighborhood school, we expect the estimated travel disutility to public schools to be upward biased in absolute value. Our distance coefficients reflect the difference in marginal cost of transportation due to the use of different transportation modes – mostly walking in the case of public schools, and not walking (driving or using public transportation) in the case of charter and private schools. According to our estimates, the marginal disutility of traveling is higher when walking than when driving or taking public transportation, possibly because traveling an extra mile on foot generally takes longer than by car or public transportation, and may be less safe (see Appendix F for further details). Note, also, that the coefficient on tuition is negative and significant. It implies that a \$1000decline in private school tuition would raise the relative odds of attending the school by 28 percent (= (exp(-0.246 * (-1)) - 1) *100).³⁴

Students of all races prefer to attend a school with a greater fraction of white students. For instance, a school's 10-percentage point increase in percent white students raises the relative odds of attending the school by 109, 282 and 186 percent for black, white and Hispanic students respectively. Whites, who have the strongest preference for other white students, are willing to pay approximately \$5,500 (= (7.377 + 6.038) * 0.10 * 1000/0.2456) for an extra 10 percentage point white students. Further, whites have the highest ability to pay for such a school. Hispanics have strong same-race preferences as well and are willing to pay approximately \$2,400 for an extra 10 percentage points Hispanic. These preferences are consistent with the fact that students are quite segregated by race across schools.³⁵

³⁴Throughout, the "relative odds" of making a particular choice is the odds ratio. In this case, the relative odds is the ratio between the odds of attending a private school when the tuition is \$1,000 lower divided by the odds of attending a private school at its original tuition. "Odds", in turn, is the ratio between the probability of making a choice and the probability of not making it. In this case, the odds of choosing the private school are equal to the probability of choosing it divided by the probability of not choosing it. When the probability of making a particular choice is small, the "relative odds" is approximately equal to the ratio between making it.

³⁵In our data, while 74, 17 and 9 percent of the students are black, white, and Hispanic 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, and the average Hispanic student attends a school that is 37 percent Hispanic. Focusing on public and charter schools, Filardo et al (2008) finds similar racial segregation across schools.

	All Excep	Wards 7 and 8		
School Level	Public	Charter	Public	Charter
MHS=0	0.116	0.395	0.150	0.455
MHS=1	-0.149	0.229	-0.861	0.453

 Table 9: Average Public v. Charter School Quality

Note: school quality is the residual of the minimum-distance estimation regression of campus fixed effects on timeinvariant school characteristics. MHS= 1 if school level is middle, middle/high, high, or elementary/middle/high. Ward corresponds to the school's location. Statistics are weighted by enrollment in the last year of the school in the sample.

Recall that our school quality estimates capture unmeasured school characteristics such as school culture, proximity to transportation, and facilities' characteristics.³⁶ These estimates reflect characteristics that affect utility directly as well as indirectly through expected achievement given that we cannot disentangle the two channels, as explained in Section 4. Thus, in Table 9 we compare average school quality in public and charter schools. Recall that Ward 3, located in the West, is the most advantaged in the city. Outside Ward 3, the average quality difference makes a family 32 and 46 percent more likely to choose a charter school for non-MHS and MHS grades, respectively. In Wards 7 and 8, the difference makes the family 36 and 272 percent more likely to choose the average charter for non-MHS and MHS grades, respectively. Note that the average quality premium commanded by charters relative to public schools is particularly large for MHS grades. Outside Ward 3, a family would be willing to pay about \$1,500 for such premium, an amount that would rise to about \$5,300 in Wards 7 and 8.³⁷

6.2 Supply Side

Table 10 shows estimates for (23) based on 2009 data, used to calibrate variable and fixed costs. To place the estimates in perspective, note that in 2009 the average perstudent reimbursement is approximately equal to \$10,000. According to the estimates, variable costs per student are approximately equal to \$7,300, and 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 South-east (due to buildings' poor condition and high security and insurance costs) than in the

³⁶School quality estimates also capture characteristics of the school's local surroundings below the ward level, since we control for ward in the utility function.

³⁷School capacity constraints might bias the parameter estimates of the utility function. Consider, for instance, the estimated negative coefficient on the charter indicator. If neither public nor charter schools faced capacity constraints, this negative coefficient would indicate that parents prefer public over charter schools, all else equal. Yet in the presence of charter capacity constraints, the negative coefficient could also indicate lack of space in charters even if families preferred them over public schools. Distinguishing between these possibilities requires capacity and excess demand data for all schools, not just charters. Unfortunately these data are not available. Nonetheless, we expect capacity to have a negligible bias on our estimates given our assessment of excess demand for public and charter schools based on data from Filardo et al (2008). Detailed calculations are available upon request.

Independent Variable	Estimates
Enrollment	7.332
	(0.232)
West (=1 if school is in West region)	423.0
	(180.0)
Southeast (=1 if school is in Southeast region)	255.3
	(82.77)
High (=1 if school serves grades 9-12)	245.3
	(122.8)
Mixed levels (=1 if school serves mixed levels)	88.90
	(83.71)
Constant	-49.72
	(88.66)
Number of observations	64
R ²	0.950
s.e. of regression	296.78
Mean of dependent variable	2526

Table 10: Charter School Costs

Note: Unit of observation: charter school campus. Dependent variable: total costs at the campus level, expressed in \$1,000. OLS; standard errors in parentheses. Data: charter schools budgets for school year 2009-2010 from www.dcpcsb.org. Before running the regression, the dependent variable was multiplied by (0.82)*(7/10) to incorporate the following: 1) charter reimbursements account for about 82 percent of charter revenues (which also include sources not modeled in this paper, such as federal grants for specific programs); 2) charter average reimbursements in 2003 and 2009 were approximately equal to \$7,000 and \$10,000, respectively.

Northeast. These estimates are consistent with the fact that most entry has taken place in the Northeast and has served elementary or middle school students.³⁸

Table 11 presents the MLE estimates. As Appendix Table 5 shows, our estimates capture observed entry patterns. They also match the number of relocations and the distribution of relocation distance (see Appendix Figure 2). The estimated entry fee, equal to \$36,000, captures set-up costs such as building renovations; fees from legal, accounting and real estate services; cost of student and teacher recruiting, etc. The estimate is reasonable, as it is of the same order of magnitude as charters' average and median profits (equal to \$21,000 and \$34,000 respectively in the 2009 financial data). Intuitively, if the entry fee were much higher, charters would have incurred a loss when entering the market; forecasting this loss, the regulator would not have authorized their entry. The 95 percent confidence interval for the estimate is wide, reflecting the infrequent entry, limited cost data and wide variation in actual set-up costs (related, for instance, to variation in initial facilities expenses).

The estimated standard deviation of profits σ_v is approximately equal to \$295,000, which is of the same order of magnitude as the standard deviation of observed charters'

³⁸We also learned from members of the DC charter school community that while some early charter entrants opened high schools, they quickly found that students were not ready for high school-level work. Thus, subsequent charter entrants decide to start with lower grades, perhaps expand to upper grades later.

Variable	Coefficient
Entry fee (ζ)	36.00
(in \$1,000)	(123.0)
Std. dev. of profits (σ_v)	294.8**
(in \$1,000)	(174.7)
Relocation intensity parameter ($\check{\alpha}$)	-4.292*
	(0.453)
Relocation sensitivity to distance $(\tilde{\beta})$	3.182*
(distance in miles)	(1.109)
Closing intensity parameter (a^q)	1.405
	(1.793)
Closing sensitivity to math proficiency (bq)	-0.294*
(proficiency between 0 and 100)	(0.114)
Closing sensitivity to eligibility (c^q)	3.390*
	(1.667)
Log-Likelihood	-310.8

Table 11: Parameter Estimates: Supply Side

Notes: Maximum Likelihood Estimates based on 3,900 observations for entry probabilities, 169 observations for closing probabilities and 165 observations for relocation probabilities.

profits (equal to \$165,000). The estimate indicates potential entrants' heterogeneity in financial aspects observed by the regulator but not by us, such as actual costs, business plan quality and additional revenue sources. The estimates for $\check{\alpha}$ and $\check{\beta}$ indicate that schools are averse to moving and seek close destinations when moving. Estimates for b^q and c^q indicate that charters are more likely to be closed if their academic performance is low, particularly if they have been open for more than five years.

6.3 Academic Proficiency

Table 12 presents estimates of the passing rate function for math. Since we have at most five annual observations per school, these estimates should be taken with much caution. 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 lower in MHS than in non-MHS. When comparing a single-campus charter with a public school, the relative odds of passing are 79 percent lower for the charter at non-MHS but 34 percent higher at MHS. The relative odds of passing are 53 percent lower for multi-campus charters than for public schools at non-MHS, but 205 percent higher at MHS.³⁹ Schools offering Other and Arts raise the relative odds of passing relative to those offering Core. Coefficients on percent white and non-poor students are not significantly different from zero.

Recall that our school productivity estimates capture unmeasured school characteristics affecting proficiency, such as leadership and culture, instructional style, teacher recruiting practices, and length of school day and year. As Table 13 shows, outside Ward 3 average productivity in charters is higher than in public schools for at the elementary,

³⁹This "middle school advantage" in math is consistent with Betts and Tang (2011), Clark et al (2011) and Dobbie and Fryer (2013).

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*
2010 - 20	(0.053)
Percent White	-0.002
	(0.015)
Percent Hispanic	0.009*
and S. Handeley Constant of Contractions	(0.004)
Percent Non-Poor	0.007
	(0.009)
Mean of Dependent Vble.	-0.340
Mean of Passing Rate (%)	42.29
Std. Error of Regression	0.574
Pseudo-R ²	0.810

Table 12: Parameters Estimates: Math Proficiency Rate

Notes: Based on 871 school-year observations corresponding to schools with at least 2 years of data. Passing rate is expressed between 0 and 100. 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). Pseudo-R² equal to the squared correlation between observed and predicted values of the dependent variable.

elementary/middle and middle school levels, with a particularly large premium in the last two. Furthermore, in wards 7 and 8 charters have higher productivity at all levels.

Taken together, the data shown in Section 3 and the parameter estimates discussed in this section shed light on the observed patterns of charter entry in the city. Recall that poor, non-white students reside mostly in the Northeast and Southeast, where public schools have their lowest proficiency, school quality and school productivity. Further, our estimates show that poor, non-white students have the strongest preference for charters, and that while many students have a preference for specialized curricula, public and private schools offer little curricular variety. Poor, non-white students have fewer

 Table 13: Public v. Charter School Productivity

	All Wards I	Except Ward 3	Ward 3 Wards	
School Level	Public	Charter	Public	Charter
Elementary	-0.074	0.270	-0.446	0.084
Elementary/Middle	-0.022	0.887	-0.547	1.361
Middle	-0.011	0.614	-0.533	0.078
Middle/High and High	-0.322	-0.653	-0.878	-0.618

Note: school productivity is the residual of the minimum-distance estimation regression of campus fixed effects on time-invariant school characteristics. Statistics weighted by Fall 2007 enrollment.

school options than their more advantaged counterparts at all grade levels, but particularly at the middle and high school level. This combination of household preferences, characteristics and choice sets, along with the geographic distribution of school options, quality and productivity helps explain why most charter entry has taken place in the Northeast and Southeast, while offering curricular variety. It does not explain, however, the lack of further entry in the areas of greatest need, namely at the high school level and in the Southeast. Our supply side estimates provide this explanation, based on the fact that fixed costs are highest in those areas.

7 Policy Analysis and Counterfactuals

In this section we quantify the social value of charter schools and analyze counterfactual policies. "Baseline" denotes the Fall 2007 benchmark equilibrium, calculated as follows. Starting from the set of actual operating schools in Fall 2007 *except* for actual entrants, we generate 1,000 market structures through Monte Carlo simulation of potential entrants and steps of the stage game. For each simulated entrant we draw demand shocks ξ_{jgt} , and productivity shocks ξ_j^q and $\Delta \xi_{jt}^q$, and compute the predicted equilibrium following the steps of the stage game. Thus, each predicted equilibrium reflects the sorting, proficiency, school openings and openings associated with its market structure.⁴⁰ We average over the 1,000 simulated equilibria to obtain the baseline equilibrium. We calculate the equilibrium for each counterfactual similarly.

7.1 Baseline

Table 14's column 1 reports the baseline. On average, 9.1 new charters enter the market and capture 3.3 percent of total K-12 enrollment. These predictions are consistent with the observed annual average number of entries in 2004-2007 (equal to 8.25). Projected to Fall 2013, the predictions are consistent with the observed number of regular charters (equal to 93 according to www.dcpcsb.org) and charter market share (equal to 35 percent) in Fall 2013, as explained in Appendix G. The model matches the actual distribution of entrants by region and focus. It predicts almost no public or private closings, since such closings were mostly idiosyncratic during our sample period, and predicts the closing of three charters. This predicted number of closings (equal to about a third of the predicted number of openings) is consistent with the fact that about a third of the charter schools that were open in 2007 were closed in the following years. The model also replicates observed market share by school type, and fraction of students not enrolled in

⁴⁰We allow for a response on the part of public and private schools when computing baseline and counterfactual equilibria. We assume that in Step 3 of the stage game (Spring of calendar year 2007), public and private schools close if their predicted enrollment (computed to take into account entry of approved charters in Fall 2007) falls below 20 percent of their lowest enrollment during the sample period. With this threshold choice we approximately match the sample closing rate for non-charter schools.

	Baseline (1)	No Charters (2)	Funding Increase (3)	Approve All (4)	Lower App. Costs (5)	Close Public (6)
Charter Entry						
Number of charter entrants	9.08		11.88	17.72	18.04	9.08
Charter entrants by region						
Fraction entering in Northeast	0.53		0.48	0.41	0.53	0.53
Fraction entering in Southeast	0.29		0.31	0.31	0.29	0.29
Fraction entering in West	0.18		0.20	0.28	0.18	0.18
Non-Charter Closings						
Number of public school closings	0.003		0.003	0.003	0.005	48.981
Number of private school closings	0		0.00	0.00	0.00	0.00
Charter Closings	3.18		2.99	3.47	3.47	3.02
Market Shares						
Fraction of students in public schools	0.555	0.764	0.549	0.541	0.537	0.493
Fraction of students in charters	0.254	0.000	0.261	0.271	0.276	0.298
Fraction in incumbent charters	0.220		0.217	0.214	0.211	0.259
Fraction in new charters	0.033		0.044	0.057	0.065	0.039
Fraction of students in private schools	0.192	0.236	0.190	0.188	0.187	0.208
Fraction in Catholic schools	0.101	0.118	0.100	0.099	0.099	0.113
Fraction of students not enrolled in school	0.048	0.068	0.047	0.046	0.045	0.054

 Table 14: Equilibrium in Baseline and Counterfactuals

Note: Each column reports average over 1,000 draws of (ξ, ξ^q) .

school.

In addition, the model replicates the observed distribution of proficiency, school quality and productivity (see Appendix Table 6). As predicted by the model, on average charter entrants have lower quality, productivity and proficiency than charter incumbents,⁴¹ yet they have higher quality than public schools outside Ward 3 and in the Southeast, and higher productivity in the Southeast.

For each student we construct a proficiency index equal to the weighted average predicted proficiency of the schools attended by the student; each school is weighted by the student's corresponding choice probability. The first row of Table 15 shows the percent of students in each (race, poverty status) demographic group, and the "Baseline" panel shows average proficiency index per student group and grade span. The index is lower for blacks than non-blacks and for poor than non-poor students, and shows a large gap between white and non-white students.

For each student *i* we calculate the willigness to pay for its choice set relative to the outside option (or welfare, for brevity) as $W_i = \ln\{1 + \sum_{k=1}^{J_{igt}} \exp(\delta_{kgt} + \mu_{ikgt})\}/\varphi$ (Train 2002). Note that *i*'s welfare depends on the number of school options J_{igt} as well as their utility (up to the idiosyncratic shock), $\delta_{kgt} + \mu_{ikgt}$, and is expressed in monetary terms through division by φ .

The "Baseline" panel of Table 16 shows average welfare for each demographic group. Welfare varies substantially depending on student race, poverty status and grade

⁴¹The reason is that charter incumbents include recent entrants (entering in 2003-2007) as well as early entrants (entering before 2003, and from whose distribution we draw the set of entrants' ξ and ξ^q). Incumbents that entered early are the survivors among all early entrants. Hence, their estimated school quality and productivity surpasses that of the average entrant, as expected from Step 6 of the stage game.

		Poor Black	Poor Hisp.	Poor White	Non- poor Black	Non- poor Hisp.	Non- poor White
Percent of Stu	dents	50.5	4.80	1.70	23.00	5.00	15.40
	Elementary	33.68	45.48	64.60	43.03	53.31	78.17
Baseline	Middle	35.11	41.60	57.32	41.35	53.32	71.91
	High	30.29	47.61	53.15	41.61	41.75	60.02
	Elementary	-1.37	2.08	-0.46	0.40	1.13	-0.18
No Charters	Middle	-6.35	-1.08	-2.47	-3.85	-1.94	-1.39
	High	-5.29	-0.09	2.02	0.23	0.12	0.20

 Table 15: Average Proficiency Index by Student Group and Grade Level

Note: "Baseline" shows average proficiency index for students of each demographic group and grade level (in percent). "No Charters" shows the difference in average proficiency index between Baseline and No Charters (in percentage points). "Elementary" refers to K-6 grades; "Middle" to grades 7 and 8, and "High" to 9-12 grades.

		Poor Black	Poor Hisp.	Poor White	Non-Poor Black	Non-Poor Hisp.	Non-Poor White
	Elementary	\$13,627	\$27,994	\$26,282	\$19,140	\$33,959	\$41,132
Baseline	Middle	\$11,625	\$24,471	\$17,146	\$15,412	\$28,338	\$33,364
	High	\$11,063	\$23,717	\$26,122	\$17,824	\$30,160	\$44,199
	Elementary	(\$1,120)	(\$905)	(\$965)	(\$899)	(\$367)	(\$229)
No Charters	Middle	(\$1,822)	(\$1,740)	(\$1,435)	(\$1,928)	(\$1,125)	(\$656)
	High	(\$1,390)	(\$6)	(\$658)	(\$458)	(\$66)	(\$58)

Table 16: Average Welfare and Welfare Gain by Student Group and Grade Level

Note: "Baseline" shows the average welfare for students of each demographic group and grade level. "No Charters" shows average compensating variation from the counterfactual for student each demographic group and grade level. (negative values are in parentheses). "Elementary" refers to K-6 grades; "Middle" to grades 7 and 8, and "High" to 9-12 grades.

span. On average, black and poor students attain lower welfare than others because they have access to fewer (particularly private) school options. They also tend to live far from public schools with a high percent of white students or of high quality. Hispanics attain greater welfare than blacks because on average they live closer to desirable public schools, enjoy strong same-race peer effects, and value non-public schools more than blacks. Whites, in turn, have higher welfare than non-whites because they have access to more school options and live closer to desirable ones. They also enjoy strong same-race peer effects and derive substantial utility from attending private schools, particularly at the MHS level. Average welfare is lower for students in MHS than non-MHS, mostly because of the lower number of options.

Table 17 presents a cost-benefit analysis of school options for the economy under multiple scenarios including the baseline. Column 1 presents total willingness to pay for schools, or total social benefits relative to the outside option (equal to the addition of W_i over all households). Column 2 presents total educational costs assuming that public school per-student cost is equal to charter reimbursement, and that private school per-student cost is equal to tuition. Costs in Column 3 assume that public school per-student cost is 20 percent higher than in charters, as D.C. charters contend that a 20-

	Policy	Total Benefits (1)	Total Costs I (2)	Total Costs II (3)	Average Benefit per student (4)	Average Cost per student I (5)	Average Cost per student II (6)
1.	Baseline	\$1,596,202,000	\$738,780,000	\$845,115,000	\$20,044	\$9,277	\$10,612
2.	No Charters	(\$76,930,000)	(\$14,010,000)	\$14,633,000	(\$966)	(\$176)	\$184
3.	Funding Increase	\$4,086,000	\$38,715,000	\$37,756,000	\$51	\$486	\$474
4.	Approve All	\$9,093,000	\$1,555,000	(\$559,000)	\$114	\$20	(\$7)
5.	Lower App. Costs	\$11,790,000	\$2,444,000	(\$361,000)	\$148	\$31	(\$5)
6.	Close Public	(\$45,629,000)	(\$8,658,000)	(\$16,059,000)	(\$573)	(\$109)	(\$202)

Table 17: Cost-Benefit Analysis

Note: Total Benefits is aggregate willingness to pay over households. Total (and average) Costs I assumes that per-student expense is the same in public and charter schools, and that per-student expense in Catholic schools equals tuition. Total (and average) Costs II assumes that per-student expense is 20 percent higher in public than charter schools, and that Catholic school tuition covers only 2/3 of per-student expense. Per-student averages are obtained by dividing totals by number of students, approximately equal to 80,000. Row 1 shows baseline costs and benefits; Rows 2-6 show changes in costs and benefits relative to the baseline (negative changes in parenthesis). Dollar amounts in columns (1)-(3) are rounded to the nearest thousand.

percent reimbursement increase would equalize their funding with public schools.⁴² In addition, column 3 assumes that Catholic schools' tuition covers about two-thirds of expenses (www.ncea.org). Thus, if students were to switch from charter to public or Catholic schools, Column 3 would yield a greater total cost than Column 2. Columns 4, 5 and 6 present per-student costs and benefits. As the "Baseline" row in Table 17 shows, total social benefits relative to the outside option exceed total costs by a factor of about 2 regardless of cost assumptions, thus reflecting the net social value attached to schools in the economy.

7.2 The Social Value of Charter Schools

In order to quantify the net social gains generated by charter schools, we run a counterfactual consisting of not having charters at all in 2007. Thus, we compute the equilibrium for the actual 2007 market structure *excluding* charters. When discussing counterfactuals, for brevity we use "now" and "before" to refer to counterfactual and baseline respectively, and "switch" to describe school choices that differ in both equilibria, even though these are not consecutive equilibria.

Column 2 in Table 14 presents the resulting no-charter equilibrium. Most students previously enrolled in charters switch into public schools, though a small proportion chooses private (particularly Catholic) schools. An additional 2 percent of students choose the outside option, including dropping out of school.⁴³ As suggested by Appendix Tables 9 and 6, charter students who switch into public schools outside Ward 3

⁴²In November 2014, the DC Association of Charter Schools, along with two DC charters filed a suit in federal court against the Mayor and the Chief Financial Officer requesting approximately this funding increase. See http://dcschoolfundingequity.org/ for additional information. The plaintiff contends that DCPS receives additional, off-formula funding that puts charter schools at a disadvantage.

⁴³Booker et al (2011) finds positive effects of charter school attendance on high school graduation rates. As of 2014, graduation rate in D.C. is 69 and 58 percent for charter and public school students, respectively. Source: www.osse.dc.gov

experience lower proficiency, quality and productivity than before. Proficiency losses are quite severe at the middle school level and for poor, black students, who on average lose 6.4 and 5.3 percentage points out of their baseline average proficiency of 35.1 and 30.3 percent in middle school and high school, respectively (see Table 15).

To estimate the welfare impact of eliminating charters, we compute child *i*'s compensating variation $CV_i = W_i^E - W_i^B$, where W_i^B and W_i^E are *i*'s welfare in the baseline and counterfactual experiment, respectively. Table 16 presents the results in the "No Charters" panel. On average all student groups lose welfare due to the loss of school options, but losses are the greatest for those previously most likely to attend charters. Middle school students, who gain much from the quantity and quality of options offered by charters, are particularly hurt. Further, poor blacks in middle school experience a loss of about 15 percent of their baseline welfare. For the population as a whole, losses represent about 8 percent of household income on average. The 25 percent of students most hurt by charter removal are non-white, have an average household income of \$27,000 and experience an average welfare loss equivalent to 19 percent of their income. This loss is due to having less access to specialized curricula, traveling longer to school, and losing school quality by about \$1,100.

From a social standpoint, Table 17's second row indicates that total social benefits fall by about \$77,000,000 when the 59 charters are removed. Whether total costs rise or fall with charter removal depends on cost assumptions; regardless of these, total social *net* benefit falls by at least \$62,000,000 (=-76,930,000 - (-14,010,000)). This loss is approximately equal to 10 percent of the net social value of schools in the economy; it amounts to about \$1,000 per student, and \$1,000,000 (= 62,000,000/59) per charter. Thus, eleven years after their inception in Washington, D.C. charter schools seemed to have been generating substantial net social benefits.

7.3 Charter Expansionary Policies

Given the gains from charters, we now turn to three possible avenues for charter expansion: an increase in charter reimbursement, the elimination of entry selectivity, and a reduction of application costs. Thus, we compute the Fall 2007 equilibrium for three policies. The first ("Funding Increase") is a 20 percent increase in charter reimbursements, approximately similar to the one requested by charters in ongoing litigation. In the second ("Approve All"), the regulator approves all charter applications, regardless of expected profits. The third ("Lower Application Costs") lowers entrant application costs by doubling the application probability (or probability of drawing a positive nonpecuniary net benefit from running a charter school), γ^{B_+} .

In the simulations we assume that the corresponding policy change takes place just before step 1 of the stage game in Spring 2006 and hence affects entry in Fall 2007. We then compare the resulting equilibrium for each policy change with the baseline. Our analysis focuses on short-run effects. We assume that costs of Approve All or Lower Application Costs are negligible relative to charter reimbursements.

Columns (3)-(5) in Table 14 illustrate these effects. The three policies increase charter entry, but not at the same rate. While Funding Increase raises the number of entrants by about a third, Approve All and Lower Application Costs double the number of entrants. Entry patterns by focus and grade span are similar to those in the baseline, yet Funding Increase and Approve All lead to a (slightly) greater fraction of entrants in the Southeast and West. Since entrants in these regions face relatively high fixed costs, Funding Increase raises their expected profits and hence approval probability. By approving all applications, Approve All raises entry probability disproportionately in these regions, where applications are otherwise more likely to be turned down due to negative expected profits. Nonetheless, the fact that charter expansion remains limited in the areas of greatest need (i.e., the Southeast and the upper grades) suggests that a targeted and larger funding increase might be necessary to further expand entry in those areas.

All three policies increase charter market share. New entrants attract students away from all incumbent schools, and from the outside option. However, the policies have different effects on charter closings. Funding Increase raises the profitability of all charters, including incumbents, and hence (slightly) lowers charter closings. In contrast, Approve All and Lower Application Costs raise charter closings as the additional entrants cannibalize incumbent charters.

The three expansionary policies have small, if any, proficiency effects (see Appendix Table 7). Because of the additional school options, average welfare effects are positive for all student groups (see Appendix Table 8); they are greatest for those most likely to attend charters, and for poor or middle-school students. Among the top-25 percent winners from these policies are poor, non-white families with low-quality nearby public schools for whom welfare gains amount, on average, to 3 percent of income.

Since Funding Increase leads to the entry of about three additional schools and an increase in total social benefits of \$4,086,000 (see row 3 of Table 17), the social benefit per additional entrant is about \$1,450,000. Nonetheless, the increase in total social costs from Funding Increase is larger than the increase in benefits. As lack of data prevents us from modeling the relationship between funding and school quality, we do not capture quality improvements that all charters (including incumbents) might attain with greater funding. We do, however, capture cost increases. Thus, we can only provide a lower bound on social welfare gains from Funding Increase.

In contrast, Approve All and Lower Application Costs raise net social benefits because they almost double entry without reimbursement increases (see rows 4 and 5 of Table 17). Although these two policies expand charters at about the same rate, total social benefits are larger for Lower Application Costs by \$2,697,000 (=11,790,000 - 10,000)

9,093,000). Further, based on the most conservative estimates for net charter gains (associated with Table 17's column 2), Lower Application Costs produces a *net* social gain of \$1,043,000 (=(\$11,790,000 - \$2,444,000)/9 entrants) per entrant relative to \$872,000 from Approve All. The reason is that the selective regulator of Lower Application Costs only authorizes the entry of charters with a sufficiently large expected enrollment (and hence social value). These charters, in addition, are expected to be financially more robust and less likely to be closed in the future. Thus, our counterfactuals indicate that the combination of selective charter approval and policies that encourage the supply of potential charter entrants (for instance, by minimizing charter application costs) can deliver sizable social gains. Current charter advocacy in Washington, D.C. points to the importance of lowering application costs - for instance, by facilitating charters' access to unused public school buildings.⁴⁴

7.4 Public School Closings

Unlike public schools, charter schools must close if they are unable to cover their costs. To investigate the effect of this rule on public schools, in the absence of public school cost data we simulate a counterfactual ("Close Public") whereby a public school must close if its predicted 2007 enrollment is at least 40 percent lower than its observed 2003 enrollment - namely, if it has suffered a large enrollment loss. As column 6 of Table 14 shows, in the counterfactual this leads to closing approximately 49 public schools, affecting about 14 percent of all K-12 students. Note that DCPS actually closed 33 schools between 2008 and 2012; most closings affected elementary or K-8 schools in the Northeast or Southeast. Our counterfactual replicates these aspects.

In the simulations, about 64, 29 and 7 percent of the displaced students switch into (other) public, charter and private schools respectively, consistent with the observed reallocation of students after the 2008 closings (documented in www.21csf.org). Because the schools that are predicted to close lag behind in proficiency, quality and productivity, most student groups enjoy proficiency gains through these switches (see Appendix Tables 6 and 7). For instance, middle-school black students attain an average proficiency gain of 3.17 percentage points.

Nonetheless, Appendix Table 8 shows that most students suffer welfare losses from the elimination of school options. Thus, although the closings lower total social costs (see Table 17's row 6), they lower total social benefits even more. Our estimated per-school net social loss from these closings is between \$603,000 and \$755,000 depending on cost assumptions. While the closing of charter schools would also lead to welfare losses, the per-school loss associated with charter closings is larger (equal to

⁴⁴Access to adequate facilities is a crucial challenge for charters. Although by law charters have the right of first offer on vacant DCPS buildings, the law is often not enforced (www.focusdc.org/advocacy). Greater enforcement of the law exemplifies a reduction in application costs.

about \$1,000,000) than that of public school closings.

When DCPS makes closing decisions, it considers the impact of closings on the system as a whole. It also considers multiple factors beyond enrollment, such as student travel time and facility condition. Our simplified closing rule, based on enrollment, likely overpredicts closings and hence welfare losses. Nonetheless, the greater predicted per-school loss from charter closings suggests that, at least in the short run, students might be more hurt by the closing of an average charter than of a low-enrollment public school. Further, losses from public school closings might be reversed in the long run through the entry of new charters serving the displaced students.

8 Conclusion

In this paper we develop and estimate a rich yet tractable model of charter school entry and household school choice. We model the equilibrium sorting of households across schools as well as regulator behavior. We estimate the model using data on the full choice set of schools in Washington, D.C. between 2003 and 2007. Our estimates indicate that charter schools have generated net welfare gains in the city by providing new options to serve a heterogeneous population. Welfare gains have been particularly large for middle school- and for non-white, low-income students, whose options before charters were quite limited. According to our counterfactuals, raising the supply of prospective charter entrants (for instance, by lowering application costs and providing information on charter best practices) while applying tight admission and oversight standards is a welfare-enhancing mechanism for charter expansion.

While informative, our counterfactuals must be taken with caution for several reasons. First, they only reflect short-run policy effects and ignore strategic responses from non-charter schools. Second, our results reflect the institutional environment for charters in D.C., where funding is relatively high vis-a-vis other states and the charter law is permissive. Third, we do not model the relationship between school funding and quality. Nonetheless, the counterfactuals stress the role of private initiative (facilitated by low application costs) in the charter sector. They also stress the regulator's role (through its approval and oversight activies) in attaining a high-quality charter sector.

Throughout we faced important data limitations. One was the lack of individuallevel data. As such data becomes available, researchers will be able to examine issues such as switching costs between schools.⁴⁵ Another data limitation was the lack of capacity and excess demand for individual schools.

Our findings are informative for D.C., particularly as the city adjusts to a rising

⁴⁵Filardo et al (2008) document that approximately 15 percent of K-12 students in DC switch schools before reaching their school's terminal grade, a fraction that rises up to 20 percent in the Northeast and Southeast. This relatively high switching rate, consistent with our sample amount of school openings, closings and relocations, leads to the conjecture that switching costs are low.

number of families with school-age children and highly educated parents. They are also informative for school reform in other large, U.S. cities. Finally, they are relevant for countries with private operation of public schools, such as Colombia, the UK and Spain (Patrinos et al 2009), and for nascent charter efforts in developing countries such as Uganda and Morocco.

References

- Altonji, J., C. Huang and C. Taber. 2015. "Estimating the Cream Skimming Effect of Private School Vouchers on Public School Students." *Journal of Political Economy*, 123(2): 266-324
- [2] Angrist, J. D., P. A. Pathak, and C. R. Walters. 2013. "Explaining Charter School Effectiveness." *American Economic Journal: Applied Economics*, 5(4): 1-27.
- [3] Bayer, P. and C. Timmins. 2007. "Estimating Equilibrium Models of Sorting Across Locations." *Economic Journal*, 117(518): 353-374.
- [4] Berry, S., J. Levinsohn, and A. Pakes 1995. "Automobile Prices in Market Equilibrium" *Econometrica*, 63(4): 841-890.
- [5] Berry, S., and P, Reiss. 2007. "Empirical Models of Entry and Market Structure". *Handbook of Industrial Organization*. 3:1845-1886.
- [6] Betts, J. R., & Tang, Y. E. 2011. "The Effect of Charter School on Student Achievement: A Meta-Analysis of the Literature." *Center on Reinventing Pub. Education.*
- [7] Bifulco, R. and C. Buerger. 2015. "The Influence of Finance and Accountability Policies on Location of New York State Charter Schools" *Journal of Education Finance*, 40(3): 193-221
- [8] Booker K., Sass T., Gill B. and Zimmer R. 2011."The Effects of Charter High Schools on Educational Attainment." *Journal of Labor Economics*, 29(2):377-415.
- [9] Buckley, J. and M. Schneider. 2007. "Charter Schools: Hope or Hype?" *Princeton and Oxford: Princeton University Press.*
- [10] Cardon, J.H. 2003. "Strategic Quality Choice and Charter Schools." *Journal of Public Economics*, 87 (3-4): 729-737.
- [11] Carranza, J. E., J. Houde and R. Clark. 2011. "Dynamic Entry and Firm Reconfiguration in Canadian Gasoline Markets." Working Paper, ICESI University.
- [12] Clark M., P. Gleason, C. Clark Tuttle, M. K. Silverberg. 2011. "Do Charter Schools Improve Student Achievement? Evidence from a National Randomized Study" *Mathematica Policy Research*.
- [13] Dobbie, W. and R. G. Fryer. 2013. "Getting beneath the Veil of Effective Schools: Evidence from New York City." *American Economic Journal: Applied Economics*, 5(4): 28-60.
- [14] Draganska, M., S. Misra, V. Aguirregabiria, P. Bajari, L. Einav, P. Ellickson, & T. Zhu. 2008. "Discrete Choice Models of Firms' Strategic Decisions." *Marketing Letters*, 19(3-4), 399-416.

- [15] Dubé, J., J. Fox, and C. Su. 2012. "Improving the Numerical Performance of BLP Static and Dynamic Discrete Choice Random Coefficients Demand Estimation." *Econometrica*, 80 (5): 2231-2267.
- [16] Ferreyra, M. M. 2007. "Estimating the Effects of Private School Vouchers in Multi-District Economies." *American Economic Review*, 97 (3): 789-817.
- [17] Filardo, M., M. Allen, N. Huvendick, P. Sung, D. Garrison, M. Turner, J. Comey, B. Williams and E. Guernsey. 2008. "Quality Schools and Healthy Neighborhoods: A Research Report." *Sponsored by the OSSE*. Available at www.brookings.edu.
- [18] Henig, J. R. and J. A. MacDonald. 2002. "Locational Decisions of Charter Schools: Probing the Market Metaphor." *Social Science Quarterly*, 83(4): 962–980.
- [19] Glomm, G., D. Harris, and T. Lo. 2005. "Charter school location." *Economics of Education Review*, 24(4): 451–457.
- [20] Imberman, S. A. 2011. "Achievement and Behavior of Charter Students: Drawing a More Complete Picture." *Review of Economics and Statistics*, 93 (2): 416 435.
- [21] Mehta, N. 2012. "Competition in Public School Districts: Charter School Entry, Student Sorting, and School Input Determination." Working Paper, *Western Ontario University*.
- [22] Nechyba, T. J. 2000. "Mobility, Targeting and Private School Vouchers." *American Economic Review*, 90 (1): 130–146.
- [23] Neilson, C. 2013. "Targeted vouchers, competition among schools, and the academic achievement of poor students. Working Paper, *Yale Univesity*.
- [24] Nevo, A. 2000. "Mergers with Differentiated Products: The Case of the Ready-To-Eat Cereal Industry." *RAND Journal of Economics*, 31 (3): 395-421.
- [25] Nevo, A. 2001. "Measuring Market Power in the Ready-To-Eat Cereal Industry." *Econometrica*, 69 (2): 307-342.
- [26] Patrinos, H., F. Barrera-Osorio and J. Guaqueta. 2009. "The Role and Impact of Public-Private Partnerships in Education." Washington, D.C.: *The World Bank*.
- [27] Rincke, J. 2007. "Policy Diffusion in Space and Time: The Case of Charter Schools in California School Districts." *Regional Science and Urban Economics*, 37(5): 526-541.
- [28] Salisbury, D. 2003. "What Does a Voucher Buy? A Closer Look at the Cost of Private Schools." CATO Institute Policy Analysis Paper No. 486, August.
- [29] Skrainka, B. 2012. "A Large-Scale Study of the Small Sample Performance of Random Coefficient Models of Demand." Working Paper, *University of Chicago*.
- [30] Train, K. 2002. "Discrete Choice Methods with Simulations". *Cambridge University Press.*
- [31] Walters, C. 2012. "A Structural Model of Charter School Choice and Academic Achievement." Working Paper, *U. of California-Berkeley*.

For Online Publication: Appendices

A Data

A.1 School-Level Data

A.1.1 Public Schools

The starting point for this dataset is audited enrollments from the District of Columbia Office of State Superintendent of Education (OSSE), available at http://osse.dc.gov. This gives us the list of public schools and their grade-level enrollment. From the original list we exclude alternative schools, special education schools, early childhood centers (as long as they never include any of grades 1 through 12 during the sample period) and schools with residential programs. Our data pertain to grades kindergarten through 12th.

For each school we collect the information listed below:

- Address: from the Common Core of Data (CCD). We geocode all addresses.
- School enrollment: total school enrolment excluding ungraded and adult students. Source: own calculations based on OSSE.
- Grade-level enrollment: for each grade between kindergarten and 12th. Source: OSSE.
- Focus: Source: Filardo et al (2008).
- Percent of white students: calculated based on CCD. For cases in which CCD data are not available, we use the demographics reported to OSSE in order to fulfill No Child Left Behind (NCLB) requirements (see http://www.nclb.osse.dc.gov/). Note, however, that the NCLB requirements pertain to students enrolled in the grades tested by law, not to the entire student body. We include "other ethnicities" (such as Asian students) among white students.
- Percent of black students, percent of Hispanic students: constructed similarly to percent of white students.
- Percent of low income students: calculated as the percent of students who receive free or reduced lunch. Source: own calculations based on CCD. For the few cases in which the CCD data are not available we use the demographics reported in fulfillment of NCLB requirements.
- Reading proficiency: percent of students who are proficient in reading. Source: OSSE. In 03 and 04, proficiency levels were determined according to the Stanford-9 assessment. To be considered proficient, a student was supposed to score at the national 40th percentile or higher. Since 05, proficiency has been determined according to DC CAS (Comprehensive Assessment System).

Prior to 05, grades tested were 3, 5, 8 and 10 (according to the School Performance Reports for PCBS-authorized charter schools, and according to our own calculations comparing grade-level enrollment with number of students tested). Since 05, grades tested have been 3, 4, 5, 6, 7, 8 and 10 (according to OSEE, School Performance Reports and our own calculations comparing grade-level enrollment

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

- Math proficiency: percent of students who are proficient in math. Constructed similarly as reading proficiency.
- Year of Opening: year the school opened if it was open after 2003. Using the CCD "status" variable and web searches we verify the school's initial year, which is the first year for which we have records.
- Year of Closing: first year that the school is no longer open. We verify the content of this variable using the CCD "status" variable and web searches.
- Year of Merge: year the school merges with another school. The variable stores the first year that the school no longer operates separately, which is the first year for which we have joint records.

Ethnic composition and low-income status of the student body are missing for 2 and 4 (out of 701) observations respectively; these are schools with very low enrollment. To the cases of missing ethnic composition we impute the school's average ethnic composition over the years for which we do have data. When possible, we impute the predicted value coming from a school-specific linear trend. Achievement is missing in 16 out of 701 observations. To these observations, we impute the predicted achievement coming from the regression of school-level proficiency rates on year dummies, ethnic composition variables, percent of low income students, enrollment, and school fixed effects. In cases in which we have no proficiency data at all, we run a similar regression excluding school fixed effects and including dummies for school level and use the resulting predicted values for our imputations.

A.1.2 Charter Schools

As with public schools, the starting point for this dataset is audited enrollments from the District of Columbia Office of State Superintendent of Education (OSSE). This gives us the list of charter schools along with their grade- and school-level enrollment. For consistency with public schools, we exclude alternative schools. We also exclude schools in which ungraded or adult students constitute the majority of the student body, and schools with residential programs.

By law, charter schools cannot serve special education students exclusively. However, they can offer services targeted to specific populations. We exclude schools whose services target special ed students. We exclude early childhood schools only if they never add regular grades during our sample period. We also exclude online campuses. Some non-early childhood charters opened an early childhood campus during the sample period; we only included these campuses if at some point during the sample period they add regular grades.

Below is the list of variables for charter schools:

- Address: geographic location of the campus. For PCSB-authorized charters, the main source is the School Performance Reports (SPRs). For BOE-authorized charters, the main source is the CCD. We supplement these sources with web and Internet archive searches. We geocode all addresses. Several schools moved in the middle of the school year, temporarily relocated, or closed during the sample period. We consult the SPRs and various web sites to handle these cases. If the school moved in the middle of a school year, the address variable contains the more recent address. Some schools relocated some students for a few months during renovations. Since this was a temporary, anticipated arrangement, we do not consider these cases as address changes.
- Statement: the school's mission statement. Source: schools' web sites, FOCUS, SPRs.
- Focus: the school's curricular focus. Source: school statements, and Filardo et al (2008).
- School enrollment: total school enrollment, excluding ungraded and adult students. Source: own calculations based on OSSE.
- Grade-level enrollment (grades kindergarten through 12). Source: OSSE.
- Percent of white students: for PCSB charters, the source is the SPRs when available; if not, we use data reported for NCLB purposes. For BOE charters in 2007, the source is the SPRs (in 2007, the PCSB began including the BOE-authorized charters in its reports). For BOE charters before 2007, the source is the NCLB web site. If necessary, we supplement these sources with CCD data. When the school has multiple campuses but we only have one set of ethnic composition data, we impute it to all campuses.
- Percent of black students, percent of Hispanic students: constructed similarly to percent of white students.
- Percent of low income students: for PCSB charters, the source is the SPRs. For BOE charters, the source is NCLB information in http://www.nclb.osse.dc.gov/. These sources are supplemented by CCD when necessary and possible. When the school has multiple campuses but we only have one set of low-income variables, we impute it to all campuses.
- Reading proficiency: sources are the same as for public schools. Some schools span elementary as well as secondary grades and, for some years, have separate proficiency rates per grade span. In these cases we combine the rates into a single proficiency indicator for comparability with years for which we have a single indicator. For multi-campus charters we usually have proficiency data per campus. When we do not, we impute the available data to all the campuses. As with public schools, we do not have proficiency data for some campuses and years for the reasons described above. In the case of PCSB schools for which the NCLB web site does not report test scores due to low enrollment, we obtain proficiency rates from the SPRs. This is not possible for BOE schools with low enrollment since

the SPRs only cover PCSB schools before 07. In cases in which we cannot find proficiency data, we make imputations (see below).

- Math proficiency: constructed similarly as reading proficiency.
- Year of Opening: source: SPRs, FOCUS, web searches. The variable stores the Fall of the first academic year that the school is open.
- Year of Closing: first year that the school is no longer open. The sources are the Center for Education Reform, current SPRs and PCSB listings of charter schools, current NCLB reports, and web searches.
- Reason for Closing: classified as academic, financial or mismanagement. Source: Center for Education Reform, SPRs, web searches.
- Multi-campus: an indicator variable that equals 1 if the school belongs to an organization that has multiple campuses by the end of the sample period.

Percent of low-income students is missing for 9 out of 228 observations. These schools have low enrollments. To most of these cases we impute the school's average percent of low-income students, calculated over the years for which the school does have data. In the case of missing proficiency rates (36 out of 228 observations), we make imputations similar to those described for public schools, the only difference being that we used school-fixed effects (as opposed to campus-fixed effects) in the predicting regressions.

A.1.3 Private Schools

The starting point is the list of private schools from the Private School Survey (PSS). Since PSS is biennial, we use the 2003, 2005 and 2007 waves. PSS classifies schools as regular, vocational, special ed, and other/alternative. For the years of interest, 92 percent of the schools in Washington, D.C. are classified as regular, and the remaining schools are classified as other/alternative. Although an alternative public school usually serves students with behavioral problems, an alternative private school is usually a regular school with a specialized curriculum. Hence, we keep most alternative schools. We eliminate vocational schools because they enroll ungraded students exclusively. We also eliminate special ed schools, early childhood centers (as long as they never have enrollment in regular grades during the sample period), and other schools that only teach ungraded students.

Since PSS does not have a 2004 wave, we assign 2004 values to the variables through linear interpolation of 2003 and 2005, and similarly for 2006. For instance, we calculate percent white for 2005 as the average between percent white in 2003 and in 2005. In cases in which a school does not report to the survey in a particular year, we make imputations based on the school's reported data for the other years. If a school does not appear again in PSS after a particular wave, we assume that the last year of operation is the year of the last wave in our data.

For the list of variables below, PSS is the main source of data:

• Address: if needed, we supplement PSS with web and Internet archive searches. We geocode all addresses.

- Type: Catholic, other religious or non-sectarian. Source: PSS.
- School enrollment: total school enrollment, excluding ungraded and adult students. Source: own calculations based on PSS.
- Grade-level enrollment: number of students in each grade between K and 12.
- Percent of white students: source: own calculations based on the reported number of white students and the total enrolment. "White" includes other ethnicities as well.
- Percent of black students, percent of Hispanic students: constructed similarly to percent of white students.
- Percent of low income students: since PSS does not collect this information, we impute it based on the following logistic regression. Using data for public and charter schools, we regress percent low income on school percent white and percent Hispanic, school enrollment, and average household income of the school's tract. We use this regression to predict percent low income in private schools. We check our predictions by comparing OSSE data on the percent of students receiving free and reduced lunch in private schools. Our predictions compare favorably with OSSE data.
- Tuition: annual tuition for the 2002/03 school year. Source: Salisbury (2003). Tuition is expressed in dollars of 2000.

A.2 Market Size and the Outside Good

Since a market is a grade-year combination, market size M_{gt} is equal to the number of children eligible for grade g in year t between 2003 and 2007. This number is not available, and neither is the number of children by age. Hence, we estimate market size based on the following, available data for Washington, D.C.:

- 1. The 2000 Census count of children by age;
- 2. The intercensal estimates of the number of children in the 5-13 and 14-17 year old brackets;
- 3. The 2000 Census count of enrolled and not enrolled children by age group. The resulting percent of children not enrolled in school is our best proxy for the outside good share in 2000.
- 4. Observed enrollment for each grade and year between 2003 and 2007. Use N_{gt} to denote aggregate enrollment in grade g and year t.

We estimate market size as $M_{gt} = N_{gt} * \vartheta_{gt}$, which implies an outside good share equal to $O_{gt} = 1 - N_{gt}/M_{gt}$. Adjustment factors ϑ_{gt} are chosen so that O_{gt} matches the 2000 Census fractions of children not enrolled in school. We adjust these fractions slightly to account for the fact that our enrollment data is based only on regular schools and excludes early childhood centers. Thus, we use fractions equal to 3 percent for ages 5-14 (corresponding to grade K-8) and 10 percent for ages 14-17 (grades 9 through 12). For computational reasons we impose the following constraint: $O_{gt} \ge 0.01$ (see Appendix E.2).

An appealing feature of our solution is the consistency of M_{gt} with the growth rate for child population implied by intercensal Census estimates. In particular, the

estimated M_{gt} grows at the following rates between 2003 and 2007: -13 percent for grades K through 8, and 7 percent for grades 9 through 12. These rates line up with the Census growth rates for the corresponding age groups (equal to -13 percent and 13 percent, respectively) for the same period.

A.3 Household Characteristics

We describe the estimation of the joint distribution of household location, child age and race, parental income and child poverty status for year 2000, and the adjustments made to this distribution for years 2003-2007. The term "demographic type" refers to a combination of race (black, white and Hispanic), income (16 values for income, each one representing the midpoint of the corresponding Census income bracket), and poverty status (eligible for free- or reduced-lunch, or not eligible). This yields a total of 96 demographic types. For each of the 13 grades and 433 locations (i.e., block groups) in our data, we estimate the number of children of each demographic type.

A.3.1 Household Types for Year 2000

We do not observe the joint distribution of child age, race, household income and poverty status at the block group level. Instead, the Census provides us with the following information:

- tract-level joint distribution of age and race;
- tract-level joint distribution of age bracket, race and poverty status;⁴⁶
- tract-level joint distribution of family income (by brackets) and race;
- block group-level joint distribution of age brackets and race.

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

- 1. Assuming the same distribution of age among the block groups of a given tract, we estimate the number of children of each age and race by block group.
- 2. For each block group, race and age we impute the poverty distribution that prevails for the corresponding tract, race and age. For each block group we obtain n_{arp} , which is the number of children of each age *a*, race *r* and poverty status *p*.
- 3. The tract-level income distribution for families is not adjusted by family size and hence does not reflect income per child. In the absence of data on the joint distribution of family income and size, we calculate tract-level average family income and average family size by race, and construct the city-level joint distribution of average family income and size. Then we reweight the original tract-level family

⁴⁶Per federal guidelines, in order to qualify for free (reduced) lunch, a child must live in a household whose income is below 130 (185) percent of the Federal poverty guidelines for that household size. We pool children eligible either for free or reduced lunch into a single category. Thus, "poverty status" is a binary variable that describes whether the child is eligible for free- or reduced-lunch or not.

income distribution to reflect differences in family size by income bracket, in an attempt to reflect the distribution of income per child.

- 4. To determine how many of the n_{arp} children in the corresponding (a, r, p) combination a given block group fall in each income bracket, we assign a low-income status to the lowest incomes. For instance, consider a block group in which 20 percent of 5-year old white children are poor, and the remaining 80 percent are not. In the corresponding tract, 5 percent of white families have incomes below \$20,000; 15 percent have incomes between \$20,000 and \$40,000, and the remaining 80 percent have incomes between \$40,000 and \$60,000. Thus, we assign a family income of \$10,000 (i.e., the midpoint for the \$0-\$20,000 income bracket) to a quarter of the 5-year old white children, where 1/4 = 0.05 / 0.20, and a family income of \$30,000 (midpoint for the \$20,000-\$40,000 income bracket) to three-quarters of those children. To the 80 percent of 5-year old white children who are not poor, we assign an income of \$50,000 (midpoint of the \$40,000-\$60,000 income bracket).
- 5. Based on step (4), for each block group *l* we calculate the number μ_{lam} of children of each age *a* and demographic type *m*.

Calculating the number of children aged 18-years old in each demographic type and location is challenging for D.C. because the number of 18-year olds is much higher than the number of 17-year olds. The age bracket 18-24 has different demographics than the age bracket 12-17, most likely because it reflects college-age students, many of whom are not originally from Washington, D.C. Thus, we set the block-group level number of 18-year olds equal to the average number of children by age in the 12-17 year-old bracket. We assign to 18-year olds the average demographics of the 12-17 year-old bracket.

A.3.2 Household Types for Years 2003-2007

Recall our assumption that each grade draws equally from the two most frequent ages in the grade, and only from those ages (for instance, 50 percent of second graders are 6 years old, and 50 percent are 7 years old). We also assume that while the marginal distribution of child age may change over time, the distribution of demographic types conditional on age remains constant. We assume, then, that all demographic types of a given age grow at the same rate ϑ_{at} .

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

For each year, these measures imply a breakdown of the children eligible for each grade by race and poverty status. When compared with the observed breakdown of student enrollment by race and poverty status, two discrepancies arise. The first is that the resulting fraction of white children is lower than the fraction of the student body that is

white (perhaps because the fraction of white children in the population grew at a higher rate during the sample period). The second is that the resulting fraction of low-income children is lower than the fraction of the student body that receives free or reduced lunch. Hence, we apply upward adjustments to the measures of the corresponding household types in order to minimize discrepancies and faciliate the fit of the data.

B Tables

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 1: Charter School Entry Patterns, 2004 - 2007

Table 2: Ward Indicators in Utility Function

Independent Variable	Estimates
Ward 1	0.278
ward I	(0.570)
Ward 2	0.316
Ward 2	(0.401)
Ward 3	-0.222
Ward 5	(0.732)
Ward 4	1.011*
	(0.389)
Ward 5	0.502*
in and o	(0.114)
Ward 6	0.171
it and o	(0.157)

Note: Omitted category is Wards 7 and 8, located in the Southeast (i.e., the city's most disadvantaged area). Estimates corresponding to the Baseline Utility specification in Equation (8) in the paper, obtained via Minimum-Distance Estimation as described in Section 5.2 and Appendix E.1.

	Scho	ol Choice b	y Student F	Race and Pove	erty Status –	Observea	l and Predi	cted Values	s, 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		

2.76

12.39

1.29

Hispanic

Non Poor

Low Inc.

72.14

50.60

69.83

14.29

11.64

20.92

8.80

14.57

6.23

1.61

10.43

1.61

Table 3: Goodness of Fit: School Choice

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

3.16

12.76

1.40

70.28

52.22

68.97

12.86

10.69

22.22

11.33

14.51

6.05

2.76

10.18

1.47

	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 (76)					Fredicted values (76)				
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 4- 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 5- Goodness of Fit. Number of Entries Detween 2004	-2007
--	-------

	Observed Values	Predicted Values
All Entries	33	35.31
Level		
Elementary	19	19.37
Middle	9	8.96
High	1	1.62
Mixed	4	5.36
Focus		
Core	11	7.75
Non-Core	22	27.56
Region		
Northeast	20	18.15
Southeast	8	10.67
West	5	6.49

 Table 6- Average proficiency (in percent), productivity and school quality

 Baseline and Counterfactuals (weighted by expected enrollment)

Baseline and Counterfactuals	weighten by ex	Declea enroll	Data Catant Chaine
	Baseine	No Charters	Public School Closings
Avg. School Professory, New MUS Schools	(1)	(2)	(3)
Public	44.02	42.52	44.92
Charter incumbents	44.02	42.35	44.83
Charter entrants	37.48		37.38
Outside Ward 3:	18.00		18.08
Bublic	20.74	20.24	20.02
Charter incumbents	38.74	38.34	27.59
Charter entrants	10.40		37.36
In SE-	18.48		18.51
Public	20.26	20.65	27.22
Charter incumbents	28.30	28.03	27.32
Charter incumbents	39.02		39.78
Avg. School Professory, MUS Schools	18.30		18.32
Avg. School Honciency-WHS Schools	27.00	25.44	22.22
Fublic Charten in such ante	37.98	35.44	39.20
Charter incumbents	43.54		44.79
Charter entrants	36.59		36.48
Outside ward 5:			
Public	32.69	31.53	33.37
Charter incumbents	41.57		42.92
Charter entrants	36.48		36.38
In SE:			
Public	18.17	18.15	19.04
Charter incumbents	36.39		36.77
Charter entrants	36.59		36.48
Avg. School Quality			
Public	0.07	0.05	0.08
Charter incumbents	0.41		0.45
Charter entrants	0.05		0.05
Private	0.55	0.40	0.52
Outside Ward 3:	the second		
Public	0.00	-0.01	0.00
Charter incumbents	0.39		0.43
Charter entrants	0.04		0.04
In SE:			
Public	-0.15	-0.19	-0.16
Charter incumbents	0.48		0.53
Charter entrants	0.01		0.01
A			
Avg. school value Added		0.00	0.00
Charten in such ante	0.04	-0.03	0.05
Charter incumbents	0.11		0.15
Charter entrants	-0.44		-0.44
Duiside Ward 5:			
Public	-0.14	-0.17	-0.16
Charter incumbents	0.10		0.15
Charter entrants	-0.43		-0.43
In SE:			
Public	-0.55	-0.56	-0.57
Charter incumbents	-0.21		-0.17
Charter entrants	-0.42		-0.43

		Poor Black	Poor Hisp.	Poor White	Non-poor Black	Non-poor Hisp.	Non-poor White
Percent of Students		50.5	4.80	1.70	23.00	5.00	15.40
	Elementary	33.68	45.48	64.60	43.03	53.31	78.17
Baseline	Middle	35.11	41.60	57.32	41.35	53.32	71.91
	High	30.29	47.61	53.15	41.61	41.75	60.02
	Elementary	-1.37	2.08	-0.46	0.40	1.13	-0.18
No Charters	Middle	-6.35	-1.08	-2.47	-3.85	-1.94	-1.39
	High	-5.29	-0.09	2.02	0.23	0.12	0.20
Raise Funding	Elementary	-0.25	-0.39	-0.33	-0.16	-0.25	-0.19
	Middle	-0.07	-0.20	-0.41	-0.03	-0.28	-0.43
-	High	0.10	-0.24	-0.02	0.03	-0.12	-0.13
	Elementary	-0.64	-1.16	-1.18	-0.45	-1.06	-0.68
Approve All	Middle	-0.15	-0.42	-1.15	-0.08	-0.74	-1.19
0.02040422	High	0.14	-0.32	-0.02	0.05	-0.11	-0.17
	Elementary	-0.74	-1.01	-0.93	-0.53	-0.71	-0.47
Lower App.	Middle	-0.20	-0.63	-1.06	-0.11	-0.83	-0.89
Costs	High	0.40	-0.83	-0.02	0.11	-0.41	-0.20
	Elementary	0.23	-2.35	0.76	0.35	-0.42	0.44
Close Public	Middle	2.75	-0.59	1.69	4.10	1.98	1.11
	High	0.07	0.00	0.01	0.05	-0.01	0.00

 Table 7: Average Proficiency Index by Student Group and Grade Level (in percent)

Note: "Baseline" shows average proficiency index for students of each demographic group and grade level (in percent). "No Charters" shows the difference in average proficiency index between Baseline and No Charters, and similarly for the other counterfactuals (in percentage points). Statistics weighted by students' weights. "Elementary" refers to K-6 grades; "Middle" to grades 7 and 8, and "High" to 9-12 grades.

		Poor Black	Poor Hisp.	Poor White	Nonpoor Black	Nonpoor Hisp.	Nonpoor White
Prop. Of S	tudents	50.5	4.8	1.7	23.0	5.0	15.4
	Elementary	\$13,627	\$27,994	\$26,282	\$19,140	\$33,959	\$41,132
Baseline	Middle	\$11,625	\$24,471	\$17,146	\$15,412	\$28,338	\$33,364
	High	\$11,063	\$23,717	\$26,122	\$17,824	\$30,160	\$44,199
No Charters	Elementary	(\$1,120)	(\$905)	(\$965)	(\$899)	(\$367)	(\$229)
	Middle	(\$1,822)	(\$1,740)	(\$1,435)	(\$1,928)	(\$1,125)	(\$656)
	High	(\$1,390)	(\$6)	(\$658)	(\$458)	(\$66)	(\$58)
Raise Funding	Elementary	\$60	\$54	\$46	\$37	\$48	\$23
	Middle	\$81	\$65	\$98	\$41	\$71	\$34
	High	\$55	\$114	\$41	\$40	\$62	\$26
	Elementary	\$154	\$152	\$149	\$103	\$157	\$69
Approve All	Middle	\$166	\$132	\$245	\$95	\$166	\$79
	High	\$81	\$168	\$59	\$62	\$94	\$40
· · · · · · · · · · · · · · · · · · ·	Elementary	\$171	\$145	\$120	\$112	\$133	\$55
Lower App.	Middle	\$240	\$226	\$282	\$129	\$190	\$61
Costs	High	\$175	\$305	\$121	\$118	\$165	\$64
	Elementary	(\$764)	(\$1,174)	(\$647)	(\$819)	(\$1,036)	(\$500)
Close Public	Middle	(\$1,251)	(\$602)	(\$354)	(\$1,363)	(\$825)	(\$134)
	High	(\$23)	(\$16)	(\$5)	(\$13)	(\$10)	(\$3)

 Table 8: Average Welfare and Welfare Gain by Student Group and Grade Level

Note: "Baseline" shows the average welfare for students of each demographic group and grade level. "No Charters" shows average compensating variation from the counterfactual for student each demographic group and grade level, and similarly for the other counterfactuals (negative values are in parentheses). "Elementary" refers to K-6 grades; "Middle" to grades 7 and 8, and "High" to 9-12 grades.

C Appendix Figures

Figure 1: Percent of Children in Private Schools by Census Tract in 2000







Note: the horizontal axis depicts distance (in miles), and the vertical axis depicts number of charter schools. The light (dark) grey bars are the observed (predicted) number of charters whose moving distance is greater than the distance on the horizontal axis.

D Model

D.1 Charter entry: institutional details

If a charter wishes to open in the Fall of calendar year X, it must submit its application no later than February of (X-1). According to the Washington, D.C. charter law, the application must include a description of school focus and philosophy, targeted student population (if any), educational methods, intended location, strategies for student recruiting and enrollment projections. In addition, the applicant must file letters of community support and specify two potential parents for the school board. The application must also contain a plan for growth – what grades will be added, at what pace, etc.

When submitting its application, the school must provide reasonable evidence of its ability to secure a facility. The authorizer evaluates the enrollment projections by considering elements such as enrollment in nearby public schools and incumbent charters, the size of the school's intended building, and expected fixed costs.

The applicant learns whether it was approved in the Spring of (X-1). If the charter is approved and has already secured a building, then the charter and the regulator begin negotiating on a number of issues. The school then uses the following twelve months to hire and train prospective school leaders and teachers, conduct building renovations, recruit students, and finalize preparations before formally openings its doors. Charters are very aggressive when recruiting students. They contact parents directly, advertise in churches, contact parents directly, post flyers in 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.

Based on projected enrollment, a charter opening in Fall of X receives its first installment in July of X. An enrollment audit is conducted in October of X and installments are adjusted accordingly. Charters can run surpluses, as is the case of charters that plan to expand in the future. Although they can also run deficits, PCSB only tolerates them temporarily and provided the school is academically in good standing.

D.2 Expected Proficiency Rate

As described in Subsection 4.1, student *i*'s achievement in school *j*, grade *g* and year *t*, represented by A_{ijgt} , is a function of school time-invariant characteristics y_j , student body composition \overline{D}_{jt} , student own characteristics D_i , and the student-school interaction $[y_j \otimes D_i]$. We assume that the probability q_{ijgt} that *i* passes the proficiency test is monotonically related to her achievement, and is given by the following specification:

$$q_{ijgt} = y_j \beta^q + \overline{D}_{jt} \alpha^q + D_i \omega^q + [y_j \otimes D_i] \tilde{\beta}^q + \xi^q_{igt} + v^q_{ijgt}, \qquad (25)$$

where v_{ijgt}^q is a zero-mean idiosyncratic shock. A student who passes the test is deemed "proficient".

The school-level expected share of proficient students is

$$q_{jt} = \frac{\sum_{g \in G_{jt}} \sum_{i=1}^{N_{jgt}} q_{ijgt}}{N_{jt}}.$$

where N stands for the number of enrolled students. Averaging q_{ijgt} over students and grades we obtain the following:

$$q_{jt} = y_j \beta^q + \overline{D}_{jt} \phi^q + [y_j \otimes \overline{D}_{jt}] \tilde{\beta}^q + \xi^q_{jt}, \qquad (26)$$

where the identity $D_{jt} = \frac{\sum_{g \in G_{jt}} \sum_{i=1}^{N_{jgt}} D_i}{N_{jt}}$ is applied. The following new variables are intro-

duced:
$$\phi^q = \alpha^q + \omega^q$$
 and $\xi_{jt}^q = \frac{\sum_{g \in G_{jt}} \sum_{i=1}^{r_{jgt}} (\xi_{jgt}^q + v_{ijgt}^q)}{N_{jt}}$.⁴⁷

In (26), we decompose ξ_{jt}^q as follows

 $\xi_{jt}^q = \xi_j^q + \xi_t^q + \Delta \xi_{jt}^q$. where ξ_j^q is the school's contribution to proficiency, or school productivity. Substituting the above expression into (26) we obtain the following expression for the expected share of proficient students:

$$q_{jt} = y_j \beta^q + \overline{D}_{jt} \phi^q + [y_j \otimes \overline{D}_{jt}] \tilde{\beta}^q + \xi_j^q + \xi_t^q + \Delta \xi_{jt}^q.$$
(27)

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

$$\bar{q}_{jt} = y_j \alpha^q + \overline{D}_{jt} \phi^q + [y_j \otimes \overline{D}_{jt}] \omega^q + \xi_j^q + \xi_t^q + \Delta \xi_{jt}^q + \nu_{jt}^q$$
(28)

where $v_{jt}^q = \overline{q}_{jt} - q_{jt}$ incorporates sampling and measurement errors, and is conditionally mean-independent of all the explanatory variables in (28). However, it is possible that $\Delta \xi_{it}^{q}$ is correlated with $\Delta \xi_{igt}$, in which case \overline{D}_{it} is correlated with $\Delta \xi_{it}^{q}$. Hence, we use 2SLS for (28).

Estimation Е

E.1 Moment conditions

Recall that we have $J^X = 8,112$ school-year observations for share moments, $J^D = 1,269$ school-year observations for demographic moments and $J^{C}=153$ neigborhood-year observations for neighborhood moments. In total we have $J^S = 281$ campuses in our data. We use GMM to estimate the following 324 utility function parameters: 3 coefficients on peer composition (coefficients on fraction white, fraction Hispanic and fraction nonpoor), 21 coefficients on interactions between student and household characteristics, 3 distance-related parameters, 281 campus fixed effects, 12 grade fixed effects and 4 year fixed effects.

Below we describe how to form the GMM objective function in (22). Let Z_{jgt}^X be a row vector of L^X instruments for share moments, Z_{jt}^D be a row vector of L^D instruments for demographic moments and Z_{kt}^C be a row vector of L^C instruments for neighborhood moments. In our preferred specification, $L^X = 310$, $L^D = 102$ and $L^C = 54$. 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).

Recall our mean-independence assumptions $E\left[\Delta\xi_{jgt} \mid Z_{jgt}^{X}\right] = 0, E\left[u_{jt}^{D} \mid Z_{jt}^{D}\right] = 0$ and $E\left[u_{kt}^{C} \mid Z_{kt}^{C}\right] = 0$. Also, recall that vector u_{jt}^{D} has $\widetilde{D} = 3$ elements, and u_{jt}^{C} has $\widetilde{\widetilde{C}} = 3$ elements. The mean-independence assumptions yield the following $L^X + \widetilde{D}L^D + \widetilde{C}L^C$

 $^{^{47}}$ This averaging is possible because the probability of passing the test is specified as a linear function.

moment conditions:

$$E\left[\left(Z_{jgt}^{X}\right)'\Delta\xi_{jgt}\right] = 0, \ E\left[\left(Z_{jt}^{D}\right)'u_{jt}^{d}\right] = 0 \text{ and } E\left[\left(Z_{kt}^{C}\right)'u_{kt}^{c}\right] = 0,$$
(29)

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

In order to interact the sampling error for each demographic characteristic with every instrument in Z^D we introduce matrix \tilde{Z}^D , which is block diagonal and repeats Z^D along the diagonal for a total of \tilde{D} times. Similarly, block-diagonal matrix \tilde{Z}^C repeats Z^C along the diagonal for a total of \tilde{C} times.

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

$$\lambda_X(\Delta\xi) = \frac{1}{J^X} Z^{X'} \cdot \Delta\xi, \ \lambda_D(\Delta\xi, \theta^d) = \frac{1}{J^D} \widetilde{Z}^{D'} \cdot u^D \text{ and } \lambda_C(\Delta\xi, \theta^d) = \frac{1}{J^C} \widetilde{Z}^{C'} \cdot u^C,$$

with L^X , DL^D and CL^C elements respectively.

In the GMM weighting matrix, we use $V_X = (Z^{X'}Z^X)^{-1}$, $V_D = (\widetilde{Z}^{D'}\widetilde{Z}^D)^{-1}$ and $V_C = (\widetilde{Z}^{C'}\widetilde{Z}^C)^{-1}$. 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. The weighting matrix has block structure because we assume that errors u_{jt}^D and u_{kt}^C are independent. Further, they are independent of the elements upon which students base their choices, including $\Delta\xi_{jgt}$.

Finally, we use Minimum Distance Estimation (MDE) to obtain separate estimates for the coefficients on time-invariant school characteristics (β) and school qualities (ξ_j). Denote by Θ the $J^S \times 1$ vector of campus fixed effects estimated by GMM; by y the $J^S \times Y$ matrix of time-invariant characteristics β , and by ξ the $J^S \times 1$ vector of schoolspecific demand shocks. From (9) and $\xi_{jgt} = \xi_j + \xi_g + \xi_t + \Delta \xi_{jgt}$, the content of the campus dummies is $\Theta = y\beta + \xi$. We assume that $E(\xi_j | y_j) = 0$, which allows us to recover the estimates of β and ξ as $\hat{\beta} = (y'y)^{-1}y'\hat{\Theta}$ and $\hat{\xi} = \hat{\Theta} - y\hat{\beta}$ respectively. The standard errors of $\hat{\beta}$ are corrected to account for the estimation error of $\hat{\Theta}$.

Note that MDE minimizes the sum of squared residuals using the identity matrix as a weighting matrix. Thus, it produces the same coefficients as OLS. Nonetheless, we correct the standard errors to account for the estimation error of $\hat{\beta}$.

Since one of the variables in y_j is tuition (which is positive for private schools, and zero for public and charters), the assumption $E(\xi_j | y_j) = 0$ might not hold. This problem might not be severe because it only affects about a quarter of schools in the sample (see Table 1). Further, since y_j also includes ward indicators and school type, these variables

should absorb much, if not most, of any possible correlation between ξ_j and tuition given that the two private school market segments described in Section 3 differ mostly along the lines of geographic location and school type.

Nonetheless, in order to investigate the potential endogeneity of tuition, we run three alternative Instrumental Variable regressions with the following instruments for tuition:

- 1. Demographics of the school's tract as of 1990;
- 2. Distance to the closest Catholic, Other Religious and Non-sectarian private school offering the same grade span;
- 3. Distance to the closest private school (be it Catholic, Other Religious or Non-Sectarian) offering the same grade span.

We then conducted three separate Hausman tests, one for each set of instruments. In each case, we failed to reject the null hypothesis that the IV coefficient is different from the OLS coefficients. Thus, for efficiency reasons we continued to use the OLS coefficients.

E.2 Computational Considerations

We code 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 use the automatic differentiation capabilities in TOMLAB's TomSym package (included in the Base module). This enables 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 TOM-LAB makes 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 (2012) supply second-order derivatives to the KNITRO solver and use the Interior/Direct algorithm. Avoiding the provision of analytical first- or second-order derivatives greatly facilitates our use of MPEC.

We use both the SNOPT and MINOS solvers in the following manner: we run 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 hand over the problem to MINOS in a "warm-start" fashion to converge to the local optimum. This combination allows us to exploit the virtues of each solver and solve the problem in the most efficient way. Broadly speaking, SNOPT is better suited for a large numbers of unknowns, but makes progress only by changing its limited-memory approximation of the full Hessian of the Lagrangian between major iterations. Once it gets to the point at which it no longer updates the Hessian approximation, it stops making progress. In contrast, MINOS works with the exact Lagrangian and can also make many updates to a full quasi-Newton approximation of the reduced Lagrangian. Hence, MINOS can make progress even when SNOPT cannot provided the size of the problem is not too large. At the same time, MINOS only works well if started sufficiently close to a local minimum.

Hence, SNOPT starts the problem with the full set of unknowns, quickly solves for $\Delta \xi$ and establishes θ^d as the basis variables. After having reduced the size of the problem, it hands the optimization problem over to MINOS.

This approach proved fast and accurate, allowing us to obtain results with 5 or 6 decimal digits of precision.⁴⁸ For our preferred specification, SNOPT-MINOS takes 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.⁴⁹ The computational time compares favorably with that reported by Dube et al (2011) and Skrainka (2012) 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 and neighborhood 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. This issue motivates the constraint of a minimum outside share, as described in Appendix A.2.

F Distance Coefficients

Our distance coefficients reflect the difference in marginal cost of transportation due to the use of different transportation modes – mostly walking in the case of public schools, and mostly not walking (driving or using public transportation) in the case of charter and private schools. We expect the marginal disutility of traveling to be higher for walking than for driving or taking public transportation because traveling an extra mile on foot takes longer (in general) than by car, and may be less safe. Indeed, our estimates are consistent with this expectation. Below we provide a full explanation of our distance coefficients.

Filardo et al (2008) find that the median distance traveled by public and charter school students is equal to 0.57 and 1.77 miles, respectively. Note that D.C. public schools do not provide bussing.

⁴⁸The 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 use an optimality tolerance of 1e-6 and re-scale the problem as needed to ensure that the dual variables had order unity. The output logs report the Jacobian's condition number, and these are 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 find that the solvers are 3-5 times faster by employing this scaling.

⁴⁹The workstation has many cores, but the SNOPT-MINOS solvers are single-threaded and so use only one core. The solvers have a peak memory consumption of 10GB when the derivatives are symbolically computed, and then work with 5GB of RAM. On our 64GB workstation we can therefore run multiple jobs at once from multiple starting points.

Since median travel distance for public schools is relatively low, and 58 percent of public school students attend elementary school, we believe that most public school students walk to school. Conversely, the median travel distance to charter schools leads us to believe that most charter school students do not walk to school. Although we do not have data on travel distance to private schools, we treat private and charter schools similarly because there are fewer private or charter schools than public schools (which means that, on average, a given student lives farther away from a private / charter school than from a public school). Private and charter schools are also similar in that they do not have residence requirements, which allows students to attend more distant schools.

The above suggests that people walk to school when distance is below a certain threshold, and use other transportation modes (henceforth referred to as non-walking) otherwise. Hence, ideally we would like to model travel costs as a function of a threshold distance that determines transportation mode. For each transportation mode, we would also like to model a fixed and a variable cost. We would expect the fixed cost of non-walking (for instance, getting the car out of the garage in the morning and finding parking at the school) to be higher than that of walking. We would also expect the marginal cost of walking to be higher than that of not walking (for instance, walking an extra mile with an elementary school child takes more parental time and effort than driving him an extra mile, and may be less safe).

Such a travel cost function would require five parameters: a threshold for transportation mode choice, two fixed costs, and two marginal costs. Further, we might also want to have different parameters per child age (for instance, one set of parameters for children in K-6 grades, and another for children in middle and high school), for a total of 10 parameters. This is a large number of parameters.

After trying a number of specifications (most of which yielded imprecise estimates) we chose the current one because it is parsimonious and provides the best fit of the data. In this specification, we allow the marginal travel cost to differ by school type as a proxy for transportation mode. The marginal travel cost is captured by the coefficient on distance (for public schools), and the additional marginal cost is captured by the coefficients on distance*charter and distance*private (for charter and private schools, respectively). The fixed travel cost is absorbed into the utility function constant (for public schools); the additional fixed cost for non-public schools is absorbed into the charter and private school dummies.

According to our estimates, the marginal disutility of walking (to public schools) is equal to -1.114 (standard error =0.034), the marginal disutility of non-walking to charter schools is equal to -0.029 (=-1.114+1.085; standard error = 0.048), and the marginal disutility of non-walking to private schools is equal to 0.115 (=-1.114 + 1.129; standard error = 0.061). These estimates are consistent with our expectation that the marginal cost of walking be greater than that of non-walking. At the 5 percent level, we cannot reject the null hypothesis that the marginal cost of non-walking is zero (or close to it).

Since there are fewer charter (and private) than public schools in D.C, on average a student lives farther from a non-public than a public school. Hence, if the student chooses to attend a non-public school, she will travel farther, on average, than to a public school. This means that as long as our counterfactuals yield small increases in the number of charter schools (so that public schools continue to outnumber charters), our distance coefficients will not bias our results. Our counterfactuals indeed yield small expansions in the number of charters.

G Market projections

The 59 charters that were open in Fall 2007 captured a market share of 21.5 percent. Of these schools, 17 had closed by Fall 2013, for a charter exit rate of approximately 0.3. Hence, we can expect $6.4 \ (=0.7*9.1)$ of the 9.1 baseline entrants to last in the long run, capturing 2.3 (=0.7 * 3.3) percent of the market. Assuming the same entry rate for the following six years yields an increase in charter share due to entry approximately equal to 13.8 (=2.3*6) percentage points.

In addition, 33 public schools (or 24 percent of all public schools open in school year 2007) were closed between 2007 and 2014, and about 1/6 of the displaced students shifted to charter schools (source: http://www.21csf.org/csf-home/publications/ Memo-ImpactSchoolClosingsMarch2009.pdf). Assuming that the closed schools captured 24 percent of public school enrollment (equal to 57 percent of total K-12 enrollment in 2007), we estimate that 2.3 (=1/6*0.24*57) percent of all students switched from the closed public schools to charters – enough to support 6.4 additional charters in the long run. Thus, the total charter share for 2013 would be equal to 21.5 + 13.8 + 2.3 = 37.6 percent, close to the observed 2013 charter share of 35 percent.

Similarly, the predicted number of charters for 2013 is the addition of the surviving charters from our sample, entries between 2008 and 2013, and additional entries associated with public school closings, or 42 + 6.4*6 + 6.4 = 87 charters, close to the actual 93 regular charters in Fall 2013.