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THE DISTRIBUTIONAL EFFECTS OF CHARTER SCHOOL ENTRY

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This thesis is dedicated to my wife, Moria. I am deeply grateful for her support, patience, high expectations, coaching, copy editing, and MATLAB tutoring. This work is proof that we can accomplish amazing things together.

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ABSTRACT

Charter schools in urban neighborhoods, especially those that employ "No Excuses" methods, often successfully raise their students' test scores. On the other hand, charter schools in suburban neighborhoods often do not (e.g., Abdulkadiroglu et al. 2011, Angrist et al. 2013). Though location appears to be an important factor in the success of a charter school, few papers have studied the determinants of charter school location. In this dissertation, I document the neighborhood characteristics associated with charter school entry in Chicago between 1998 and 2003, the period immediately after Illinois passed the first Charter school law. I find that charter schools are more likely to enter disadvantaged neighborhoods—those with low student test scores, low household income, a low proportion of white residents, and high public school enrollment. Charter schools also are more likely to enter neighborhoods with low Catholic school enrollment and prevalent public transportation. While charter school entry is associated with a low level of Catholic school enrollment, event studies show that any potential crowd-out effect was likely small. To measure the benefits of charter school entry, I estimate a utility model for schools and calculate the total consumer surplus provided by charter entry from 1998–2013. In 2013, when the stock of charter schools had reached its peak, charter schools provided $1,319 of surplus per charter school student. The surplus accrued disproportionately to disadvantaged areas. Neighborhoods at or below median income obtained 73% of the total benefits from charter schools, and neighborhoods at or below median in math test scores obtained 69% of the benefits from charter schools. In addition to these benefits, an analysis of the costs of Chicago Public Schools (CPS) shows that the growth of the charter sector creates significant cost savings for CPS.

CHAPTER 1

INTRODUCTION

This dissertation contains two chapters that study the first two decades of charter school entry in Chicago. Chapter 2, "The Neighborhood Determinants of Charter School Entry," documents the neighborhood characteristics associated with charter school entry in Chicago and examines whether charter school entry contributed to the decline of the Catholic sector. Chapter 3, "The Aggregate and Distributional Welfare Effects of Charter School Entry" estimates a utility model for schools and uses the estimates to quantify the consumer surplus that charter school entry created for students and families.

In Chapter 2, I use the introduction of Chicago's charter school program as a case study to document where charter schools locate when a large urban school district opens up to charter school entry. Chicago is an interesting setting for such a study since it is composed of neighborhoods with disadvantaged populations as well as neighborhoods that appear suburban, with high incomes and private school attendance. Through a combination of visual evidence and descriptive regressions, I find that charter schools overwhelmingly entered disadvantaged neighborhoods — those with low test scores, low income, and high public school enrollment. Furthermore, charter schools entered areas where public transportation was most available and the Catholic sector was weak.

My descriptive regressions suggest that the level of public enrollment in a neighborhood and school quality, as measured by test scores, are the strongest predictors of charter school entry. One thousand additional public school students in a neighborhood is a associated with a 0.05 increase in the probability of charter school entry, and one standard deviation increase in school quality is associated with a 0.18 decrease in the probability of charter school entry.

My studies also show that charter schools entered neighborhoods with low Catholic enrollment share and avoided those where the Catholic enrollment share was high. In 1997, twenty-eight neighborhoods had a 15% or higher Catholic enrollment share, and charter schools only opened in two of them. In fact, a charter campus never opened in a neighborhood in which the Catholic share of enrollment exceeded 25%.

I also measure the effect of charter school entry on neighborhood Catholic enrollment. An event study shows that neighborhood Catholic enrollment was 174 students lower four years after first charter school entry. Through additional difference-in-difference and robustness checks, I conclude that this is probably an upper bound, and if charter entry decreased Catholic enrollment, then the effect was likely small.

In Chapter 3, "The Aggregate and Distributional Effects of Charter School Entry," I quantify the consumer surplus of charter school entry. Using grade-level enrollment data on the universe of schools in Chicago from 1992–2013 and a sample of student-level data, I estimate a utility model for schools and calculate the change in consumer surplus associated with charter school entry during the sample period. Charter schools provided approximately \$44 of consumer surplus per student (regardless of sector of enrollment) during 1998 to 2013. In 2013, most recent year of my sample, charter schools provided approximately \$138 of surplus per student in Chicago. In that same year, the total benefit per charter student was over \$1,319.

In addition to calculating total welfare, I also calculate welfare by neighborhood. My calculations show that the surplus from charter school entry accrued disproportionately to neighborhoods with low income and test scores. Neighborhoods at or below median income enjoyed 73% of the benefits from charter schools while neighborhoods at or below median in math test scores enjoyed 69% of the benefits from charter schools. While families enjoy the increased consumer surplus from charter school entry, CPS enjoys significant cost savings from having to educate fewer students.

In Chapters 2 and 3, I use data from several sources. In Chapter 4, I document how I created datasets, verified their quality, and prepared the raw data for analysis.

CHAPTER 2

THE NEIGHBORHOOD DETERMINANTS OF CHARTER SCHOOL ENTRY

2.1 Introduction

Since the first charter school opened in 1992, numerous school districts have added charter schools to their menu of schooling options. Today, charter schools exist in all of the twenty-five most populous urban areas in the United States.[1] As the charter school sector has grown immensely, the literature continues to hone in on identifying the settings in which they are most successful. Charter schools in urban neighborhoods, especially those that employ "No Excuses" methods, often successfully raise their students' test scores. On the other hand, charter schools in suburban neighborhoods often do not (e.g., Abdulkadiroglu et al. 2011, Angrist et al. 2013).[2] It is still an open question whether urban charter schools are successful because they are more likely to employ "No Excuses" policies or because they serve more disadvantaged students, who have a lower baseline level of achievement. However, the finding remains that charter schools that open in urban areas have positive effects on students' test scores.[3]

Though location appears to be an important determinant of the success a charter school, few papers have studied the determinants of charter school location. Here, I use the introduction of Chicago's charter school program as a case study to document where charter schools locate when a large urban school district opens up to charter school entry. Chicago is an interesting setting for such a study since it is composed of neighborhoods with dis-

1. Source: U.S. Census Bureau's July 1 2016 population estimates and author's calculations.

2. For a summary, see, Dynarski, Susan, "Urban Charter Schools Often Succeed. Suburban Ones Often Don't." *New York Times.* November 20, 2015.

3. Angrist et al. (2013) suggests that in Boston, utilizing "No Excuses" practices accounts for the "urban effect." In a geographically diverse sample, Clark et al. (2015) find positive effects among disadvantaged students and negative effects among advantaged students.

advantaged populations as well as neighborhoods that appear suburban, with high incomes and private school attendance.

To frame the study, I first document the policies that shaped which charter schools Chicago's charter authority approved. When the initial charter school law was passed in Illinois in 1997, the State instructed school districts to favor schools that served "at-risk" students, and the Chicago charter authority preferred charter applicants that targeted disadvantaged students. However, neither the state or the city had complete control over where charter operators opened their campuses. Therefore, I outline a model that describes which neighborhood characteristics a charter operator considers when it chooses which neighborhood to enter.

In my model, the charter operator chooses the neighborhood where it has the highest potential demand. That is, it will choose the neighborhood that has the most students who have a switching cost low enough to justify leaving their local school for a new charter campus. This switching cost consists of the direct travel cost to the new campus as well as an opportunity cost, the quality of schooling the student would forgo if she leaves her local school. The model predicts that the charter operator will choose neighborhoods that have many school-age residents, poor public schools, and few private school alternatives. Furthermore, the charter operator will choose neighborhoods with available public transportation so that it can import students from other neighborhoods.

To quantify the patterns of charter school entry, I assemble a unique collection of datasets to create neighborhood-level proxies of determinants of charter school demand: neighborhood school quality, population of school-aged children, the presence of Catholic schools, and the availability of public transportation. To quantify how these characteristics contribute to charter school entry, I run regressions of a neighborhood-level entry indicator on these proxies neighborhood characteristics. Importantly, since I study the period surrounding the first entry of charter schools in Chicago, I measure these neighborhood characteristics prior to charter school entry so that the estimates are not contaminated by changing neighborhood demographics due to charter school entry.

In Section 2.6, I document the charter school entry patterns. These patterns reflect the institutional details and predictions of the entry model. Charter schools overwhelmingly opened in low-SES neighborhoods where the existing public schools were low quality. In fact, nineteen charter campuses opened under the first charter school law in Chicago and none of them opened in a neighborhood in the top quintile of income. Similarly, none opened in a neighborhood where the schools had top quintile test scores. The charter entry regressions show that a one standard deviation increase in school quality (as measured by test scores) is associated with a 0.18 decrease in the probability of charter school entry, and this relationship is robust to alternative measures of test score quality.

Historically, Catholic schools have stepped in to educate urban minorities in neighborhoods where the public schools are poor (Neal 1997). This was the case in Chicago prior to charter school entry. Figure 2.1 shows that Catholic schools were the dominant private option in Chicago during before charter schools entered in 1998. After the charter law passed, charter operators chose neighborhoods where the Catholic enrollment share was low. In fact, only two entered neighborhoods where the Catholic enrollment share was above the average (16%), and the entry regressions show that a one standard deviation increase in Catholic enrollment share in a neighborhood is associated with a 0.15 decrease in probability of charter entry.

As a social planner interested in maximizing available schooling options for families, it may be appealing to place charter schools in neighborhoods where the Catholic sector is weak. However, it is possible that charter school entry could crowd out private school enrollment,[4] and recent literature has shown that policies that support schools in the public

4. Toma et al. 2006 and Buddin 2012 find negative relationship between charter schools and private school enrollment while Chakrabarti and Roy (2011) find no causal effect of charter entry on private school enrollment.

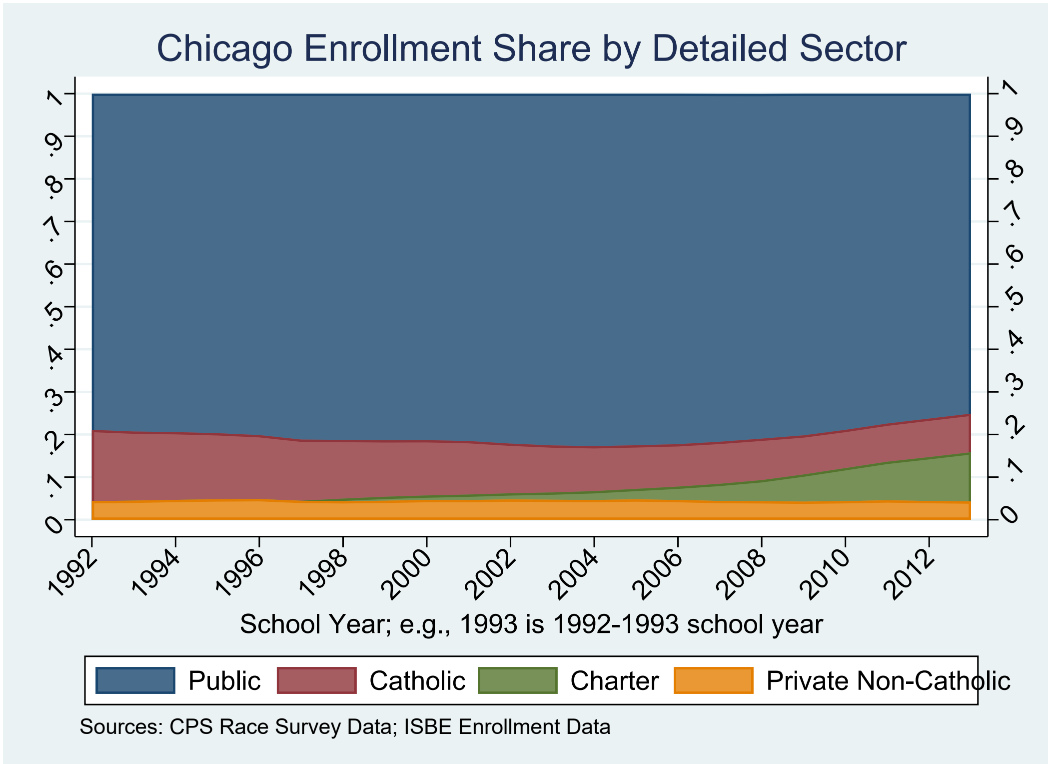

Figure 2.1: Enrollment shares by sector from 1992 to 2013. In Chicago, Catholic enrollment share was declining before charter schools first entered in 1997-1998. Catholic enrollment share was 17% in 1992 and 14% in 1997, the year before first charter entry. By 2011, charter schools enrolled a higher share of students than Catholic schools. As of 2013, charter schools had a 12% enrollment share and Catholic schools had declined to a 9% share.

sector can negatively affect private schools (Dinerstein and Smith 2016). If charter school entry negatively affects Catholic schools, then charter school entry would not represent an influx of additional quality educational options but rather a substitution away from existing private schools. To investigate this, I use difference-in-difference studies to analyze whether charter school entry affected Catholic enrollment, comparing Catholic enrollment in neighborhoods where charter schools had entered to neighborhoods that had not yet experienced charter school entry. My studies show that if charter school entry decreased Catholic enrollment, then the effect was likely small. Therefore, it appears that charter schools did not diminish the Catholic sector, another source of superior school choices in neighborhoods with poor public schools.

Finally, since Chicago charter school policy allows charter schools to enroll students from any neighborhood in the city, charter school operators have an incentive to open in neighborhoods where public transportation is prevalent. I create a new index that measures the neighborhood-level availability of public train stops to test this hypothesis. Indeed, a standard deviation increase in the Transportation Index is associated with a 0.16 increase in probability of charter school entry.

The remainder of the paper proceeds as follows. Section 2.2 contains a brief history of charter schools in Chicago, focusing especially on the institutional details that impacted what types of charter schools opened in Chicago and what neighborhoods they entered. Section 2.3 presents a conceptual framework that outlines a charter operator's choice of neighborhoods.

Section 2.4 describes the data I use for the charter entry regression. I combine a variety of sources to construct the backbone of my data, which consists of a long panel of grade-level enrollment and detailed school location. I also create datasets of test scores from 1990-1996 by digitizing archived Chicago Tribune articles. Finally, I use the U.S. Censuses and Chicago Transit Authority data to identify neighborhood characteristics.

Section 2.6 contains the main results. I use regressions of a neighborhood-level charter entry indicator on neighborhood characteristics to quantify the relationship between neighborhood characteristics and charter school entry. Finally, in Section 2.6.2, I study the relationship between charter school entry and the Catholic sector, and I conclude in Section 2.7.

2.2 Charter School Entry: 1998–2003

In 1996, Illinois Governor Jim Edgar signed the Charter Law ("the Law"), which began the charter school program in Chicago and governed it until 2003. This section contains background on these years, which comprise the sample period in the main results of Section 2.6. I focus especially on the program details that helped determine the location and type of charter schools that opened in the city. Through a combination of its own preferences and its heeding the guidance of Illinois charter school law, CPS mainly opened charter schools that served minority students.

CPS intended its charter school program to be a small set of publicly-funded schools that could experiment with innovative education practices. Charter schools did not have to follow a prescribed curriculum, and they could hire teachers who did not have state teaching certificates. Moreover, they were not subject to local school boards' teachers union contracts, and in Chicago charter school teachers were banned from joining the Chicago Teachers Union (The Civic Federation, 2011).[5] The Law allowed 15 charters in Chicago. Each charter authorized an organization, or "charter operator," to operate at least one charter school campus. [6]

The Law outlined an application process whereby local school boards reviewed charter applications. This law gave the local school boards guidance on how to run the application process, but ultimately gave the local school boards autonomy over which charters to approve or deny. For CPS, the Chicago Board of Education ("The Board") was the local school board. The Board awarded six charters in its first year, and by 2002, CPS had authorized 15 charters, the maximum allowed by law (Figure 2.2). The Law provided information to local school boards about how to evaluate applications, but it mostly left the final decision up to the local school board. The Law required applicants to propose a facility, grade range, and estimated enrollment. It also instructed local school boards to give preference to applications that had

5. Though charter schools today are a contentious political issue, then Chicago Public Schools CEO Paul Vallas called the charter schools program "an extension of our small schools project." Twenty-three "small schools" operated in Chicago at the time. Even Illinois Federation of Teachers spokeswoman Gail Purkey showed only modest opposition to the bill because it allowed charter schools to hire teachers who did not have state teaching certificates. She said "We do not oppose charter schools. We oppose this bill." See, Martinez, Michael. "Parents Find Hope In Charter Schools Law Would Offer Chance To Innovate" March 10, 1996. *Chicago Tribune.*

6. Some operators opened multiple campuses under one charter. I refer to organizations that run multiple charter campuses as "charter networks."

community support and demonstrated a commitment to serving "at-risk" students.[7]

Charters approved and denied by year

Year	Cap	Charters	Approved	Denied/Withdrawn	Closed/Revoked
SY1998	15 Charters	6	6	32	0
SY1999	15 Charters	10	5	18	1
SY2000	15 Charters	12	2	0	0
SY2001	15 Charters	13	1	0	0
SY2002	15 Charters	15	2	10	0
SY2003	15 Charters	14	0	0	1

Sources: CPS Board Reports 97-0122-EX4 and 97-1217-EX2;
ISBE Annual Report dated January 2001 at p.12
ISBE Annual Report dated January 2004; Table 1.

Figure 2.2: Charters approved, denied, and revoked by year for school years 1997-1998 to 2002-2003. "Charters" is the stock of charters CPS had awarded by year. "Approved" is the flow of charters awarded by year. "Denied/Withdrawn" are the number rejected applicants by year. "Closed/Revoked" is the number of charters CPS revoked by year.

Though CPS did not have a rubric for accepting or denying applicants, we can infer their preferences from the types of charters they approved and their rationale for rejecting applicants. Based on the types of schools the Board approved, it appears the Board heeded the State's instruction to serve "at-risk" students. Table 2.1 provides the mission statements of the charters in Chicago as of 2003. Nine of the thirteen mission statements profess a commitment to minority, urban, or disadvantaged students.

Broadly, the Board approved two types of charter schools. First, the Board approved standalone (one campus) schools that targeted at-risk students and offered an innovative educational program. For example, The Young Women's Leadership Academy used a science-focused curriculum and enrolled urban minority girls.[8] Second, the Board approved net-

7. The Law did not further define the term "at-risk."

8. Also see, *e.g.*,

- Two former CPS teachers founded the Academy of Communications and Technology (ACT). ACT had small class sizes and a curriculum focused on developing communication skills. "ACT's emphasis

Table 2.1: Missions of the charters approved between 1998 and 2003. *Source:* 2004 Illinois State Board of Education Annual Report

Charter	**Mission**
ACT	ACT cultivates a small school environment and considers all community members partners in creating a school that attempts to break the cycle of poverty.
ACORN	[ACORN] strives to make college entrance a viable alternative for all its students. It is a dual language high school located in Little Village.
Alaine Locke	This school is dedicated to bringing excellence in academic and social development to children in an under-resourced,urban community and to help them achieve their full potential.
Betty Shabazz	[Shabazz] balances core instruction with African-centered themes, arts and humanities, and technology and links students to local community resources as well as those in South Africa, Brazil, and Ghana.
CICS	[CICS's] mission is to operate K-12 charter schools that provide a rigorous, college preparatory education to every student.
Chicago Prep	The now-closed Chicago Preparatory Charter High School was perhaps the most novel experiment in the charter school movement: It served mostly teens with drug and alcohol problems, and its founder came from Mayor Richard Daley's Office on Substance Abuse Policy.
Global Village	The multiple campuses of this school shared a mission to provide a specialized curriculum based on Chicago's rich multicultural heritage and world-renowned cultural, artistic, and scientific traditions.
Noble Street	[Noble] prepares urban youth in grades 9-12 to function successfully in society by emphasizing commitment to educational excellence; civic responsibility; and respect for the community, the environment, and others.
UChicago	[UChicago] provides an education to students in grades preK-8 while also serving as a school development center for urban teachers.
Octavio Paz	It uses repetition, reinforcement, and mastery to improve student achievement and it provides a disciplined environment, high academic standards, and intensive English instruction. It serves a diverse student population from Pilsen and the Near West Side.
Perspectives	This plan focuses on creating positive self-perceptions, building strong communication techniques, and helping students recognize their responsibility to make a valuable contribution to the community.
Triumphant	This school serves grades 6-8 and is committed to transforming the average or below average student into a scholar poised for success in high school, college and beyond. Classes are of mixed age and ability.
Young Women's Leadership	The focus is on a rigorous career and college preparatory curriculum emphasizing math, science, and technology; leadership; and personal and social development.

worked schools backed by philanthropic foundations that promised to provide an education to at-risk students at a lower cost than CPS could provide. The UNO Charter Network, the Noble Network, and Chicago International Charter School Network are examples. For example, describing the appeal of one such proposal, CPS CEO Paul Vallas said, "[they] brought $1 million to the table to serve an African-American Community with an acclaimed African American educator."[9]

CPS also revealed its preferences in the applicants it rejected. In 1996, CPS evaluated 38 potential charter applications and rejected 32 of them. See Figure 2.2. Figure 2.3 summarizes the CPS's cited deficiencies of charter applicants. The top three deficiencies in applications were finance (71% of rejected applicants), educational programs (68%) and community support (56%).[10] The networked charters backed by philanthropic organizations satisfied CPS's desire for financially strong organizations that served disadvantaged neighborhoods, and the standalone charter schools promised an innovative educational program and community support.

While CPS controlled which charters they approved, they did not choose the campuses' exact locations. In most cases, the charter operator proposed a possible neighborhood in their application, and the charter operator ultimately chose the exact location.[11] In the next section, I model the how a charter operator's chooses a location for its campus.

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is on communication." Rosalind Rossi. *Chicago Sun-Times.* July 12, 1998.

- The Betty Shabazz Charter School uses an Afrocentric curriculum. "School Bd. approves plans for final 2 charter schools." Rosalind Rossi. *Chicago Sun-Times.* April 30, 1998.

9. "6 more charter schools may open doors next fall." Rosalind Rossi. *Chicago Sun-Times* December 17, 1997.

10. Author's calculations based on CPS Board Report 97-0226-EX8

11. When journalist covered charter school applications, they usually referred to each school and its potential neighborhood. See, *e.g.,* Martinez, Michael. "Parents Find Hope In Charter Schools Law Would Offer Chance To Innovate" March 10, 1996. *Chicago Tribune.*

Cited Deficiencies in Charter Applicants: School Year 1997-1998

Cited Deficiency	N	%
Finance	20 of 28	71%
Educational Program	19 of 28 rejected applicants	68%
Community Support	16 of 28	57%
Governance	15 of 28	54%
Management	11 of 28	39%
Facilities	10 of 28	36%
Mission/Vision	3 of 28	11%
Leadership	2 of 28	7%

Source: CPS Board Report 97-0226-EX8

Figure 2.3: Cited Deficiencies of 28 rejected charter applications from 1997–1998.

2.3 Conceptual Framework

The main results in Section 2.6 contain descriptive regressions of a charter entry indicator on neighborhood characteristics. The conceptual framework in this section motivates these regressions. Consider a charter school operator choosing a neighborhood in which to open a charter school campus. Specifically, the charter operator makes a discrete choice among 77 Chicago Community Areas (CCAs) in the city (Figure 2.4). As I describe in more detail in Section 2.4, dividing the city into the CCAs suits the analyses in this paper for several reasons. Most importantly, Census tract boundaries match those of the Chicago Community Areas, which makes it straightforward to assign neighborhood characteristics to CCAs.

Each charter school has an endowment that allows it to provide a given quality. The potential demand for the charter school depends on this quality and its neighborhood choice. Conditional on the level of quality, the charter operator chooses the neighborhood where its

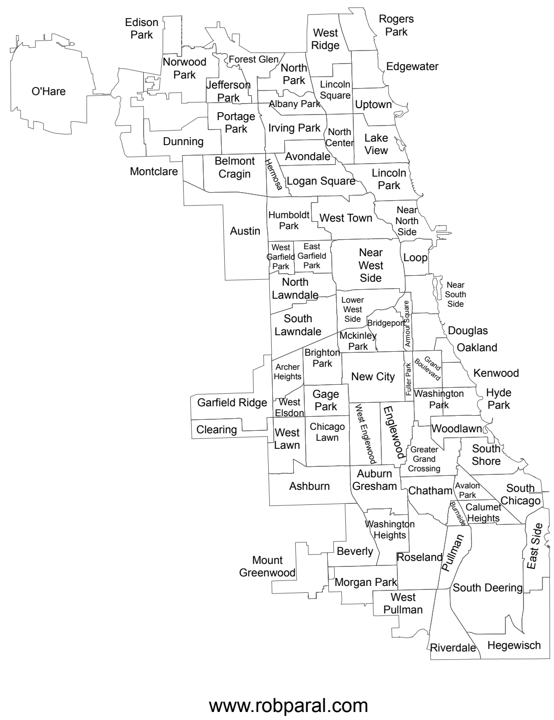

Figure 2.4: Chicago Community Areas. Source: Rob Paral

school has the highest potential demand.[12]

Potential demand in a neighborhood consists of the set of students whose switching cost is low enough to justify switching from their current school of attendance to a new charter school. This switching cost depends on a direct cost, her travel cost to attend the new charter school and an opportunity cost, the utility the student would forgo if she were to remain in her current school.

I consider several neighborhood factors that determine the number of students willing to switch from their current school to a new charter school. Equation 2.1 is the basis of the empirical analysis of this paper. Using OLS regressions, I quantify the impact of neighborhood characteristics on the probability of charter school entry. The probability that

12. If the school is capacity constrained, and this constraint is likely to bind, then the charter operators' problem is similar. Rather than maximizing potential demand *per se*, the charter operator seeks to attract the school's capacity with the least amount of effort. We might think of this effort as recruiting expenditures or the principals' and teachers' time spent convincing students to choose their school.

a charter school enters neighborhood n is a function of the following factors:

$$Pr(Entry_n) = f(D_n, P_n, A_n, C_n) \tag{2.1}$$

- D_n Quality of existing public schools in neighborhood n
- P_n Number of school-aged children in neighborhood n
- A_n Availability of public transportation in neighborhood n
- C_n Presence of private school alternatives n

First, demand depends on P_n, the number of school-aged children in neighborhood n. All else equal, neighborhoods with a larger potential pool of students will have a larger set of students willing to switch to a charter school. Therefore, the probability of charter entry is increasing in P_n:

$$\frac{\partial Pr(Entry)}{\partial P_n} > 0$$

Second, the charter operator will also consider D_n, the quality of the local schools. If the local schools are poor in a neighborhood, then there will be more students with a low opportunity cost of remaining in their local school, and would thus be willing to switch to a charter school:

$$\frac{\partial Pr(Entry)}{\partial D_n} < 0$$

.

Third, potential demand depends on C_n, the presence of private school alternatives. In low-SES areas, Catholic schools have traditionally served as an alternative for families who are unsatisfied with the local public school. Therefore, neighborhoods that lack a Catholic school presence will also hold students willing to switch charter campus.

$$\frac{\partial Pr(Entry)}{\partial C_n} < 0$$

.

Finally, since charter schools can enroll students from anywhere in the city, the charter operator will prefer neighborhoods that have available public transportation A_n:

$$\frac{\partial Pr(Entry)}{\partial A_n} > 0$$

In these neighborhoods, there is a larger set of students whose travel costs are low enough to switch to a charter school.[13]

This simple model of charter school entry illustrates the factors that determine potential demand for a charter school. Here I discuss some of the features the model does not contain and I argue why the simple model will suffice. First, the model does not contain a role of the Board, who approves charter schools in Chicago. A more complicated model might include a period prior to entry during which a charter operator submits its planned location to the Board, which considers the planned location when deciding whether or not to award the operator a charter. Though this version of the model contains more informational content, its predictions would not change. For the predictions to change, it would be necessary for the Board to approve charters on the basis of factors that negatively influence how many students a charter campus is able to attract. The information provided in Section 2.2 indicates that this is not the case. Specifically, The Law and the Board favored schools that served at-risk students — i.e., neighborhoods that had a lower D_n. Furthermore, the Board supported

13. Note that when considering potential demand from outside the neighborhood, schools along the train route also determine potential demand. For example, consider two schools, School A and School B, each of which is located at the end of a different train line. If the neighborhoods along School A's train route contain numerous high-quality schools, School A will compete with those schools when it tries to attract students from outside of its neighborhood. If School B is the only appealing option on its train route, it will face substantially less competition for students who live outside of its neighborhood. I do not utilize data on this aspect of potential demand and acknowledge it as a possible factor.

charter schools that planned to locate in areas with community support. Schools with less attractive public school options (D_n) and private school options (C_n) would have more support for a charter school.

Second, though it is not common, CPS has assigned neighborhood boundaries to some charter campuses. In these cases, CPS and the charter operator jointly decide where the charter campus will locate. Such a decision process can change the relative importance of the determinants of entry described above. However, the direction of the effects will not change. For example, if CPS targeted an area where the public school was overcrowded, then CPS would consider P_n positively in the entry decision, just like in the case of the simple model. Like in the previous case, for the predictions to differ, it would be necessary that CPS would influence a charter operator to open in an area where it would be more difficult to attract students.

To measure the effects of the variables listed above on entry, I create proxy variables that I measure at the Chicago Community Area (CCA) level. The next section describes the data, and Section 2.5, describes the measurements of each proxy variable.

2.4 Data

In order to measure the neighborhood determinants of charter school entry, I use three types of data. The School Data contain a panel of grade-level enrollment for each school in Chicago during 1992 to 2013. I also use neighborhood and school characteristics in order to characterize the neighborhoods in Chicago during the sample period. The sections below summarize these three sources of data.

2.4.1 School Data

I assemble a dataset that includes grade-level enrollment and school location for the universe of schools in Chicago between 1992 and 2013, a period that includes data before and after the first charter schools entered in Chicago in 1998. To create this dataset, I combine a variety of sources. For traditional public schools, I use grade-level enrollment and school addresses from the NCES Common Core from 1992 to 2013. The NCES makes these data available to the public.

No such public dataset exists for charter schools, so I combine publicly available data and information from archived Illinois Charter Annual Reports.[14] I use charter school enrollment and location data from the CPS Racial and Ethnic Survey for the years 2004 to 2013. For 1998 to 2003, I manually compile the data from ISBE Charter Annual Reports.

Similarly, for private schools there is no publicly available dataset that contains annual grade-level enrollment and location.[15] For private schools, I obtained the necessary data via the Freedom of Information Act (FOIA). Through FOIA, the Illinois State Board of Education provided me with grade-level enrollment and school location from 1992 to 2013.[16]

2.4.2 Neighborhood and School Characteristics

Neighborhood and School data

I supplement the School Data with data that describe Chicago's neighborhoods. In Section 2.6, I use these datasets to create independent variables in the charter supply regressions. To measure the accessibility of neighborhoods, I use Chicago Transit Authority data on locations of train stops. To measure the quality of schools in neighborhoods, I created datasets of grade-level test scores by digitizing archived Chicago Tribune articles. Finally, I use the 1990 U.S. Census for neighborhood demographics.

Neighborhood Definition

14. NCES and ISBE data contain data on charter schools, but they do not always disaggregate the data by charter campus within a charter network.

15. I considered the Private School Survey (PSS). My data provide two main advantages over the PSS. First, my data are annual, allowing me to observe year-to-year changes in enrollment. Second, the data contain school location back to 1992. Before 2002, the PSS location data is unreliable.

16. ISBE has similar files that are publicly available, but they do not contain grade-level enrollment and the earliest year they offer is SY2004.

As illustrated in Figure 2.4, I define the neighborhoods as Chicago's 77 Community Areas (CCAs). To create CCA-level variables, I construct weighted averages of census tract variables or weighted averages of school variables. CCAs are an appropriate neighborhood definition for four reasons.

1. CCA boundaries have not changed since members of the University of Chicago Social Sciences Research team invented them in the 1920s.[17]
2. CCAs match Census Tracts with minimal overlap.[18]
3. The City of Chicago recognizes CCAs as statistical areas.[19]
4. Residents of Chicago use CCAs to refer to neighborhoods.[20]

In the analyses in Section 2.6 the cross-sectional unit of observation is the Chicago Community Area. In the sections that follow I refer to neighborhoods and CCAs interchangeably. When I subscript a variable with n, it is measured at the CCA level.

2.5 Proxy Variables and Summary Statistics

In Section 2.3, I model charter school entry as a function of four neighborhood characteristics: the number of school-aged children (P_n), the quality of existing schools (D_n), the availability of public transportation (A_n), and the presence of private school alternatives (C_n). In this section, I describe the proxy variables I create for each of these measures.

17. See, e.g., https://www.lib.uchicago.edu/e/collections/maps/censusinfo.html

18. I link 2000 and 2010 Census Tracts to Chicago Community Areas using equivalency files available from Rob Paral and Associates, a Chicago-based research company.

19. See, e.g., https://www.lib.uchicago.edu/e/collections/maps/censusinfo.html

20. For example, Coldwell Banker's residential home search function allows users to enter names of community areas to narrow their search for a home.https://www.coldwellbankerhomes.com/il/chicago/archer-heights/recent-sales/?dym=archer\%20heights

2.5.1 Public School Quality D_n

I use two test score proxies for the attractiveness of existing schools D_n. My preferred measure of public school quality D_n is the Average Math Test Score (AMTS), a neighborhood-level index of 1990 math test scores. To create the AMTS, I first create z-scores of 1990 math test scores for each school-grade: $z_{jg,1990}$. Then the AMTS for a given neighborhood is the weighted-average of z-scores among the set $\mathcal{J}_n$, school-grades in the neighborhood n. The weights are number of students in the school-grade: w_{jg}. Average Math Test Score is defined as the following:

$$AMTS_n = \frac{1}{W} \sum_{jg \in \mathcal{J}_n} z_{jg,1990} \times w_{jg}$$

where $W = \sum_{jg \in J_n} w_{jg}$, the total number of students in neighborhood n. Table 2.2 contains summary statistics of AMTS. This measure ranges from -0.96 to 1.73 with a standard deviation of 0.7. In my main regressions, I consider how a one unit increase in AMTS affects charter school entry. A one unit increase is a large increase, representing a move from the bottom of the distribution of AMTS to the middle.

As an additional proxy for the attractiveness of local public schools, I construct Cohort Value-Added. I do not have student-level data, so I am unable to construct a conventional value-added measure. However, the test score data contain multiple consecutive years of grade-level data, so I am able to construct a cohort-level value-added measure CVA_n.

To create Cohort Value-Added, I use three 6th grade cohorts from 1993, 1995, and 1996. First, I run the following regression:

$$MathTest_{j6t} = \alpha MathTest_{j3,t-3} + \gamma_t + \theta_j + \epsilon_{jgt}.$$

The dependent variable $MathTest_{j6t}$ is the grade 6 math test score at public school j at time t. I regress this on the test scores of the same cohort — the third graders at school

Table 2.2: This table contains summary statistics of the 77 Chicago Community Areas. I create CCA-level variables by aggregating Census tract-level and school-level data. Proportion Nonwhite and Median Income are measured with the 1990 Census. Public Enrollment is the number of students in public school in 1997, measured in 1000s. Average Math Test Score is the average standardized math test score for school-grades in 1990. Transportation Index is an index standardized to have mean of zero and standard deviation one that measures the availability of public transportation.

Variable	Obs	Mean	Std. Dev.	Min	Max
Charter ever opened in CCA during 1998-2003	77	.29	.45	0	1
Max charters in a CCA-year during 1998-2003	77	.32	.55	0	2
Proportion Nonwhite Residents 1990	77	53.34	37.26	.96	99.87
Median Income 1990 (1000s)	77	49.69	18.53	11.82	95.07
Public Enrollment 1997 (1000s)	77	5.45	3.84	.46	17.17
Average Math Test Score	76	.27	.7	-.96	1.73
Catholic Enrollment Share 1997	77	16.26	15.17	0	77.4
Catholic Share Growth 1992-1997	77	-19.58	36.57	-200	38.85
Catholic Share Change 1992-1997	77	-2.76	4.66	-18.37	10.75
Transportation Index	77	0	1	-.96	3.48

j three years prior — using $MathTest_{j3,t-3}$. γ_t and θ_j are year and school fixed-effects, respectively. I divide the school fixed effect θ_j by 3 to create a one-year value added measure for each school. Then, I average the value-added measures within each neighborhood to create a neighborhood Cohort Value-Added measure (CVA_n):

$$CVA_n = \frac{1}{E_n} \sum_{j \in \mathcal{J}_n} \frac{\hat{\theta}_j}{3} \times E_j$$

where E_j is the number of students enrolled at school j and E_n is the total number of students in neighborhood n.

This measure is highly correlated with the Average Math Test Score ($\rho = .90$). Plus, recent research suggests that families rely more on average test scores when they choose a school than they do on value-added (Abdulkadiroglu et al. 2017). Thus, I use the Average Math Test Score as my preferred proxy variable. My main results do not change substantially when including Cohort Value-Added instead of Average Math Test Score. See Appendix A.3 and Table A.2.

2.5.2 School-aged Children P_n

My proxy for P_n is the total enrollment in public schools in a neighborhood in 1997, the year prior to first charter school entry:

$$PubEnroll_{n,1997} = \sum_{j \in \mathcal{J}_n} PubEnroll_{j,1997}$$

Table 2.2 shows that public enrollment varies widely by neighborhood. In some neighborhoods, public enrollment numbered less than 1000 students while in others there were over 17,000 students enrolled in a public school.

As an additional proxy for school-aged children, I use the 1990 Decennial Census count of students aged 6-18. This is highly correlated with $PubEnroll_{n,1997}$ ($\rho = 0.90$).

2.5.3 Public Transportation A_n

My proxy for A_n is the Transportation Index, an index that measures the availability of public trains stops in a neighborhood. This index treats each neighborhood as a collection of points, namely the centroids of the census blocks in a neighborhood.[21] For each neighborhood, the index represents how many of these points are near a train stop. For example, in a neighborhood that has one train stop in its far northeast corner, very few of the neighborhood's points will be near this stop, and the neighborhood will have a low Transportation Index. On the other hand, in a neighborhood where two train lines run through the middle of the neighborhood, more of the neighborhood's points will be near a train stop, and it will have a high Transportation Index.

I create the Transportation Index according to the following steps:

1. Identify the Census blocks in each Chicago Community Area (CCA).

21. There are approximately 130 census blocks per Chicago Community Area.

2. Calculate $StopCount_{bn}$ for each Census Block: the number of train stops within 2 miles of the centroid of the Census Block.

3. Calculate Average Stop Count, the average of $StopCount_{bn}$ in each CCA.

4. Create the CCA-level Transportation Index by standardizing the Average Stop Count to have a mean of zero and a standard deviation of 1.

Steps 1 to 3 yield the following formula for the non-standardized Transportation Index (TI'_n)

$$TI'_n = \frac{1}{B_n} \sum_{b=1}^{B_n} StopCount_{bn}$$

where B_n is the number of Census blocks in neighborhood n.

and the measure I use, the standardized Transportation Index is the following:

$$TI_n = \frac{TI'_n - \bar{TI'_n}}{s.d.(TI'_n)}$$

where $\bar{TI'_n}$ and $s.d.(TI'_n)$ are the is the citywide average and standard deviation, respectively.

2.5.4 Private School Options C_n

I utilize three proxies for C_n. First, I define Catholic enrollment share in neighborhood n in 1997 as the following:

$$CatholicShare_{n,1997} = \frac{\sum_{j \in \mathcal{J}_{Catholic,n}} E_j}{\sum_{j \in \mathcal{J}_n} E_j} \times 100$$

where E_j is the enrollment at school j, $\mathcal{J}_n$ is the set of all schools in neighborhood n, and $J_{Catholic,n}$ is the subset of Catholic schools in neighborhood n.

$CatholicShare_{n,1997}$ measures the level of Catholic enrollment share in percentage points in neighborhood n in 1997, the year prior to first charter school entry. Table 2.2 shows that in 1997, the average neighborhood's Catholic enrollment share varied widely. Some neighborhoods had no Catholic schools, while in others Catholic enrollment accounted for over 77% of total enrollment. I also construct two proxy variables that measure whether the Catholic sector was growing or declining during the five years prior to the first charter school entry.

$ShareDiff_{n,(1992-1997)}$ measures the difference in Catholic enrollment share from 1992 to 1997 for neighborhood n:

$$ShareDiff_{n,1992-1997} = CatholicShare_{n,1997} - CatholicShare_{n,1992}$$

During 1992 to 1997, the Catholic sector in Chicago was in aggregate decline. The average neighborhood declined in Catholic share by 2.76 percentage points. Of the 77 CCAs, 57 declined in Catholic share. Moreover, of the twenty neighborhoods where Catholic share did not decline, fourteen neighborhoods increased in Catholic share by less than one percentage point. Thus, while in some neighborhoods Catholic share grew, in the vast majority of neighborhoods it either declined or grew only slightly.

The raw difference in Catholic share does not take into account the baseline Catholic enrollment share in 1992. That is, a one percentage point change in share difference may be large in a neighborhood where the initial share is low, but small in a neighborhood where the initial share is high. To take into account the level of Catholic share in an neighborhood, I create $ShareGrowth_{n,1992-1997}$:

$$ShareGrowth_{n,1992-1997} = \frac{CatholicShare_{n,1997} - CatholicShare_{n,1992}}{\frac{1}{2}\left(CatholicShare_{n,1997} + CatholicShare_{n,1992}\right)}$$

Like $ShareDiff_{n,1992-1997}$, $ShareGrowth_{n,1992-1997}$ shows that the average neighborhood in Chicago has a declining Catholic sector immediately prior to Charter school entry. This measure is positively correlated with $ShareDiff_{n,1992-1997}$ ($\rho = 0.90$).[22]

These three measures capture different aspects of the presence of the Catholic sector in a neighborhood, and together depict how Catholic share was changing within and across neighborhoods immediately prior to charter school entry. For one, $CatholicShare_{n,1997}$ is negatively correlated with $ShareDiff_{n,(1992-1997)}$ ($\rho = -0.30$). This means that neighborhoods that had a higher Catholic share had higher raw declines in Catholic share during 1992 to 1997.

$ShareGrowth_{n,1992-1997}$, on the other hand is uncorrelated with $CatholicShare_{n,1997}$ ($\rho = 0.03$). This means that controlling for initial level of Catholic enrollment share, the changes in share across neighborhood were similar during this time period. In fact, ordering of neighborhoods by Catholic share is highly persistent between 1992 and 1997. The rank order correlation between Catholic enrollment share in 1997 and Catholic enrollment share in 1992 is 0.96. In summary, in the five years prior to charter school entry, Catholic enrollment was declining in the aggregate. Across neighborhoods, Catholic enrollment declined such that the ranking of neighborhoods according to Catholic enrollment share did not change.

2.5.5 Neighborhood Income I_n.

Lastly, I discuss neighborhood income as an important neighborhood characteristic related to charter school entry. The measures above all represent clear determinants of charter school entry. On the other hand, neighborhood income is a proxy for many aspects of a neighborhood that could affect whether a charter school enters.

First, neighborhood income proxies for the price of land in a neighborhood. In neighbor-

22. By construction, if a neighborhood declines from a positive Catholic enrollment share in 1992 to a negative Catholic enrollment share in 1997, then $ShareGrowth_{n,1992-1997} = -200$. This is the case for two neighborhoods. I estimate my main regressions with and without these neighborhoods, and my conclusions do not change.

hoods where land values are higher, charter schools' operating costs will be higher. To test this hypothesis, I use median income and rent measures from the 1990 Decennial census. As expected, 1990 neighborhood average income and 1990 neighborhood average rent paid are positively correlated ($\rho = 0.82$). Higher operating costs in a neighborhood in the form of higher rent will deter charter schools from entering.

Second, neighborhoods with high incomes will feature public schools where parents are more involved in the volunteer organizations and PTA. Thus, neighborhood income represents a portion of school inputs not measured directly by, but correlated with, test scores. Indeed, AMTS and median income are also highly correlated. ($\rho = 0.72$).

Finally, neighborhood income represents residents' ability to pay for Catholic schools and other private schools. Using school data from 1992, Catholic enrollment share is positively correlated with 1990 median income ($\rho = 0.43$).

Neighborhood income proxies for all three of these characteristics of a neighborhood, all of which decrease the demand for an entering charter school. In my main regressions, I measure the relationship between neighborhood income and charter school entry, but since it does not proxy for one specific neighborhood characteristic, I consider it separately from the previously discussed proxy variables.

2.6 Results

2.6.1 Visual Evidence

In this section, I provide visual evidence of the relationship between charter school entry and the proxy variables described in the previous section. For each proxy variable above, I present neighborhood maps of Chicago that contain two main features: they contain markers that indicate the locations of charter campus locations as of 2003, and the neighborhoods are colored to show the magnitude of the proxy variable of interest.

Charter school entry was especially prominent in the West and South sides of Chicago. As the maps in the following sections show, these neighborhoods have the characteristics that we expect to be correlated with charter school entry. These are the poorer areas of Chicago where public enrollment is high and test scores are low. Plus, these neighborhoods have low Catholic enrollment, and, numerous train lines serve the West Side.[23]

Existing Schools D_n

Figure A.1 displays Chicago neighborhoods by the quintile of Average Math Test Score. As of 2003, charter schools opened almost exclusively in neighborhoods where the schools had low test scores. Only four of nineteen charter campuses were located in neighborhoods where the test scores were 3rd quintile or better. Moreover, three of these four campuses were on the border of a bottom quintile neighborhood. [24]

School-aged Children P_n

Figure 2.5 maps neighborhoods according to their level of public school enrollment in 1997. Charter campuses were much more likely to enter neighborhoods where the level of public school enrollment was high. Only two of the nineteen campuses open in 2003 opened in neighborhoods in the first or second quintile of public enrollment. Figure A.4 shows that this relationship also holds when proxying for the school-aged population with the number of residents between 6 and 18 years old as measured by the 1990 Census.

Public Transportation A_n

Figure 2.6 maps charter campus locations and Chicago's public train system. In Chicago the public train system provides multiple routes that extend out of the center of the city and

23. As additional checks, in Appendix A.6 I include maps using additional proxy variables.

24. This pattern also holds for reading test scores. See Figure A.3.

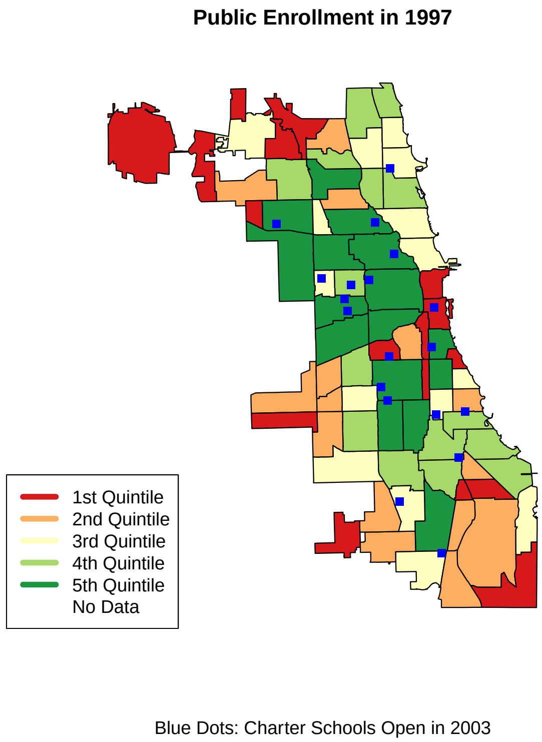

Figure 2.5: Charter school campuses in 2003 (Blue Squares). Colors indicate Chicago Community Area's quintile of public school enrollment in 1997. "1st Quintile," *e.g.*, indicates the lowest income neighborhoods.

into the near West and South sides. However, only some routes extend to the far northwest side, the far southwest side, or the far south side. Even then, those lines do not extend to the borders of the city. Numerous charter campuses opened in neighborhoods on the near South and West side, where there are many available train stops. Of the nineteen campuses open in 2003, only 3 campuses are located in a neighborhood without a train stop.

Private School Options C_n

In 1997, neighborhoods in Chicago varied widely in the level of Catholic presence. Some neighborhoods had no Catholic enrollment while in others the share was over 77%. On the west side of Chicago, where the most charter schools entered, many neighborhoods were in the lower half of the distribution of Catholic enrollment share. The neighborhoods that

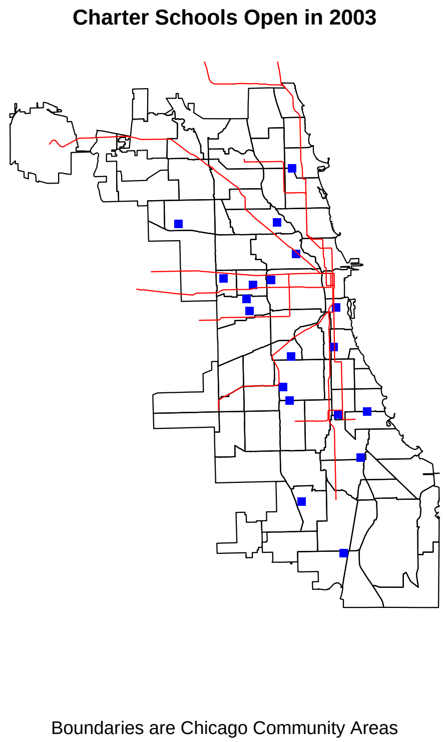

Figure 2.6: Charter school campuses in 2003 (Blue Squares). Red lines are Chicago Transit Authority (CTA) Rail Lines.

have the highest Catholic share are located in the Far Southwest and Far Northwest sides of Chicago. Figure 2.7 shows that none of these neighborhoods had a charter school in 2003.

Figure 2.8, which plots two histograms, further corroborates the negative relationship between charter school entry and Catholic share. The green histogram shows the distribution of $Share_{n,1997}$ in neighborhoods where charter schools had entered as of 2003. The clear histogram shows the distribution of $Share_{n,1997}$ where charter schools had not entered as of 2003.

The two histograms only overlap on the left tail of the $Share_{n,1997}$, showing that charter schools avoided neighborhoods with high Catholic enrollment share. Twenty-eight neighborhoods had a 15% or higher enrollment share; charter schools only opened in two of them. In fact, a charter campus never opened in a neighborhood in which the Catholic share of enrollment exceeded 25%.

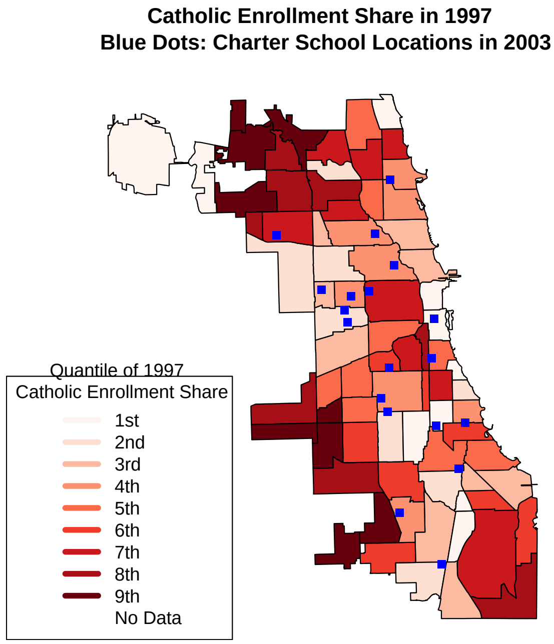

Figure 2.7: Charter school campuses in 2003 (Blue Squares). Colors indicate Chicago Community Areas's Catholic enrollment share. "1st Quintile," *e.g.*, indicates the lowest Catholic Enrollment share.

Neighborhood Income I_n

Figure 2.9 displays neighborhoods by the quintile of 1990 median income. In 2003, all but three charter campuses were in neighborhoods in the middle quintile of income or below, and none of the richest neighborhoods had a charter campus. Eleven of the nineteen campuses were in the neighborhoods in the bottom quintile of income.

The visual evidence provided in this section is compelling because it matches the predictions of the simple model in Section 2.3. Charter schools entered neighborhoods where their potential demand would be highest. In the following sections, the entry regressions quantify the relationships that are clear from the visual evidence.

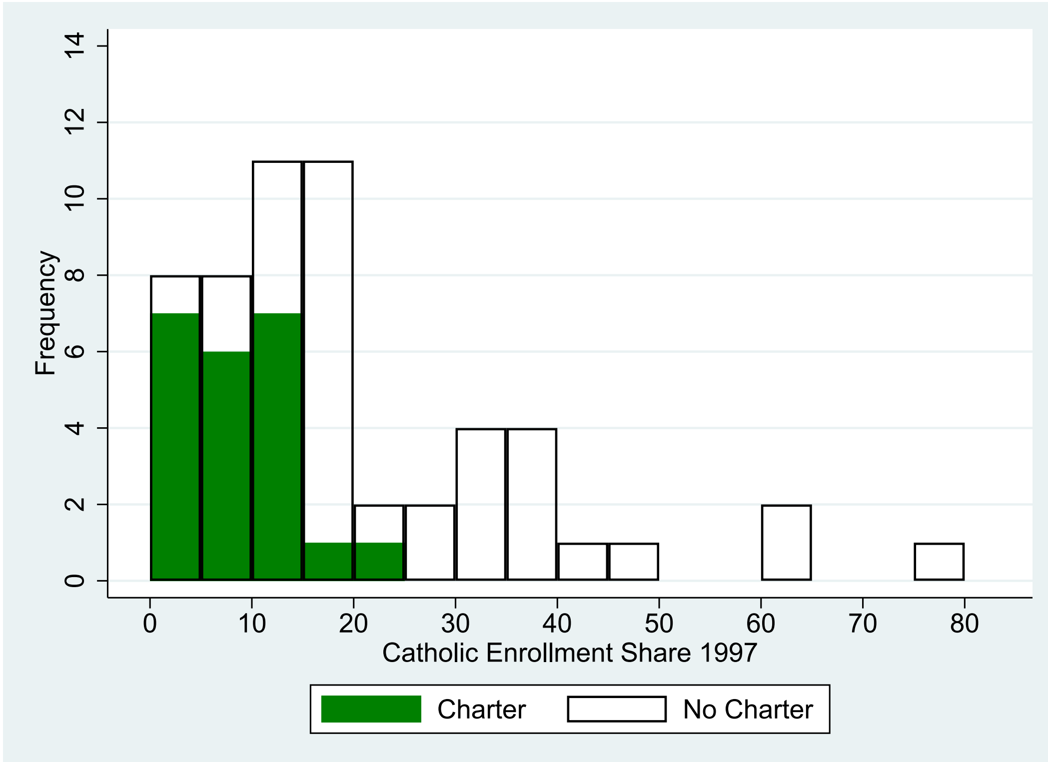

Figure 2.8: Histograms of 1997 Catholic Enrollment Share. "Charter" histogram (green) represents Chicago Community Areas (CCAs) that ever had a charter between 1998 and 2003. "No Charter" histogram (no color) represents CCAs that never had a charter between 1998 and 2003. The unit of observation is a CCA.

2.6.2 Charter Entry Regressions

The maps in the previous section clearly show that charter schools entered neighborhoods that had low income, many school-aged children, low-quality schools, a low Catholic presence, and available public transportation. In this section, I use descriptive regressions to quantify these patterns. In each regression the dependent variable is $Y_{n,2003}$, which is an indicator equal to one if a charter school ever located in neighborhood n as of 2003.[25]

The independent variables are the proxy variables that I describe in the previous section.[26] Recall that all of these proxy variables measure neighborhood characteristics prior

25. By using this dependent variable, I define entry into a neighborhood as either 1) a new charter school opens in a neighborhood or 2) an existing charter school moves to a neighborhood.

26. As noted in Section 2.5, neighborhood income represents numerous characteristics related to charter

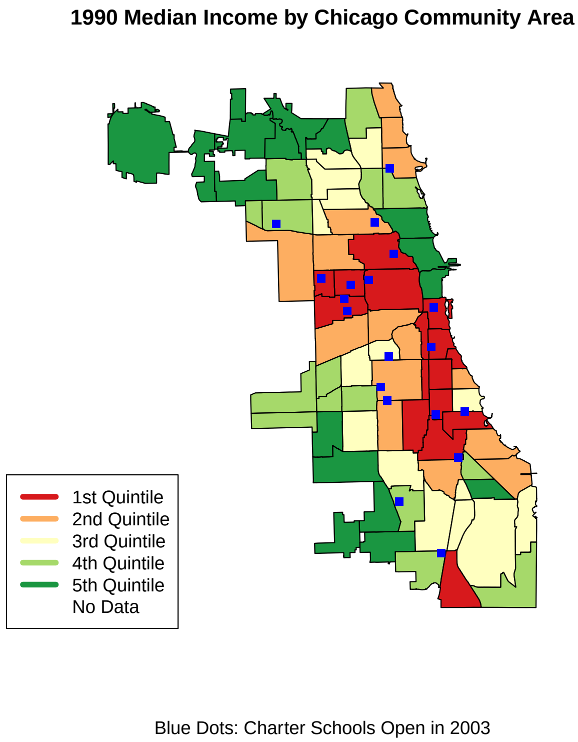

Figure 2.9: Charter school campuses in 2003 (Blue Squares). Colors indicate Chicago Community Area's quintile of median income according to the 1990 Census. "1st Quintile," *e.g.*, indicates the lowest income neighborhoods.

to charter school entry. This shuts down the possibility that neighborhood demographics changed due to charter school entry itself.

The regressions study the first five years of charter school entry, from 1997-1998 to 2002-2003. School year 2002-2003 represents a natural end point to the study because the Board did not award any new charters that year, and in the summer of 2003, Illinois passed a new charter law that increased the charter cap to 30 charters, starting a new era of entry.

Public Enrollment, School Quality, and Transportation Index

Table 2.3 contains estimates of three univariate regressions and one multiple regression. Column 1 of Table 2.3 contains the estimate of the following regression:

school entry. This makes what it proxies for unclear, so I study it separately in Appendix A.2.

$$Y_{n,2003} = \beta_0 + \beta_1 P_{n,1997} + \epsilon_n$$

where $P_{n,1997}$ is the number of students (in thousands) enrolled in public school in neighborhood n in 1997. For each additional 1,000 public school students ($.26\sigma$) in a neighborhood, the probability of charter school entry increases by 0.045 percentage points. A one standard deviation increase is associated with an increase in entry probability of 0.18.

As an illustration of the magnitude of this effect, consider two example neighborhoods. In 1997, among the 77 Chicago Community Areas, South Deering was in the 25th percentile of public school enrollment with 2,058 students. West Pullman was the median neighborhood with 5,145 public school students. Based only on their levels of public enrollment, a charter school would be 14 percentage points more likely to enter West Pullman than South Deering.

Column 2 of Table 2.3 contains the estimate of the following regression:

$$Y_{n,2003} = \beta_0 + \beta_2 D_{n,1990} + \omega_n$$

where $D_{n,1990}$ is the Average Math Test Score (AMTS) in neighborhood n in 1990. As seen in the maps in the previous section, charter entry is negatively correlated with the AMTS. A one unit increase (1.42σ) in the AMTS is associated with a 0.26 decrease in the probability of charter school entry, and a standard deviation increase is associated with a decrease in entry probability of 0.18, similar in magnitude to the effect size of public enrollment P_n.[27]

Column 3 of Table 2.3 contains the estimate of the following regression:

$$Y_{n,2003} = \beta_0 + \beta_3 A_n + \psi_n$$

27. My main results do not change when including Cohort Value-Added instead of AMTS. See Appendix A.3 and Table A.2

where A_n is the Transportation Index, a standardized index that measures the availability of public train stops in neighborhood n. The Transportation Index is increasing in the number of public train stops in the neighborhood.

A one standard deviation increase in the Transportation Index is associated with a 0.16 increase in the probability of charter entry. To illustrate, consider two West Town, neighborhood immediately northwest of the Loop, Chicago's central business district, and Washington Park on the South Side of Chicago, which is separated from the Loop by 3 other neighborhoods. Three different train routes service West Town while only two train lines run north and south through Washington Park, and one of them is on its western border. Consequently, West Town's Transportation Index is approximately one unit larger than Washington Park's differ by approximately one unit in the Transportation Index. The regression in Column 3 of Table 2.3 predicts that, all else equal, a charter school is 0.16 percentage points more likely to enter West Town than Washington Park.

The three univariate regressions indicate that public school enrollment, test scores, and availability of public transportation all influence charter school entry at approximately the same magnitude. To further explore the relative effect sizes of these variables, I estimate a multivariate regression that includes all three variables.

Column 4 of Table 2.3 estimates the following multivariate regression model:

$$Y_{n,2003} = \gamma_0 + \gamma_1 P_{n,1997} + \gamma_2 D_{n,1990} + \gamma_3 A_n + \upsilon_n$$

where $P_{n,1997}$, $D_{n,1990}$, and A_n are defined as above.

All coefficients retain the same sign in this regression, providing further evidence of their relationships with charter school entry. The magnitudes of the coefficients, though, decrease slightly. Conditional on the other variables, a one standard deviation increase in public enrollment, the AMTS, and the Transportation Index are associated with an increase in charter entry probability of 0.11, 0.12, and 0.08, respectively.

Table 2.3: This table shows coefficient estimates from four OLS regressions. The unit of observation is a Chicago Community Area (CCA). In each regression, the dependent variable is an indicator variable equal to 1 if a charter school ever located in that CCA during 1998-2003. I create the CCA-level independent variables by aggregating Census tract-level and school-level data. Public Enrollment is the number of students in public school in 1997, measured in 1000s. Average Math Test Score is the average standardized math test score for school-grades in 1990. Transportation Index is an index standardized to have mean of zero and standard deviation one that measures the availability of public transportation.

	(1)	(2)	(3)	(4)
Public Enrollment 1997 (1000s)	0.045***			0.029**
	(0.013)			(0.014)
Average Math Test Score		-0.255***		-0.170**
		(0.069)		(0.072)
Transportation Index			0.157***	0.076
			(0.049)	(0.054)
Constant	0.040	0.344***	0.286***	0.167*
	(0.084)	(0.051)	(0.049)	(0.097)
Observations	77	76	77	76
R^2	0.15	0.16	0.12	0.25

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The comparison of the coefficients in the univariate models and the multivariate model indicate that public enrollment and school quality are strong predictors of charter school entry. For both public enrollment and AMTS, the magnitude of the coefficient is approximately two-thirds as large as in the their respective univariate regressions, and both are statistically significant in the multivariate model. In contrast, the coefficient on the Transportation Index is about half the size in the multivariate regression compared to the univariate regression and no longer statistically significant. Charter schools certainly entered neighborhoods where there was more public transportation, but these regressions show that Transportation Index does not explain as much of charter entry as public enrollment and school quality.

Using the multivariate model, I assess the economic significance of the estimates. Consider a hypothetical neighborhood that has average levels of public school enrollment, test scores, and availability of public transportation. According to Column 4 of Table 2.3, a charter school will enter this average neighborhood with probability of 0.11. West Ridge, on Chicago's Far North Side has a predicted probability of charter entry similar to that of the hypothetical average neighboorhood. It is near the average in Transportation Index, slightly above average in the AMTS, and in 1997, had slightly more public school students then the average neighborhood. Although its higher test scores make it less attractive to charter school entry, its numerous school-aged residents make it attractive. According to the multivariate regression, decreasing West Ridge's AMTS by one unit would double the likelihood that a charter school enters.[28]

As an illustration of the extremes, West Town is an especially attractive neighborhood for charter schools. Its high public school enrollment (17,170), low AMTS (-0.21), and high Transportation Index give it the highest predicted probability of charter school entry. On the other hand, Dunning, a neighborhood on the Northwest border of Chicago, has below

28. Of course, this is a static effect. If a neighborhood's tests scores suddenly decreased by one standard deviation on average, students would likely leave those schools, and this would make it less attractive to charter school entry in the future.

average public school enrollment (2,414), above-AMTS (1.56), and low Transportation Index (-0.94), making it a neighborhood with low potential demand, and it has the lowest predicted probability of charter school entry.

To summarize, a neighborhood with one standard deviation above (below) the mean in public enrollment, one standard deviation above (below) the mean in Transportation Index, and one standard deviation below (above) the mean in math test scores has a 0.59 (0.07) probability of receiving a charter school.

Catholic Variables

In this section I study the relationship between charter school entry and the Catholic sector. Then, in the following section, I present results from combined regressions that study the Catholic proxy variables together with all of the neighborhood characteristics.

Both charter schools and private schools act as a release valve for students who are unsatisfied with their local school.[29] Therefore, some families likely view private schools and charter schools as substitutes. If charter and Catholic schools are substitutes, then charter operators would avoid neighborhoods where Catholic presence is high in order to avoid competing with Catholic schools. The histograms and maps in Section 2.6.1 showed that charter schools avoided neighborhoods with high Catholic enrollment share, and in this section, I quantify this relationship.

The maps and histograms in the previous section clearly show that charter schools entered neighborhoods that had low Catholic enrollment share. In this section, I use descriptive regressions to quantify these patterns. In each regression the dependent variable is $Y_{n,2003}$, which is an indicator equal to one if a charter school ever located in neighborhood n as of 2003. The independent variables are the three proxy variables that I describe in the previous section.

29. For private schools, see Neal (1997) and Neal and Grogger (2000). Dynarski (2010) provides a review of the potential benefits of charter schools.

Table 2.4 contains estimates of these regressions. Columns 1 to 3 of Table 2.4 display univariate regressions of Y_n on the three proxy variables for Catholic presence described in Section 2.5. Column 1 of Table 2.4 contains the estimates of the following regression:

$$Y_{n,2003} = \delta_0 + \delta_1 CatholicShare_{n,1997} + \epsilon_n$$

where $Share_{n,1997}$ is the Catholic enrollment share in neighborhood n in 1997. Catholic presence in a neighborhood appears to deter charter school entry. A one percentage point increase in neighborhood Catholic enrollment share is associated with a 0.01 decrease in charter entry probability, and a one standard deviation increase is associated with a 0.15 decrease in the probability of charter entry. This effect size is slightly smaller in magnitude to those from the univariate regressions of $Y_{n,2003}$ the AMTS, and public school enrollment.

Columns 2 and 3 of Table 2.4 contain estimates of regressions of the charter entry indicator on measures of the change in Catholic school presence from 1992 to 1997: $ShareGrowth_{n,1992-1997}$ and $ShareDiff_{n,1992-1997}$. These regressions provide evidence on whether charter school operators decided to enter in neighborhoods where the Catholic sector was declining more briskly than in other neighborhoods. Column 2 of Table 2.4 contains estimates of the following regression:

$$Y_{n,2003} = \delta_0 + \delta_2 ShareGrowth_{n,1992-1997} + \omega_n$$

where $ShareGrowth_{n,1992-1997}$ is the raw change in Catholic enrollment share in neighborhood n from 1992 to 1997, divided by the average level of Catholic enrollment share over these two years. Column 3 of Table 2.4 contains estimates the regression:

$$Y_{n,2003} = \delta_0 + \delta_3 ShareDiff_{n,1992-1997} + \psi_n$$

where $ShareDiff_{n,1992-1997}$ is the raw difference in Catholic enrollment share in neighborhood n between 1992 and 1997. Columns 2 and 3 of Table 2.4 show that neither measure of change in Catholic presence is related to charter school entry.

Table 2.4: This table shows coefficient estimates from four OLS regressions. The unit of observation is a Chicago Community Area (CCA). In each regression, the dependent variable is an indicator variable equal to 1 if a charter school ever located in that CCA during 1998-2003. I create CCA-level demographic variables by aggregating Census tract-level and school-level data.

	(1)	(2)	(3)	(4)	(5)
Catholic Enrollment Share 1997	-0.010***			-0.009***	-0.010***
	(0.003)			(0.003)	(0.003)
Catholic Enrollment Growth: 1992-1997		-0.002		-0.001	
		(0.001)		(0.001)	
Catholic Share Change 1992-1997			0.009		0.006
			(0.011)		(0.011)
Constant	0.448***	0.245***	0.310***	0.420***	0.462***
	(0.072)	(0.059)	(0.061)	(0.086)	(0.077)
Observations	77	77	77	77	77
R^2	0.11	0.03	0.01	0.11	0.11

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Of the three proxies for Catholic school presence, the most important predictor of charter school entry is the level of Catholic enrollment share in 1997. In some neighborhoods, the formidable Catholic presence may have deterred charter operators from entering. Since these regressions are descriptive, we cannot identify the exact mechanism of deterrence, but it is possible that charter schools wanted to avoid competing with Catholic schools, the most salient substitute for charter schools at the time.

Combined Regressions

The regressions in Section 2.6.2 show that charter schools entered neighborhoods where there were many public school students, the schools were poor, and public transportation was prevalent. The multivariate regression in Column 4 of Table 2.3 shows that the AMTS and the level of public school enrollment were the most important determinants of charter school entry. In this section, I study the combined effects of these factors and neighborhood Catholic enrollment share. Column 3 of Table 2.5 displays results from the following regression:

$$Y_{n,2003} = \alpha_0 + \alpha_1 AMTS_{n,1990} + \alpha_2 P_{n,1997} + \alpha_3 A_n + \alpha_4 CatholicShare_{n,1997} + \nu_n \quad (2.2)$$

where $AMTS_{n,1990}$ is the AMTS in neighborhood n in 1990, $P_{n,1997}$ is the public school enrollment in neighborhood n in 1997, A_n is the Transportation Index, and $CatholicShare_{n,1997}$ is the Catholic enrollment share in neighborhood n in 1997. Table 2.5 contains estimates of short versions of this regression leaving out the Transportation Index and Catholic share, respectively (Columns 1 and 2).

Across all three specifications of Table 2.5, the coefficients on $P_{n,1997}$ and $AMTS_{n,1990}$ are statistically significant and consistent in magnitude. On the other hand, in multivariate specifications, Catholic share and the Transportation Index do not appear to predict charter school entry as strongly. Column 1 of Table 2.5 shows that conditional on AMTS and pubic enrollment, the transportation index is positively correlated with charter school entry, but the relationship is not statistically significant. Similarly, Column 2 of Table 2.5 shows that conditional on AMTS and pubic enrollment, the Catholic enrollment share is negatively correlated with charter school entry, but we cannot reject a zero relationship.

Though the coefficients on the Transportation Index and Catholic enrollment share are not statistically significant, they still contribute to the story of the types of neighborhoods charter schools entered. Based on all of the regressions in this section, charter operators clearly targeted neighborhoods that had many school-aged residents and low-quality schools. The relationship between charter school entry and Catholic enrollment share is less strong. While the visual evidence and univariate regressions show clearly that charter schools avoided neighborhoods with high Catholic shares, this relationship is not obvious in the multivariate

Table 2.5: This table shows coefficient estimates from four OLS regressions. The unit of observation is a Chicago Community Area (CCA). In each regression, the dependent variable is an indicator variable equal to 1 if a charter school ever located in that CCA during 1998-2003. I create the CCA-level independent variables by aggregating Census tract-level and school-level data. Public Enrollment is the number of students in public school in 1997, measured in 1000s. Average Math Test Score is the average standardized math test score for school-grades in 1990. Transportation Index is an index standardized to have mean of zero and standard deviation one that measures the availability of public transportation. Catholic Enrollment Share 1997 is the neighborhood-level share of enrollment at Catholic schools

	(1)	(2)	(3)
Public Enrollment 1997 (1000s)	0.029**	0.033**	0.028*
	(0.014)	(0.014)	(0.014)
Average Math Test Score	-0.170**	-0.152*	-0.156*
	(0.072)	(0.080)	(0.080)
Transportation Index	0.076		0.072
	(0.054)		(0.055)
Catholic Enrollment Share 1997		-0.003	-0.002
		(0.004)	(0.004)
Constant	0.167*	0.176	0.193
	(0.097)	(0.117)	(0.117)
Observations	76	76	76
R^2	0.25	0.24	0.25

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

regressions that condition on AMTS and public enrollment.

A likely explanation for this constellation of findings is that since Catholic enrollment share is positively correlated with the AMTS ($\rho = 0.48$) and negatively correlated with public enrollment ($\rho = -0.31$), there is no residual variation of Catholic enrollment share remaining across neighborhoods after controlling for AMTS and public enrollment. Therefore, the evidence here does not allow us to claim that Catholic enrollment share is negatively related to charter school entry even conditional on test scores and public enrollment. However, the fact remains that charter schools entered neighborhoods where there were a lot of public school students and poor schools, and many of these neighborhoods had low levels of Catholic enrollment share.

If charter operators targeted neighborhoods where the Catholic sector was weak, this begs the question of whether charter school entry contributed to further decline of the Catholic sector in these neighborhoods. I explore this in the next section.

2.6.3 How did charter school entry affect neighborhood Catholic enrollment?

Historically, Catholic schools have supplied high-quality education to students in urban neighborhoods that have poor public school options (Neal 1997). Furthermore, private schools help a school district operate more like a competitive market. They break the link between residential choice and school choice and they improve match quality between families and schools (Neal 2009). If charter school entry causes a decline in the availability of Catholic enrollment, then charter schools do not create surplus education choices; instead, they substitute for existing schools in the private sector and "crowd-out" private sector enrollment.

The literature is mixed on the potential effects of charter school entry on Private school entry. Chakrabarti and Roy (2011) provide evidence from Michigan that charter school entry did not crowd out private school enrollment. That said, Dinerstein and Smith (2017) find direct evidence that changes in the public schooling sector affect the private sector. They find that increased funding for private schools increases the probability that nearby private schools will close.

In this section, I study how charter school entry affected neighborhood-level Catholic enrollment. I estimate two types of models in which the observation is a neighborhood-year: an event study and difference-in-difference studies. Both types of analyses show how neighborhood Catholic enrollment changes after the first time a charter school enters. The event studies allow the effects to vary year-by-year, which helps determine whether Catholic enrollment was already declining prior to charter school entry. The difference-in-difference estimates aggregate years in order to summarize the effects of charter school entry on Catholic enrollment.

Aggregate Trends

The analyses in this section must be interpreted through the aggregate trends in Catholic enrollment. During the sample period, the Catholic sector's enrollment decreased, while the charter sector's enrollment increased. Figure 2.10 displays enrollment by sector from 1992 to 2013. In 1992, over 86,000 students were enrolled in a Catholic school in Chicago. By 1998, the first year of charter school entry, Catholic enrollment had decreased to 72,000 students. Over the next fifteen years, enrollment continued to decrease. In 2003, 57,540 students attended a Catholic school and by 2013, there were 39,000 students in the Catholic sector, less than half of the enrollment in 1992.

We also observe this aggregate decline in enrollment shares. Figure 2.1 shows enrollment shares by sector from 1992 to 2013. Catholic enrollment share had begun to decline even before charter schools first entered in 1997-1998. Catholic enrollment share was 17% in 1992 and 14% in 1997. By 2011, charter schools enrolled a higher share of students than Catholic schools; In 2013, charter schools had a 12% enrollment share and Catholic schools

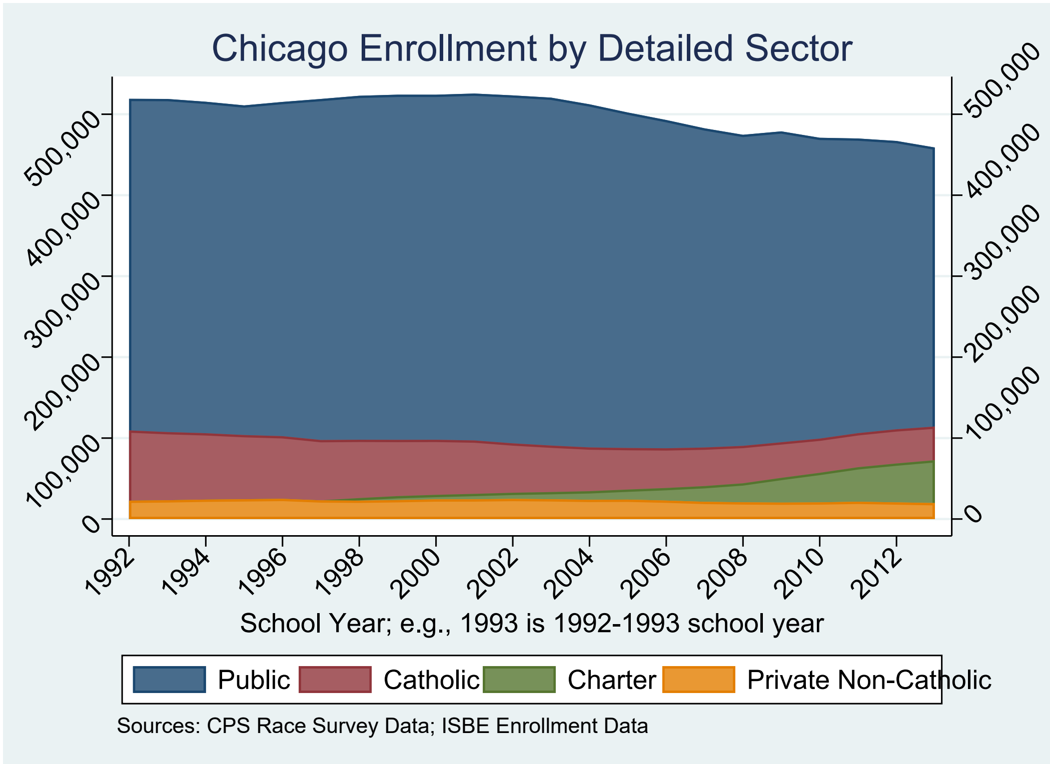

Figure 2.10: Enrollment by sector from 1992 to 2013.

had declined to a 9% share. With the aggregate trends in mind, I turn to the analyses of how charter school entry affected Catholic enrollment.

Unit of Observation

I collapse the School Data to create a neighborhood-year panel from 1992 to 2013. Previous papers on private school crowd-out [30] define the unit of observation as a school-year and assign treatment status to observations according to whether a charter school is within some radius of the school. In my study, the unit of observation is a neighborhood-year, and I assign treatment status to observations according to whether a charter school has entered a neighborhood as of that year.

Using a school as the cross-sectional unit of observation would not provide a clear measure of the effect of charter school entry. In Chicago, the Archdiocese acts as a city-level entity

30. See, e.g., Toma et al. 2006 and Chakrabarti and Roy (2011)

that decides whether to close schools. When it does, it frequently designates a nearby "receiving school" that will make seats available for students from the closed school. The following hypothetical example shows how defining the unit of observation as a school would lead to mismeasurement in this setting.

Consider a neighborhood that has two Catholic schools, each with 200 students. St Agnus is well-liked by neighborhood residents, while St. Bartholomew is less attractive. When a charter school enters within one mile of both of these schools, it steals 100 of St. Bartholomew's students but it does not steal any of St. Agnus's students. Noticing the decrease in enrollment at St. Bartholomew, the Archdiocese closes the school, sending its remaining 100 students to St. Agnus. After charter school entry, St. Agnus has 300 students, St Bartholomew has 0 students, and the entire neighborhood Catholic enrollment declined from 400 students to 300 students.

In a school-level study, both schools would be assigned to the treatment group, and it would appear that charter school entry increased enrollment at St. Agnus and decreased enrollment at St. Bartholomew. In contrast, a neighborhood-level study, would attribute the neighborhood's overall decline in Catholic enrollment to the charter school entry.[31] Using neighborhood-year as the unit of observation captures the variation in enrollment due to charter school entry when Catholic schools close.

Sample Restrictions

I make two sample restrictions. First, I restrict the analysis to neighborhoods that eventually got a charter school. As shown in Section 2.6.2, charter schools entered a distinct type of neighborhood that included a low Catholic enrollment share. Thus, I compare neighborhoods where charter schools entered to each other over time.[32]

31. Note that defining the unit of observation does not completely solve this issue if the Archdiocese sends students from closed schools to receiving schools outside of the neighborhood, but it is an improvement over the use of school-level observations.

32. As a robustness check, Appendix A.7 contains estimates of the regressions with a sample that includes all neighborhoods.

The first sample restriction defines the treatment and control groups. Broadly speaking, these analyses compare Catholic enrollment in neighborhood-years that have a charter school (treatment observations) to Catholic enrollment in neighborhood-years that do not yet have a charter school but that eventually get one (control observations).

Second, for each neighborhood, the sample only contains the observations during the period 6 years prior to first charter school entry and 4 years following first charter school entry. I choose this analysis window because jumps in charter campus entry occurred in 1998, 2004, and 2009. Using this analysis window allows me to include 6 years prior and 4 years following each of these important years of entry.

Choice of Dependent Variable

My preferred dependent variable is the level of Catholic enrollment in a neighborhood n at time t.I considered two other potential dependent variables, enrollment share and log enrollment. Enrollment share will contain measurement error due to charter schools' ability to enrolls students from outside of their neighborhood. When charter schools attract students from other neighborhoods, the Catholic share will decrease mechanically, even if Catholic enrollment does not change.

While log of enrollment eliminates the concern of comparing changes in enrollment across neighborhoods with different initial levels of enrollment, a regression in which log enrollment is the dependent variable implicitly drops observations where Catholic enrollment is zero. In my sample, this drops 148 observations, around 14% of the observations.[33]

Event Study

I begin by measuring the effect of charter school entry on neighborhood-level Catholic school enrollment within an event study framework. The event study compares the Catholic enrollment in 1) a neighborhood l years away from first charter school entry to 2) the enroll-

33. As a robustness check, I estimate my regressions with log enrollment and include the results in Appendix A.7. The main conclusions from these regressions do not differ from those in which the level of enrollment is the dependent variable.

ment in neighborhoods in "year 0," the year before first charter school entry. In addition, I include neighborhood and year fixed effects to control for the average level of enrollment in a neighborhood over time and the average enrollment in a year across neighborhoods.

I estimate the following model. As noted in the previous section, the sample contains only neighborhoods that experienced charter school entry during the years in a chosen analysis window, that is, $l \in [-6, 4]$ where l is the years since the beginning of the school year in which a charter school first entered.

$$CatholicEnrollment_{nt} = \tau_n + \tau_t + \sum_{l=-6}^{l=-1} \delta_l D_{ln} + \sum_{l=1}^{l=4} \delta_l D_{ln} + e_{nt} \tag{2.3}$$

$CatholicEnrollment_{nt}$ is Catholic enrollment in neighborhood n at time t. τ_n and τ_t are neighborhood and year fixed effects, respectively. The D_{ln} terms are indicator variables equal to 1 if neighborhood n is l years away from the first charter school entry event. $l = 0$ is the excluded category. The δ_l terms represent the difference in Catholic enrollment in a neighborhood l years away from charter school entry relative to neighborhoods in "year 0," the year immediately prior to charter school entry. For example, in the case of a neighborhood that received its first charter school in school year 1997-1998, "year 0" is 1996-1997 and enrollment for 1996-1997 is measured at the end of 1996-1997. The identifying assumption in this model is that unobserved time-varying neighborhood-level determinants of when charter schools enter are not correlated with the Catholic enrollment in a neighborhood. For example, if declining Catholic enrollment were to spur demand for a charter school in a neighborhood, this could bias the estimates of δ_l.

Figure 2.11 graphs the estimates of $\delta_{-6}, ..., \delta_4$. Inspecting a graphical depiction of the results is useful for examining pre-trends. Pre-existing downward trends prior to the entry of a charter school may indicate that the estimated effects overstate the true impact. In contrast, evidence of positive, pre-entry shocks may indicate that the estimated effects overstate the entry's impact by picking up regression to the mean in the Catholic enrollment. Figure 2.11 shows that five years prior to first charter school entry, Catholic enrollment was approximately 125 students higher than during the year immediately prior to charter school entry. This pre-trend suggests that charter schools entered neighborhoods where the Catholic sector was already declining.

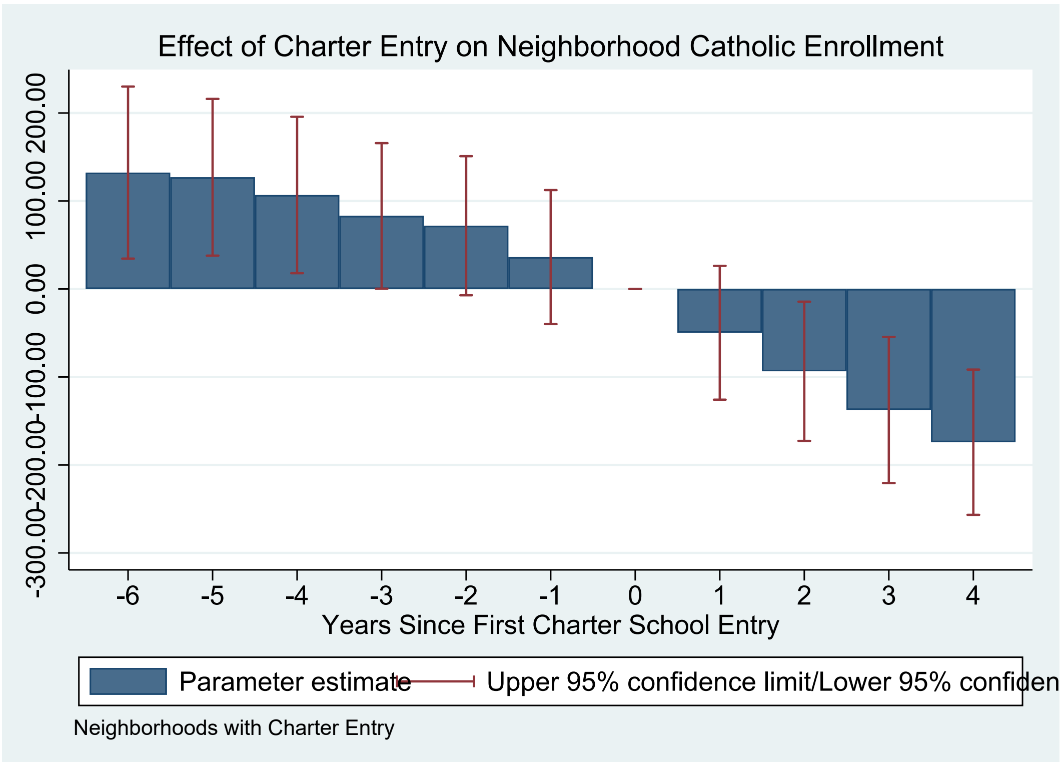

Figure 2.11: Event Study. The year-by-year effect of first charter school entry on Catholic enrollment Bars represent coefficients in the event study specification in Equation 2.3. Whiskers represent 95% confidence interval. I restrict the analysis to neighborhoods that ever experienced charter school entry in the years in a chosen analysis window. The analysis window is $l \in [-6, 4]$ where l is the years since first charter school entry. There are concentrated increases in charter campus entry in 1998, 2004, and 2009. This analysis window includes the 6 years prior and 4 years following each of these years.

Figure 2.11 shows that four years after first charter school entry, neighborhood-level Catholic enrollment is 174 students lower than during the year immediately prior to charter school entry. In this sample, the average neighborhood Catholic enrollment is 720 students with a standard deviation of 730. Therefore, a 174 student decrease represents a change of

0.24 standard deviations. As a comparison, from 1992 to 1997, prior to charter school entry, the average neighborhood lost 207 students.

According to the event study, neighborhood Catholic enrollment declines after first charter school entry. However, the existence of a negative pre-trend hampers our ability to conclude that charter entry caused the enrollment decline after charter school entry. Furthermore, even if the effect were causal, the total effect size is small.

Difference-in-Difference

Table 2.6 contains results from regressions that summarize the effects displayed in Figure 2.11. Column 1 contains results of the following univariate "pooled" regression of Catholic enrollment on an indicator for whether there is a charter school open in that neighborhood-year.

$$CatholicEnrollment_{nt} = \tau_n + \tau_t + \gamma D_{nt} + \epsilon_{nt} \tag{2.4}$$

where D_{nt} is an indicator equal to one if there is a charter school open in neighborhood n at time t and zero otherwise. This regression compares neighborhood-years that have a charter school to neighborhood-years that do not yet have a charter school but that eventually get one. In neighborhood-years in which a charter school is open, Catholic enrollment is 67.8 students lower than in neighborhood-years without a charter school.

Column 2 of Table 2.6 contains estimates of a regression that makes a similar comparison, allowing for different effects in each of the years after after first charter school entry.

$$CatholicEnrollment_{nt} = \tau_n + \tau_t + \alpha_1 D_{n1} + \alpha_2 D_{n2} + \alpha_3 D_{n3} + \alpha_4 D_{n4} + +\epsilon_{nt} \tag{2.5}$$

where D_{n1}, e.g., is an indicator equal to 1 if neighborhood n is 1 year after the first time a charter school entered neighborhood n. This model is like the event study, except it pools all of the "before" observations, those in which $l \in [-6, 0]$, into one excluded category. According to the estimates, neighborhood-years after charter school entry have lower Catholic enrollment than in those before charter school entry, and the disparity increases each year. Two years after charter school entry Catholic enrollment is approximately 61 students lower than in the year prior to charter school entry, but the effect is not statistically significant. In the fourth year after first charter school entry, the Catholic enrollment is 99 students lower than in periods before first charter school entry.

Table 2.6: OLS. Sample is neighborhoods where a charter school entered during the sample period. Column 1 displays estimates from a regression of Catholic enrollment on an indicator equal to one if a charter school exists in a neighborhood-year. Columns 2 displays estimates from a regression of Catholic enrollment on dummies for years since first charter school entry. The excluded category is year 0 and before. Year 0 is the school year prior to first charter school entry.

	(1) CN	(2) CN
Charter Indicator	-67.803**	
	(28.582)	
Charter Indicator, Year 1		-40.101
		(36.245)
Charter Indicator, Year 2		-61.169
		(40.863)
Charter Indicator, Year 3		-83.490*
		(45.828)
Charter Indicator, Year 4		-98.678*
		(51.469)
Constant	394.212***	378.957***
	(79.730)	(83.433)
Observations	477	477
R^2	0.94	0.94
Year Fixed Effects.	Yes	Yes
Neighborhood Fixed Effects	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

How do these numbers compare to the overall level of Catholic enrollment at the time? In 1998, the first year of charter school entry, when Catholic enrollment was highest, the average neighborhood in the sample had 876 students enrolled in Catholic schools with a standard deviation of 805. A decrease if 99 students in a neighborhood represents a decrease of 0.12 standard deviations.

Of the 44 neighborhoods in the sample in 1998, Uptown had the 22nd most Catholic enrollment, 744 students. A 99 student decrease would move Uptown down three spots to the 25th-most enrollment, behind Washington Heights and above North Park.

Using 2013 as a benchmark, when Catholic enrollment had been declining for two decades, the average neighborhood in the sample had 458 students with a standard deviation of 509. According to the 2013 distribution of Catholic enrollment, a 99 student decrease represents a 0.2 standard deviation decrease. To continue the example, in 2013, Uptown had 556 students, the 16th-most out of 44 neighborhoods in the sample. A 99 student decrease would move Uptown down two spots among the ranks of neighborhoods in the sample.

Both the event studies and the difference-in-difference studies indicate that if charter school entry caused a decline in Catholic enrollment, then the magnitude of the effect was modest. Furthermore, examination of pre-trends that charter entry was correlated with a decline in neighborhood Catholic enrollment. Therefore, it is possible that charter schools simply entered neighborhoods where Catholic enrollment was already declining and continued to decline while charter schools entered. In the next section, I conduct additional analyses as robustness checks. These checks confirm that charter school entry had a limited impact on the Catholic sector

Robustness Checks

Include all neighborhoods

The sample used in the main results contains only neighborhoods that ever experienced charter school entry. In this section, I explore how the main results change if I include all neighborhoods. There are two implications of including the "never-entered" neighborhoods—that is, those that never experienced charter school entry. First, they help identify the neighborhood and year fixed effects. This provides more information on the aggregate conditions of Catholic enrollment in the sample. Second, the never-entered neighborhoods provide additional control group observations. That said, including all neighborhoods changes the control group. With "never-entered" neighborhoods, the control group includes both 1) neighborhood-years that do not yet have a charter school, but get one eventually, but also 2) neighborhood-years that never got a charter school.

The right panel of Table 2.7 contains estimates of Equation 2.4 and Equation 2.5 using the sample of all neighborhoods. For comparison, the left panel of Table 2.7 contains the main results, which include only Charter Neighborhoods ("CN"). In the sample of all neighborhoods, the decline in Catholic enrollment one year after charter school entry is larger than in the main results. In the main results, the effect of charter school entry is not statistically different from zero in year one, while in the sample of all neighborhoods, charter entry is associated with a 68 student decline in Catholic enrollment in year one. Note, though, that by year 4, the effect sizes are very close. Four years after entry, the main results show that charter entry is associated with a 99 student decline in Catholic enrollment, while the all-neighborhoods results show decline of 110 Catholic students.

Exclude Zeros

Catholic enrollment is censored below at zero. Therefore, three types of "zero-observations" may affect the results. This section describes these three types of zero-observations, and which are most prevalent in this sample. Then, as a robustness check, I re-run my main results dropping all zero observations.

First, there are neighborhoods where the Catholic enrollment is zero in every year of the sample period. When a charter school enters one of these neighborhoods, the regressions will show that charter entry has no effect on Catholic enrollment. In my main results, I find a

Table 2.7: OLS. Left panel (CN): Sample is neighborhoods where a charter school entered during the sample period. Right panel (All): All neighborhoods. Columns 1 and 3 display estimates from a regression of Catholic enrollment on an indicator equal to one if a charter school exists in a neighborhood-year. Columns 2 and 4 display estimates from a regression of Catholic enrollment on dummies for years since first charter school entry. The excluded category is year 0 and before. Year 0 is the school year prior to first charter school entry.

	(1) CN	(2) CN	(3) All	(4) All
Charter Indicator	-67.803**		-99.559***	
	(28.582)		(18.215)	
Charter Indicator, Year 1		-40.101		-67.715**
		(36.245)		(28.903)
Charter Indicator, Year 2		-61.169		-86.134***
		(40.863)		(29.106)
Charter Indicator, Year 3		-83.490*		-104.926***
		(45.828)		(29.326)
Charter Indicator, Year 4		-98.678*		-109.650***
		(51.469)		(29.552)
Constant	394.212***	378.957***	298.419***	294.615***
	(79.730)	(83.433)	(60.143)	(60.280)
Observations	477	477	1049	1049
R^2	0.94	0.94	0.97	0.97
Year Fixed Effects.	Yes	Yes	Yes	Yes
Neighborhood Fixed Effects	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

negative effect of charter school entry on Catholic enrollment. Thus, dropping neighborhoods in which Catholic enrollment is always zero would move the effect sizes away from zero and make the effect more negative.

Second, some neighborhoods have positive Catholic enrollment before the first time a charter school enters and at the time of the first charter school entry. Then, after charter school entry, the Catholic sector exits the neighborhood completely. These are the type of events the studies in this section intend to measure. However, there are some observations such that when a charter school enters for the first time, there is only a small amount of Catholic enrollment remaining in the neighborhood. Therefore, the measured effect that charter school entry can have on Catholic enrollment is bounded.

Third, in some neighborhoods Catholic enrollment might have had positive enrollment, but prior to first charter school entry all of the Catholic schools exited, leaving enrollment at zero before charter schools ever enter. In my analyses, this would appear as positive enrollment before charter school entry and zero enrollment afterwards, and this would suggest a decline caused by charter school entry. Dropping neighborhoods where the Catholic sector exited before the first charter school entered would attenuate my main results.

If the first and second type of these "zero observations" are most prevalent in my dataset, then my main results will understate the negative effect of charter school entry. If the third type of zero observation is most prevalent, then the results will overstate the negative effect of charter school entry on Catholic enrollment. In my sample, the third type appears most frequently. Table 2.8 shows my main results, dropping "zero observations."

Columns 3 and 4 of Table 2.8 contain the same analyses as Columns 1 and 2 (my main result), but I further restrict the sample to neighborhoods that had nonzero Catholic during the analysis window — i.e., if $l \in [-6, 4]$. This drops 18 neighborhoods. Similar to Columns 1 and 2, the measured effect of charter school entry is negative but as suggested in the discussion above, the magnitude of the effect is smaller than those in Columns 1 and 2.

Therefore, my main results, which are already modest in magnitude, may overstate the negative effect of charter school entry on Catholic enrollment.

Table 2.8: OLS. Left panel (CN): Sample is neighborhoods where a charter school entered during the sample period. Right panel (CN, NZ): Subsample of CN, excludes neighborhoods with zero Catholic enrollment. Columns 1 and 3 display estimates from a regression of Catholic enrollment on an indicator equal to one if a charter school exists in a neighborhood-year. Columns 2 and 4 display estimates from a regression of Catholic enrollment on dummies for years since first charter school entry. The excluded category is year 0 and before. Year 0 is the school year prior to first charter school entry.

	(1) CN	(2) CN	(3) CN, NZ	(4) CN, NZ
Charter Indicator	-67.803**		-65.250*	
	(28.582)		(37.173)	
Charter Indicator, Year 1		-40.101		-31.876
		(36.245)		(48.429)
Charter Indicator, Year 2		-61.169		-56.902
		(40.863)		(54.974)
Charter Indicator, Year 3		-83.490*		-68.444
		(45.828)		(62.058)
Charter Indicator, Year 4		-98.678*		-93.068
		(51.469)		(69.922)
Constant	394.212***	378.957***	892.814***	888.990***
	(79.730)	(83.433)	(90.399)	(91.030)
Observations	477	477	326	326
R^2	0.94	0.94	0.93	0.93
Year Fixed Effects.	Yes	Yes	Yes	Yes
Neighborhood Fixed Effects	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Across all specifications in this section, the change in neighborhood Catholic enrollment four years after first charter school entry ranged from 99 student decrease to a 109 student decrease. As summarized above, an effect of this size is at most one-fifth of a standard deviation change according to the 2013 distribution of Catholic enrollment. A change of this size would only change a neighborhood's ranking in Catholic enrollment by two to three places. If charter schools did cause an enrollment change at Catholic schools, the effect likely was small.

In addition to the aggregate decline of Catholic enrollment during the sample period, another aspect of how the charter sector interacted with the Catholic sector may explain these findings. During the first wave of charter school entry, the Archdiocese leased space in recently closed Catholic schools to charter schools to use as their facilities. Figure 2.12 displays the sites where the first twenty charter campuses opened. Of the first twenty charter school campuses, 11 (55%) opened in a Catholic school or church. This is evidence that the archdiocese accommodated charter school entry. The Archdiocese may have accommodated charter entry because it did not anticipate competing with charter schools for students in these neighborhoods. If this is the case, then it is not surprising we would see modest effects of charter school entry on Catholic enrollment.

Location by Site Type: Charter Schools Opening between 1998 and 2003

Site Type	N	%
Catholic School or Church	11	55%
College	2	10%
Non-Catholic School or Church	4	20%
Non-school / non-church	2	10%
Public School	1	5%
Total	20	100%

Figure 2.12: Charter school sites during 1998 to 2003. Sample: The 20 schools that opened between 1998 and 2003. One charter school closed during this time period. I exclude Chicago Charter Preparatory which was only open for 1 full school year.

2.7 Conclusion

Charter schools have successfully educated disadvantaged students in numerous school districts. Charter schools exist in 43 states and the District of Columbia.[34] Moreover, all of the twenty-five most populous urban areas in the United States[35] have a charter school program. An extensive literature shows that charter schools can raise the test scores of their students. Furthermore, we know that charter schools that serve low-SES students often are successful while those that serve more advantaged students often are not.[36]

Here, I show that in Chicago charter schools entered disadvantaged neighborhoods that had poor schooling options, many public students, a relatively weak Catholic sector, and available public transportation. Visual evidence clearly shows that charter schools preferred to enter neighborhoods that had these characteristics, and descriptive regressions quantify these relationships. That is, in Chicago, charter schools entered exactly the neighborhoods where the literature has shown they can be successful.

There are at least two explanations for these entry patterns. First, a study of CPS's policies shows that the CPS officials who chose which charters to approve preferred schools that planned to serve "at-risk" students. Second, a simple model in which charter schools maximize their potential demand predicts that charter operators would choose disadvantaged neighborhoods where existing schooling options are weak and public transportation is prevalent.

My study looks at one large urban school district, and future studies will help determine whether these entry patterns generalize to other school districts. Although the predictions in the conceptual framework hold generally, the design of school choice programs could vary

34. National Alliance for Public Charter Schools

35. Source: U.S. Census Bureau's July 1 2016 population estimates.

36. Serving disadvantaged students, however, is not a sufficient condition for a charter school to be successful. Among schools that serve disadvantaged student, schools that employ "No Excuses" educational practices typically have success while schools that do not employ these practices often do not.

across cities, which would change the observed entry patterns. For example, the Catholic sector in Chicago was declining when charter schools began, and the Archdiocese accommodated charter school entry by providing facilities in unused Catholic school buildings. This might not have occurred in other cities when charter schools began to enter.

The results of this study can inform future policy discussions about charter schools. The current discussion often focuses on “charter caps,” or constraints on the number of charter schools allowed in a district. However, future discussions may focus on identifying the neighborhoods and and types of students that charter schools should serve.

CHAPTER 3

THE AGGREGATE AND DISTRIBUTIONAL WELFARE EFFECTS OF CHARTER SCHOOL ENTRY

3.1 Introduction

Numerous studies have investigated the potential benefits of charter school entry into a school district. These studies typically focus on how charter schools raise the test scores of their students (Abdulkadiroglu et al. 2011, Angrist et al. 2013).[1] Although test scores are an important measure of achievement, families value a variety of schooling inputs, such as sports, religious education, and arts programs (Hanushek 1981). Here I look beyond benefits generated by increased test scores and measure the total welfare that can be attributed to the addition of the charter sector in Chicago.

I use a revealed preference framework to measure the welfare effect of charter school entry. In particular, the welfare calculation assumes that charter entry changes welfare by expanding students' choice sets. Specifically, I compare the consumer surplus from a student's actual choice set, which includes charter schools, to a counterfactual choice set that does not include charter schools. I attribute the difference to the change in welfare that charter school entry generated.

To measure welfare, I estimate the parameters of a utility model, which I use to calculate consumer surplus. The utility model specifies a student's utility from attending a school-grade. The model assumes that students derive utility from three components. First, students value a fixed measure of the overall attractiveness of a school-grade, modeled as a school-grade fixed effect. Second, students pay a utility cost that is proportional to the

1. The literature also has studied whether charter school entry increases test scores in *public schools* by injecting competition into a school market (Hoxby (2002), Bettinger (2004), Bifulco and Ladd (2006), Booker et al. (2007), and Petronijevic (2016)). The empirical evidence on whether charter schools increase test scores in neighboring public schools is mixed. Measuring this potential benefit of charter schools is outside the scope of my paper.

distance from their school to their residence. Third, students derive utility from attending their zoned school. With this model, the school-grade fixed effect captures any fixed characteristic of a school that all students value equally, and the remaining components capture student-specific elements. Using the parameter estimates, I calculate the consumer surplus that charter schools added from 1998-2013.

Previous work in Chapter 2 documents that charter schools entered exactly the types of neighborhoods where we would expect them to raise test scores – those that had low income and low test scores. Motivated by these findings, I calculate total welfare by neighborhood to measure who benefited most from charter school entry. I find that surplus disproportionately accrued to neighborhoods that had low income and test scores. Neighborhoods at or below median income enjoyed 73% of the benefits from charter schools, while neighborhoods at or below median in math test scores enjoyed 69% of the benefits from charter schools.[2] As I discuss in Section 3.5, this was driven by more charter school entry in the West, South, and Southwest Sides, which had low income and low test scores.

Lastly, I combine data on tuition at Catholic schools and my utility estimates to calculate the dollar value of the consumer surplus created by the charter school sector. The model estimates that over the entire sample period, charter schools provided approximately $44 of consumer surplus per Chicago student, regardless of the sector of enrollment. In the most recent year of my sample, when the stock of charter schools reached its peak, charter schools provided $138 of surplus per Chicago student and $1,319 per charter school student. I also show that charter school entry generates cost savings for CPS by decreasing the number of students CPS needs to educate. These cost savings, along with the benefits generated from a larger menu of schooling options, explain why CPS has opened new charter schools rather than traditional public schools.

2. Median Income measured with 2000 U.S. Decennial Census

3.2 Data

I combine multiple sources of data to conduct the analyses in this chapter. I use school-grade level enrollment data, detailed school location data, and a sample of student-level data to estimate a student utility model for school-grades open in Chicago during 1998–2013. I also collect tuition data for private school-grades open as of 2015–2016, and I use it to assign a dollar value to the consumer surplus that charter schools created.

3.2.1 School Data

I compile a dataset that includes grade-level enrollment and school location for the universe of schools in Chicago between 1992 and 2013. To create this dataset, I combine a variety of sources. For traditional public schools, I use grade-level enrollment and school addresses from the NCES Common Core from 1992 to 2013. The NCES makes these data available to the public.

No such public dataset exists for charter schools, and so I combine publicly available data and information from archived Illinois Charter Annual Reports.[3] I use charter school enrollment and location data from the CPS Racial and Ethnic Survey for the years 2004 to 2013. For 1998 to 2003, I manually compile the data from ISBE Charter Annual Reports.[4]

Similarly, for private schools there is no publicly available dataset that contains annual grade-level enrollment and location.[5] For private schools, I obtained the necessary data via the Freedom of Information Act (FOIA). Through FOIA, the Illinois State Board of

3. NCES and ISBE data contain data on charter schools, but they do not always disaggregate the data by charter campus within a charter network.

4. To check whether the ISBE Annual Reports and the CPS Racial and Ethnic Survey measure enrollment differently, I compare their enrollment counts for a year in which both sources contain charter enrollment. On average, the school-level enrollment counts differ by 1%.

5. After considering the Private School Survey (PSS), I conclude that my data provide two main advantages over the PSS. First, my data are annual, which allows me to observe year-to-year changes in enrollment. Second, the data contain school location back to 1992. Before 2002, the PSS location data are unreliable.

Education provided me with grade-level enrollment and school location from 1992 to 2013.[6]

3.2.2 Simulated Student Location Data

The utility model in Section 3.3 assumes that students experience a cost of traveling to school. Therefore, I need data on where students live. Because I do not have actual student location data, I simulate student location data using the 2010 U.S. Decennial Census. The Census contains counts of school-age residents by age for each of the 46,000 Census Blocks in Chicago. I assume each student in the Census lives at the geographic centroid of her Census Block.[7] This yields a dataset of student locations for each school-age resident.[8] The utility model also incorporates students' utility of attending zoned school. To account for this, I also map the simulated student locations to the 2009-2010 CPS Zone Maps, assigning student locations to zoned schools. Then I calculate the distance in miles between student locations and their zoned schools. The simulated student location data and corresponding zoned school assignments allow me to calculate model-predicted versions of the moments that I use in the estimation.

3.2.3 Sample of CPS Student-Level Data

The utility model in Section 3.3 includes a parameter that represents the utility cost of traveling an additional mile to school. To incorporate information on students' preferences for traveling to school, I obtained a sample of two years of student-level data from CPS via FOIA. For students enrolled in a public or a charter school in 2015-2016 or 2016-2017,

6. ISBE has similar files that are publicly available, but they do not contain grade-level enrollment. Moreover, the earliest year they offer is SY2004.

7. Chicago's land area is 234 square miles. With 46,000 Census Blocks in Chicago, a Census Block is approximately 0.0005 square miles in area on average.

8. I assume that the geographic distribution of students is the same in each year of my sample period. If the geographic distribution is not stationary, then this may affect the estimation of the model parameters. In Appendix B.3, I document the change in population between 2000 and 2010 for each geographic market and discuss the implications of this change for the estimation.

these data contain each student's zoned school and actual school of attendance. With these data, I can also measure the proportion of students that attend their zoned school. When I estimate the model that I describe in Section 3.3, I use these data to create moments that help identify student preferences for traveling to school and attending zoned school.

3.2.4 Tuition Data

In Section 3.5, I use tuition data to convert consumer surplus from utils to dollars. I collect tuition data by grade for private schools open in 2015-2016, which is the most recent year for which I have private school data.[9] In particular, I determine the list price for tuition and whether the school offers sibling discounts. This results in a dataset that contains the prices by family size for for each private school in Chicago that makes tuition data available.

In the analyses in Section 3.5, I use a sample of the tuition data that includes only Catholic schools. Since in Catholic schools tuition prices vary depending on how many children a family sends to the school, the distribution of family sizes at a school affects the average tuition paid. I create average tuition paid at each school by estimating the distribution of family size in the Census Block Group that surrounds each Catholic school. Using this distribution for the weights, I calculate average tuition paid at each school. Table 3.1 contains summary statistics of the Catholic subsample of the tuition data.

Table 3.1: Summary statistics. Sample: Catholic schools. Source: Tuition Data.

Variable	Obs	Mean	Std. Dev.	Min	Max
Grade	629	4.49	2.29	1	8
School Enrollment	629	294.62	161.91	88	971
One Child List Price	629	5905.43	2474.18	900	19908
Average Discount	629	3299.59	1690.73	210.5	13290.08
Average Tuition Paid	629	2605.84	1073.36	689.5	6617.92

9. Appendix 4.1.2 contains a detailed description of how I collected the tuition data.

3.3 Geographic Market Definition and Summary Statistics

In this section I describe the geographic market definition and present summary statistics that describe the distribution of students and schools across geographic markets. I describe the number of schools in each market, how far students travel to school, and how many students attend their zoned school. Throughout, I discuss how these facts affect the parameter estimates and welfare analyses.

3.3.1 Geographic Market Definition

In the model, the geographic market defines which schools are in a student's choice set. I use the nine "Sides" of Chicago as the geographic market definition, and assume students choose among the schools in their Side. Figure 3.1 shows that Sides are collections of Chicago Community Areas (CCAs). As noted in Section 2.4.2, CCAs are a natural neighborhood definition for the following four reasons:

1. CCA boundaries have not changed since members of the University of Chicago Social Sciences Research team drew them in the 1920s.[10]

2. Each U.S. Census Tract matches one Chicago Community Area[11]

3. The City of Chicago recognizes CCAs as statistical areas.[12]

4. Residents of Chicago use CCAs to refer to neighborhoods.[13]

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10. See, *e.g.*, `https://www.lib.uchicago.edu/e/collections/maps/censusinfo.html`

11. I link 2000 and 2010 Census Tracts to Chicago Community Areas using equivalency files available from Rob Paral and Associates, a Chicago-based research company.

12. See, *e.g.*, `https://www.lib.uchicago.edu/e/collections/maps/censusinfo.html`

13. For example, Coldwell Banker's residential home search function allows users to enter names of community areas to narrow their search for a home.`https://www.coldwellbankerhomes.com/il/chicago/archer-heights/recent-sales/?dym=archer\%20heights`

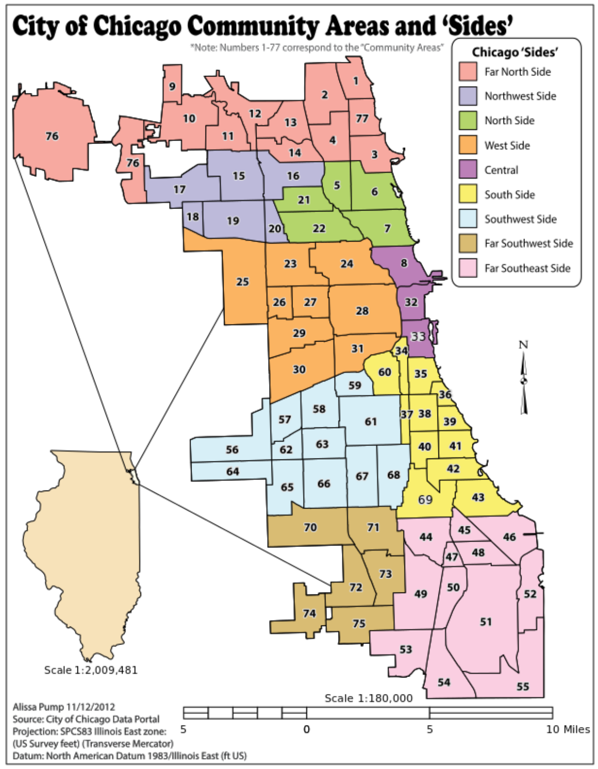

Figure 3.1: The 9 Sides and 77 Chicago Community Areas of Chicago.

Though CCAs are a natural neighborhood definition, they are too small to use as a geographic market. Assuming that students only choose among schools within their CCA would overly restrict students choice set—according to the CPS Zone Data, approximately 40% of students attend a school outside of their Chicago Community Area. However, as a collection of CCAs, Sides are also a natural division of Chicago. Additionally, like CCAs, residents and real estate trade groups use Sides to refer to areas of Chicago.[14]

To confirm that the market definition does not overly restrict students' choice sets, I use the CPS Zone Data to estimate how many public school students attend a school outside of their geographic market. The CPS Zone Data contain the school of attendance and zoned school for each student enrolled in a Chicago Public School during 2015-2016 or 2016-2017. To estimate how many students travel outside of their geographic market to attend school,

14. See, *e.g.*, `http://www.thechicago77.com/about-the-chicago-77/`.

I assume each student lives in the same Side as her zoned school.[15] Then I count how many students live in the same Side as their school of attendance. According to this analysis, 85% of CPS students in grades 1-8 attend a school in the same Side as their zoned school. Table 3.2 shows that students in higher grades are more likely to attend a school outside of their Side. 87% of first grade students attend school in their Side of residence, as do 82% of eighth grade students.

Percent of Students Attending School in Different Side by Grade

	1	2	3	4	5	6	7	8
%	13%	13%	13%	13%	14%	15%	17%	18%
N	57,304	58,582	61,944	58,106	55,792	56,436	54,781	53,246

Table 3.2: The proportion of students who attend a school outside of their Side ("%") and the total number of students in each grade ("N"). Source: 2015-2016 and 2016-2017 CPS Zone Data.

3.3.2 Summary Statistics

To estimate the model I use two types of data. First, I use data on student and school locations. To summarize this information, I present summary statistics on the geographic distribution of schools and how far students travel to school. Second, I use school enrollment shares. The shares help determine which schools provide the most utility for students. Below, I present summary statistics of charter school market shares and charter school entry over time and across geographic markets.

15. In Chicago, there are over 400 attendance areas schools and nine Sides. There may be students whose zoned school is not in their Side of residence, but this set of students is probably small.

Geographic Distribution of Schools

In the model, students choose among the schools in their Side that offer their grade. Since the set of schools varies by Side, students in different Sides and grades will have different sized choice sets. Table 3.3 shows the average number of schools by grade and Side during the sample period. For example, the smallest market, the Central Side, has the fewest schools during the sample period. The West Side, the largest market by land area, averages between 144.8 and 154.4 schools, depending on the grade. The utility model accounts for the varying choice sets by assuming that students gain more utility from schools that have higher enrollment shares within a geographic market rather than from the raw level of enrollment. Furthermore, I utilize data on student location so that students gain more utility from schools that are close to them. For example, though students in the West Side have over 140 schools in their choice set, they are less likely to attend schools that are far away from their home, so the model will discount these distant options.

	Average Number of Schools by Grade and Side							
	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5	Grade 6	Grade 7	Grade 8
Central	13.6	13.5	13.2	13.1	13.1	13.6	13.0	12.9
North Side	57.2	57.1	57.0	56.7	56.5	56.9	56.0	55.7
Far North Side	81.1	80.5	80.7	79.7	79.0	78.3	76.1	75.2
Northwest Side	50.9	50.7	50.7	49.8	49.5	49.0	44.4	44.0
West Side	154.1	154.4	154.9	153.8	154.5	153.6	145.8	144.8
South Side	89.8	89.5	89.1	88.3	88.3	88.2	85.4	84.4
Southwest Side	96.9	96.1	96.4	96.3	96.1	95.4	92.0	91.4
Far Southeast Side	80.4	80.4	80.3	80.5	79.6	78.4	73.3	73.0
Far Southwest Side	63.5	62.6	62.4	62.2	62.0	61.9	61.5	60.9

Table 3.3: Average number of schools over the sample period for each grade and Side.

I estimate the model separately for each grade, and so differences in school geography across grades and within a geographic market also will affect the interpretation of the estimated parameters. Table 3.3 shows that in most Sides, there are fewer schools that offer seventh and eighth grade and little variation in the number of schools offering grades one to six. For example, in the West Side, between 153.6 and 154.1 schools on average offer a grade between first and sixth, while between 145.8 and 144.8 schools offer seventh and eighth grades The Central, North, and Far Southwest Sides do not exhibit this pattern as strongly as the others. In those markets, the number of schools is similar across grades.

To the extent that there are differences in the geographic distributions of schools across grades, the model will consider these differences. For example, because there are fewer eighth grade schools, students have to travel farther on average to attend any given school. Therefore, if students travel far to attend an eighth grade school, the model does not reward this school as much as it would reward a school-grade for which students have many choices.

Distance Traveled to School

I use information on how far students travel to school to identify students' preference parameter of the disutility of travel. In particular, I use the sample of student-level data to calculate distance between a student's zoned school and her school of attendance. Table 3.4 shows the average distance between the zoned school and the school of attendance by grade for students who attend school in their own Side. On average, these students attend a school between 0.4 and 0.45 miles away from their zoned school, and this distance increases for older students.

For three reasons these data show that older students attend more distant schools. First, as discussed above, Table 3.3 shows that fewer schools offer higher grades, requiring students to travel farther to attend any given school. Second, older students are more willing to pay the travel costs than younger students. The demand estimation shows evidence of this pattern in Table 3.11, which reports the disutility of distance parameter estimates from the model. Students in higher grades have lower estimated disutility of distance than students in lower grades. Finally, Table B.1 shows that older students are less likely to attend their zoned school. Between 59% and 62% of students in grades one through six attend their

	Distance between Zoned School and School of Attendance			
	Attending School in Same Side		Attending School in Different Side	
Grade	Mean	N	Mean	N
1	0.41	49,779	4.49	7,525
2	0.40	50,841	4.57	7,741
3	0.39	53,842	4.44	8,102
4	0.40	50,375	4.45	7,731
5	0.41	47,949	4.58	7,843
6	0.41	48,035	4.46	8,401
7	0.44	45,496	4.31	9,285
8	0.45	43,908	4.37	9,338

Table 3.4: The average distance between zoned school and school of attendance by grade. Source: 2015-2016 and 2016-2017 CPS Zone Data.

zoned school, while for grades seven and eight the proportion drops to 56%. In the model, I include separate utility parameters for distance and zoned school to disentangle the two sources of utility.[16]

Charter School Growth

In Section 3.5 I measure which geographic markets earned the most consumer surplus from charter schools. When calculating welfare, the consumer surplus calculations consider welfare from two sources: the "base" welfare, the additional surplus a student enjoys due to having another school in her choice set, and any additional welfare from that school being more attractive. My model considers schools with higher market share more attractive, since they drew more students from their geographic market. Therefore, the welfare that charter schools created from 1998 to 2013 depends on the number of charter schools that entered

16. In Appendix B.2, I explore whether there are across-market differences in the measures presented in this section. If the aggregate patterns mask heterogeneity across Sides, then the geographic markets need to be analyzed separately. In general, I find that the patterns in each market are similar to the aggregate patterns.

and their enrollment shares.

During this period, Illinois State laws and Chicago Public Schools (CPS) policies ensured continued growth of the charter school sector by increasing available charters and supporting the growth of campuses under existing charters. Like many school districts, Chicago has a "charter cap," or a maximum number of charters permissible by law. However, throughout the sample period, the charter cap did not bind often. Table 3.5 tracks the charter cap by year and the number of charters in Chicago. In 1996, Illinois passed the first charter law, which began the charter school program in Chicago. By school year 2001-2002, CPS had authorized 15 charters, the maximum allowed by the first charter law. One year later in 2003 Illinois passed the second charter law, which increased the cap to 30 charters. This law also contained a "multi-campus provision" that allowed operators that earned a charter before 2003 to open multiple campuses under one charter. The multi-campus provision allowed prominent charter networks like Chicago International Charter Schools (CICS), Noble Street, and UNO to open campuses that did not count against the charter cap. Consequently, as of 2013, when there were 103 charter campuses, CICS, Noble, and UNO had 15, 12, and 12 campuses, respectively. As of school year 2007-2008, CPS had again awarded all of the charters available under the cap, but in 2009 Illinois passed the third charter law, which increased the cap to 75 charters, and governed the charter school program through 2013, which is the end of the sample period. Below, I further describe charter school growth over time by enrollment and enrollment shares.

Throughout the sample period, the charter sector grew on several margins. Table 3.6 shows that the number of schools and total enrollment increased. By 2006, every Side had at least one charter school. Table 3.7 shows that the average market share of charter schools also increased over time, especially in the Central and North Sides. In 2012, there were 63 total charter schools, and as we saw in Chapter 3, most of these were located in the West, South, and Southwest Sides. In those Sides, the average school had between 0.7% and

School Year (e.g, 1998 is 1997-1998)	Charter Cap	Stock of Charters	New Charters Approved
1998	15 Charters	6	6
1999	15 Charters	10	5
2000	15 Charters	12	2
2001	15 Charters	13	1
2002	15 Charters	15	2
2003	15 Charters	14	0
2004	30 Charters; Charters granted before 2003 can replicate	17	4
2005	30 Charters; Charters granted before 2003 can replicate	19	3
2006	30 Charters; Charters granted before 2003 can replicate	22	3
2007	30 Charters; Charters granted before 2003 can replicate	27	5
2008	30 Charters; Charters granted before 2003 can replicate	28	1
2009	30 Charters; Charters granted before 2003 can replicate	30	2
2010	75 Charters; Charters granted before 2003 can replicate	29	0
2011	75 Charters; Charters granted before 2003 can replicate	37	8
2012	75 Charters; Charters granted before 2003 can replicate	38	1
2013	75 Charters; Charters granted before 2003 can replicate	43	5

Table 3.5: The number of charters by year and selected regulations by year.

1.1% of enrollment. In 2012, the average charter school on the Central Side garnered 3.7% of enrollment, which was the largest school enrollment share among the nine Sides. The charter sector also grew through through additional grades at existing schools. For example, Table 3.8 shows that between 2010 and 2012, the West Side added no new schools but it added 26 new school-grades. As Section 3.5 shows, this source of growth was a substantial contributor to the total welfare created by charter schools. Lastly, Table 3.9 shows that the average enrollment grew at the school-grade level. All of these forms of growth: additional charters, additional campuses, additional grades, and additional enrollment all contribute to the welfare measured in Section 3.5.

Average Enrollment of Charter Schools by Side and Year

	1998		2000		2002		2004		2006		2008		2010		2012	
Side	Enrollment	N	Enrollment	N	Enrollment	N	Enrollment	N	Enrollment	N	Enrollment	N	Enrollment	N	Enrollment	N
Central	69	1	63	1	66	1	69	1	138	1	245	2	150	1	197	2
North Side	600	1	600	1	349	2	430	2	271	3	447	3	580	2	604	2
Far North Side		0		0		0		0	375	2	284	3	345	3	423	3
Northwest Side		0		0		0	456	1	512	1	346	2	456	2	512	2
West Side	66	1	332	3	306	4	269	5	292	8	293	13	306	20	413	20
South Side		0	156	1	221	4	253	5	249	6	302	7	319	9	306	11
Southwest Side	159	1	168	1	159	2	309	3	319	4	363	6	406	10	480	12
Far Southeast Side	252	1	278	2	350	1	424	1	344	2	383	2	326	4	305	6
Far Southwest Side	528	1	752	1	848	1	912	1	528	3	527	4	517	5	535	5

Table 3.6: Average enrollment of charter schools and number of charter schools by Side and year.

Average Market Share of Charter Schools by Side and Year																
	1998		2000		2002		2004		2006		2008		2010		2012	
Side	Share	N	Share	N	Share	N	Share	N	Share	N	Share	N	Share	N	Share	N
Central	1.4%	1	1.3%	1	1.4%	1	1.4%	1	3.1%	1	4.6%	2	3.4%	1	3.7%	2
North Side	2.2%	1	2.2%	1	1.3%	2	1.7%	2	1.2%	3	2.1%	3	2.7%	2	2.5%	2
Far North Side		0		0		0		0	1.1%	2	0.8%	3	1.0%	3	1.2%	3
Northwest Side		0		0		0	1.6%	1	1.8%	1	1.3%	2	1.7%	2	1.9%	2
West Side	0.1%	1	0.4%	3	0.4%	4	0.4%	5	0.4%	8	0.5%	13	0.5%	20	0.7%	20
South Side		0	0.4%	1	0.6%	4	0.7%	5	0.8%	6	1.0%	7	1.1%	9	1.1%	11
Southwest Side	0.3%	1	0.3%	1	0.3%	2	0.5%	3	0.6%	4	0.7%	6	0.8%	10	0.9%	12
Far Southeast Side	0.7%	1	0.8%	2	1.0%	1	1.2%	1	1.0%	2	1.3%	2	1.2%	4	1.2%	6
Far Southwest Side	2.1%	1	2.9%	1	3.1%	1	3.4%	1	2.0%	3	2.2%	4	2.3%	5	2.5%	5

Table 3.7: Average market share of charter schools and number of charter schools by Side and year.

Average Market Share of Charter School-Grades by Side and Year																
Side	1998		2000		2002		2004		2006		2008		2010		2012	
	Share	N	Share	N	Share	N	Share	N	Share	N	Share	N	Share	N	Share	N
Central	4%	3	4%	3	4%	3	4%	3	8%	3	7%	11	9%	3	12%	5
North Side	2%	8	2%	8	2%	14	2%	13	2%	16	2%	21	3%	16	3%	16
Far North Side		0		0		0		0	3%	6	3%	7	2%	12	2%	14
Northwest Side		0		0		0	2%	8	2%	8	2%	12	2%	14	2%	16
West Side	1%	1	1%	12	1%	22	1%	25	1%	36	1%	70	1%	112	1%	138
South Side		0	1%	4	1%	22	1%	27	1%	32	1%	39	2%	45	2%	49
Southwest Side	1%	3	1%	3	1%	6	1%	16	1%	21	1%	41	1%	63	1%	87
Far Southeast Side	2%	3	1%	12	1%	7	1%	8	1%	12	2%	14	2%	26	2%	32
Far Southwest Side	2%	8	3%	8	3%	8	3%	8	3%	16	3%	23	5%	20	5%	20

Table 3.8: The count of charter school-grades by Side and year and the average market share of charter school-grades by Side and year.

3.4 Model and Estimation Procedure

3.4.1 Model

In this section, I specify a utility function for school-grades and describe how I estimate its parameters. The utility that student i receives from grade g at school j at time t is the following:

$$u_{ijgt} = \delta_{jg} - \gamma_g d_{ijgt} + \rho_g z_{ijgt} + \epsilon_{ijgt}$$

where δ_{jg} is a fixed effect that represents the attractiveness of school-grade jg; $\gamma_g d_{ijgt}$ is

	Average Enrollment of Charter School-grades by Side and Year							
Side	1998	2000	2002	2004	2006	2008	2010	2012
Central	23	21	22	23	46	44	50	79
North Side	75	75	50	66	51	64	73	76
Far North Side					125	122	86	91
Northwest Side				57	64	58	65	64
West Side	66	83	56	54	65	54	55	60
South Side		39	40	47	47	54	64	69
Southwest Side	53	56	53	58	61	53	64	66
Far Southeast Side	84	46	50	53	57	55	50	57
Far Southwest Side	66	94	106	114	99	92	129	134

Table 3.9: Average enrollment of charter school-grades by Side and year.

a travel cost – the product of a disutility of travel parameter γ_g and the distance student i must travel to school j, d_{ijgt}; z_{ijgt} is a dummy equal to one if school j is student i's public zoned school; and ϵ_{ijgt} is an error term with distribution Type 1 Extreme Value, which represents a taste for variety.[17]

3.4.2 Estimation

To estimate the model, I employ simulated method of moments that uses a combination of the School Data, the simulated student location data, and the sample of empirical student-level data. I estimate the model separately for grades 1-8, which allows me to leverage the unique geographic distributions of students and schools within each grade. For each grade, I use a set of share moments, a moment that represents distance traveled to school, and a moment that represents how often students attend their zoned school. In the share moments, the estimation procedure compares the empirical enrollment shares of school-grades to their model-predicted enrollment shares. To construct the empirical market shares,

17. The parameter estimates are relative to an outside option. Within each Side and grade, I designate an outside option school. The outside option in each grade-Side is the public school with zoned students (i.e., not a charter school or magnet school) that has the largest 2013 enrollment. For each grade and Side, the outside option school is open during all years of my sample period. In Appendix B.4 I list the outside option schools by Side and grade.

I use the School Data to calculate each school-grade's average annual enrollment share in its geographic market during the sample period. The estimation procedure compares these shares to the model's prediction of the same shares.[18]

In particular, the first set of moments are the J_g equations (one for each school-grade) that compare $s_{jg}\left(\delta_{jg}, \gamma_g, \rho_g\right)$, the average annual *model-predicted* share of grade g school j, to S_{jg}, the average annual *empirical* market share for grade g of school j. Equation 3.1 defines the Share Moments:

Share Moments

$$s_{jg}\left(\delta_{jg}, \gamma_g, \rho_g\right) - S_{jg} = 0, \quad jg = 1, ..., J_g \tag{3.1}$$

where

$$\begin{aligned} s_{jg}\left(\delta_{jg}, \gamma_g, \rho_g\right) &\equiv \frac{1}{T}\sum_{t=1992}^{2013} s_{jgt}\left(\delta_{jg}, \gamma_g, \rho_g\right) \\ \textit{and} & \\ S_{jg} &\equiv \frac{1}{T}\sum_{t=1992}^{2013} S_{jgt} \end{aligned}$$

As an additional moment, I compare the average model-predicted distance a student's zoned school and her school of attendance to the empirical version of the same measure. This moment helps identify γ_g. The CPS Zone Data contain the average distance between a students' zoned school and a student's actual school of attendance.[19] Specifically, I compare the average *model-predicted* distance between the students' zoned school and their school of attendance ($\bar{\bar{d}}_g^z$) to the *empirical* version of the same measure ($\bar{d}_g^z$). Equation 3.2 defines the

18. The T1EV error structure facilitates the calculation of the model-predicted shares because it yields an analytic expression for market shares (Berry 1994).

19. CPS determines a student's zoned school based on her address. My data do not include student addresses.

Distance Moment:

Distance Moment

$$\bar{\tilde{d}}_g^z\left(\delta_{jg},\gamma_g,\rho_g\right)-\bar{d}_g^z=0 \tag{3.2}$$

Using the CPS Zone Data, I calculate the empirical distance between public student i's zoned school and her school of attendance, and I take the average to construct the empirical moment:

$$\bar{d}_g^z \equiv \frac{1}{I}\sum_{i=1}^{I} d_{ig}^z \tag{3.3}$$

To create the model-predicted counterpart I use simulated student location data:

$$\bar{\tilde{d}}_g^z\left(\delta_{jg},\gamma_g,\rho_g\right) \equiv \frac{1}{I}\sum_{i=1}^{I}\left(\frac{\sum_{l=1}^{J_l} s_{ilg}\left(\delta(\gamma_g),\gamma_g\right) d_{ilg}^{z\prime}}{\sum_{l=1}^{J_l} s_{ilg}}\right). \tag{3.4}$$

The right-hand side of Equation 3.4 is the average expected distance traveled to school conditional on attending a public school l in the set of public schools J_l. The numerator is the expected distance traveled to public schools for student i in grade g. The denominator is the probability of attending public school for student i in grade g.

The Zone Moment

For the zone moment, I compare the model-predicted share of students that attend their zoned school $\tilde{z}_g$ to its empirical counterpart $\bar{z}_g$, which I calculate using CPS Zone Data.

$$\tilde{z}_g\left(\delta_{jg},\gamma_g,\rho_g\right)-\bar{z}_g=0 \tag{3.5}$$

For each grade, the estimation procedure finds the vector of school-grade fixed-effects δ_{jg} and the pair of parameters γ_g and ρ_g that match 1) the model-predicted market shares to the empirical market shares (the share moments), 2) the average model-predicted distance between students' zoned school and their school of attendance to the empirical counterpart in the CPS Zone Data (the distance moment), and 3) the zone moment.[20]

3.4.3 Identification Discussion and Parameter Estimates

When assigning values of δ_{jg} to school-grades, the model considers a school-grade's market shares and the number of children who live nearby and are eligible for that grade. All else equal, the model will assign higher values of δ_{jg} to school-grades that have higher market shares. In addition, the model will consider the geographic distribution of students. If two school-grades have the same market share, the model will assign a higher δ_{jg} to the school-grade that has fewer eligible students nearby, indicating that students are willing to travel far to attend the school.

To identify γ_g, the model uses data on the distance between students' zoned schools and their school of attendance. If many students attend schools far from their zoned school, the model will estimate a lower γ_g. On the other hand, if many students attend their zoned school or schools near their zoned school, then the model will estimate a higher γ_g, indicating more disutility from traveling an additional mile to school. To identify ρ_g the model uses information on how often students attend their zoned school.

Figure 3.2 contains the distribution of $\hat{\delta}_{jg}$ by sector. Both the public and private sectors are larger than the charter sector, and they exhibit a larger variation in the attractiveness of schools. Table 3.10 contains the median $\hat{\delta}_{jg}$ by Side and sector. Looking across the rows of this table reveals that within a Side, how families value the median school in each sector. For example, on the West Side, the median charter school is more attractive than the median private or public school. In fact, this is the case in all Sides except for the Central Side, where the median public school has the highest mean value.

Table 3.11 displays $\hat{\gamma}_g$ and ρ_g for each grade. These estimates show that students in higher

20. See Appendix B.1 for a detailed description of the moments and the estimation procedure.

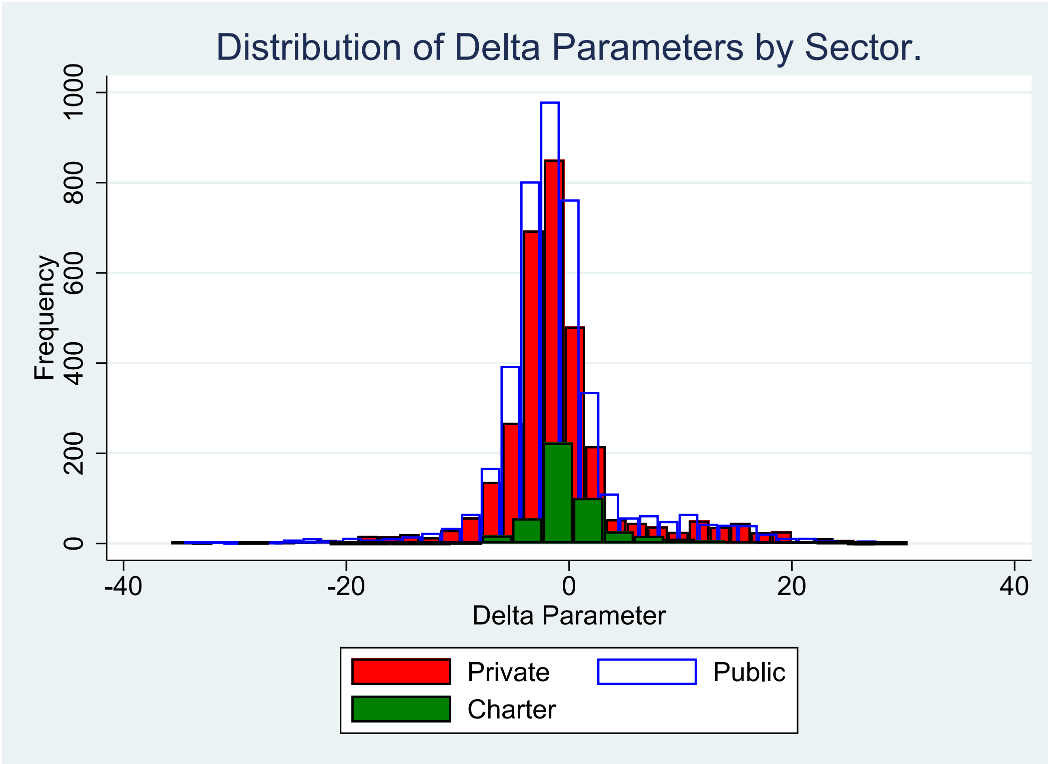

Figure 3.2: The distribution of delta parameters by sector. The unit of observation is a school-grade.

grades are more willing to travel than those in lower grades, $\hat{\gamma}_1 = -6.23$ and $\hat{\gamma}_8 = -1.36$. These estimates reflect the empirical data on distance between zoned school and school of attendance in Table 3.4, which show that students in higher grades travel farther to school.[21]

3.5 Benefits and Costs of Charter School Entry

In this section, I measure the benefits that the charter school sector created. I consider several components of the total welfare that charter schools created. First, I calculate in the model the increase in consumer surplus from charter school entry. Through the lens of the model, charter school entry is seen as an infusion of more schools into student choice sets. Through estimation of the mean value parameters, the model can also assign some

21. Appendix B.5 describes how I calculate standard errors of $\hat{\gamma}_g$.

School-Grade Fixed Effect Estimates by Side						
	Charter		Private		Public	
	Median	N	Median	N	Median	N
Central	-2.71	15	-1.14	136	-0.08	85
North Side	1.26	26	0.54	267	0.08	301
Far North Side	-0.77	23	-2.16	487	-2.98	400
Northwest Side	-0.83	24	-2.60	291	-2.71	238
West Side	-0.46	149	-2.69	528	-1.83	1,113
South Side	-3.22	58	-5.80	354	-4.41	620
Southwest Side	-1.10	106	-2.13	357	-1.42	653
Far Southeast Side	2.34	42	0.27	398	0.50	506
Far Southwest Side	2.04	44	0.66	402	-0.34	294

Table 3.10: Median δ_{jg} by Side.

Parameter Estimates								
Grade	1	2	3	4	5	6	7	8
Disutility of distance γ	-6.23	-7.51	-2.02	-2.34	-1.74	-1.51	-1.86	-1.36
	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Utility from zoned school ρ	3.99	4.01	3.73	3.43	3.38	3.51	4.02	4.06
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)

Table 3.11: Parameter estimates by grade. I use generalized method of moments to estimate the parameters. The first set of moments is each school's average enrollment share over time. The second moment is the average distance between a students' zoned school and a student's actual school of attendance. The third moment is the share of students attending their zoned school.

charter schools higher utility than others. Second, I calculate which neighborhoods enjoyed the most consumer surplus from charter school entry. In Chapter 2, I showed that charter schools entered disadvantaged neighborhoods. In this chapter, I add to these analyses by examining whether disadvantaged neighborhoods also received the most consumer surplus from charter school entry. Third, I calculate the total dollar value of the consumer surplus that charter schools created. This allows for a clear interpretation of the consumer surplus calculations and a comparison of the costs of operating a charter school sector. Next, I consider whether the benefits of charter school entry can be attributed to charter schools themselves or simply to the presence of more schools. To this end, I estimate what consumer surplus would have been had the private or the public sector provided schools at the same locations where charter schools opened. Lastly, I estimate the cost savings that CPS earns from operating a charter school sector.

Overall, the model calculates that families enjoyed considerable consumer surplus from charter school entry. My estimates indicate that this occurred because there were more schools in the choice set and not necessarily because the charter sector opened better schools than public or private sector. In evidence of this, alternative consumer surplus calculations in Section 3.5.3 indicate that if CPS had instead opened more traditional public schools then families would have enjoyed even more consumer surplus than the charter schools provided. Chicago Public Schools, however, does not directly capture the consumer surplus that families acquire from having more choice. That being said, my analysis of CPS's budget shows that diverting students from traditional public schools to charter schools does generate cost savings for Chicago Public Schools. Taken together, these analyses explain why the charter sector has grown, and this has created consumer surplus for families and decreased costs for CPS.

3.5.1 Calculating Consumer Surplus

To measure consumer surplus attributable to charter school entry, I use the model to calculate the increase in consumer surplus that occurs when charter schools are added to a students' choice set. For each student-year, I measure the additional surplus from having a choice set that includes the charter schools open in that year compared to a choice set that does not include these charter schools. I make two simplifying assumptions. First, the welfare calculations are static. That is, the existence of a charter school in year t affects welfare during year t. Second, if a student's choice set grows, she is able to switch to a new school without cost. I use the following formula to calculate $E\left(CS_{it}^{J_k}\right)$, which is the expected value of consumer surplus associated with a set of school-grades J_k to student i:

$$E\left(CS_{it}^{J_k}\right) = \frac{1}{\alpha}\log\left(\sum_{jg\in J_k} exp\left(\delta_{jg} - \gamma_g d_{ijgt} + \rho_g z_{ijgt}\right)\right). \tag{3.6}$$

where α is the change in utility associated with an increase in income. Dividing by α converts $E\left(CS_{it}^{J_k}\right)$ into dollars. Then, I define the surplus associated with charter school entry ΔCS_{it} as the following:

$$\Delta CS_{it} = CS_{it}^{J_A} - CS_{it}^{J_{CF}}. \tag{3.7}$$

where $CS_{it}^{J_A}$ and $CS_{it}^{J_{CF}}$ are the consumer surplus associated with the following two choice sets, respectively:

1. J_A, the choice set that includes all schools available during year t
2. J_{CF}, the counterfactual choice set that does not include charter schools

By calculating ΔCS_{it} for each year and student, I am able to calculate the aggregate welfare provided by charter schools as well as welfare by geographic market. In the next section, I use the consumer welfare formula to explore which geographic markets experienced the most welfare from charter school entry.[22]

3.5.2 Benefits by Geographic Market

Section 2.6 showed that in Chicago from 1998 to 2003, charter schools entered disadvantaged neighborhoods, defined as those that had low household income and low school test

22. The estimation uses the market shares of schools to identify the school-grade fixed effect. Capacity constraints at charter schools may have restricted charter schools' market shares and understate their school-grade fixed effect. Since my model identifies the δ_{jg} using enrollment shares, my model will assign a lower δ_{jg} to a capacity-constrained school than to one not capacity constrained. During each school year from 2002-2003 to 2012-2013, at least 80% of charters were oversubscribed. In many years, over 90% of charters received more applications than they had seats. See Table 3.12.

Oversubscription by Year			
Year	Number of Charters	Number of Charters Oversubscribed	Proportion of Charters Oversubscribed
SY2003	14	13	93%
SY2004	17	16	94%
SY2005	19	17	89%
SY2006	22	18	82%
SY2007	27	22	81%
SY2008	28	23	82%
SY2009	30	26	87%
SY2010	29	26	90%
SY2011	37	33	89%
SY2012	38	35	92%
SY2013	43	37	86%

Table 3.12: The number of charters that were oversubscribed by year. A charter is oversubscribed if its number of applications exceeds its number of seats. Two charters did not report data in SY2009. Source: ISBE Charter Annual Reports.

scores. Using the consumer surplus formula I can expand on this finding and determine whether disadvantaged neighborhoods enjoyed the highest proportion of the total consumer surplus. To do this, I calculate the proportion of total surplus that accrued to each Side and present correlations between these proportions and Side characteristics. Then, I discuss whether charter schools created utility due to increasing the available schooling options or by providing high-utility schools.

Figure 3.3 graphs the proportion of total consumer surplus by Side. The West, South, Southwest, and Far Southwest, enjoyed the highest proportion of surplus from charter school entry. The most consumer surplus accrued to the West Side and Southwest Side, over 25% and 21% respectively. Each of the markets on the North Side enjoyed 6% or less of the consumer surplus.

Figure 3.4 shows that neighborhoods that had low student test scores received a disproportionate amount of surplus from charter schools. The five Sides at or below the median in math test scores enjoyed 69% of the benefits from charter schools. Moreover, Figure 3.5, and Figure 3.6 both show that the poorest neighborhoods in Chicago enjoyed the most benefits of charter schools. For example, according to 2000 income measured in the U.S. Census,

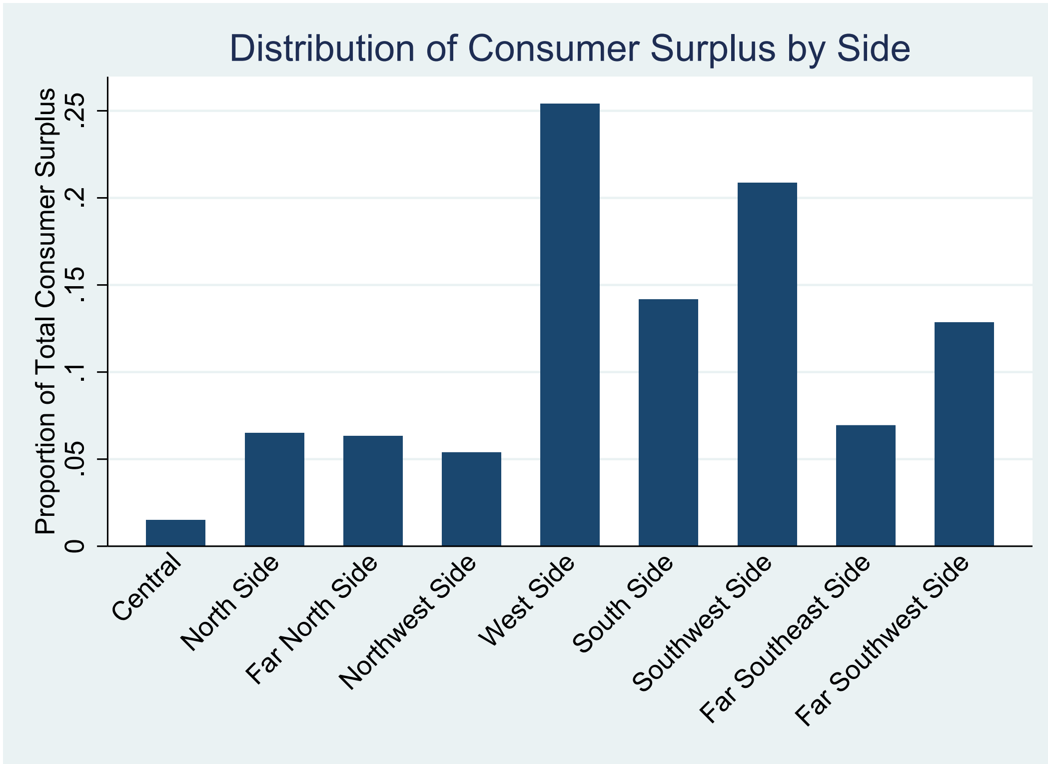

Figure 3.3: Graph of the proportion of consumer surplus from charter schools accrued to each geographic market in Chicago. I define the geographic markets as the nine Sides of Chicago. See Figure 3.1.

the five Sides at the median or below median income enjoyed 73% of the benefits that came from charter schools. These correlations show that consumer surplus from charter schools accrued disproportionately to disadvantaged neighborhoods. Taken in the aggregate, these markets could have enjoyed the most surplus because more charter schools entered them or because more high-quality (as measured by consumer surplus) charter schools entered them. I deconstruct the contributions of each of these sources below.

In some geographic markets, the number of charter school-grades that entered drove the level of consumer surplus, while in other a combination of entry and quality contributed to welfare. Table 3.13 displays welfare per school-grade and the proportion of total welfare for each Side. The four markets that enjoyed the highest proportion of charter school welfare all experienced a high level of charter school entry. The South and West Sides experienced

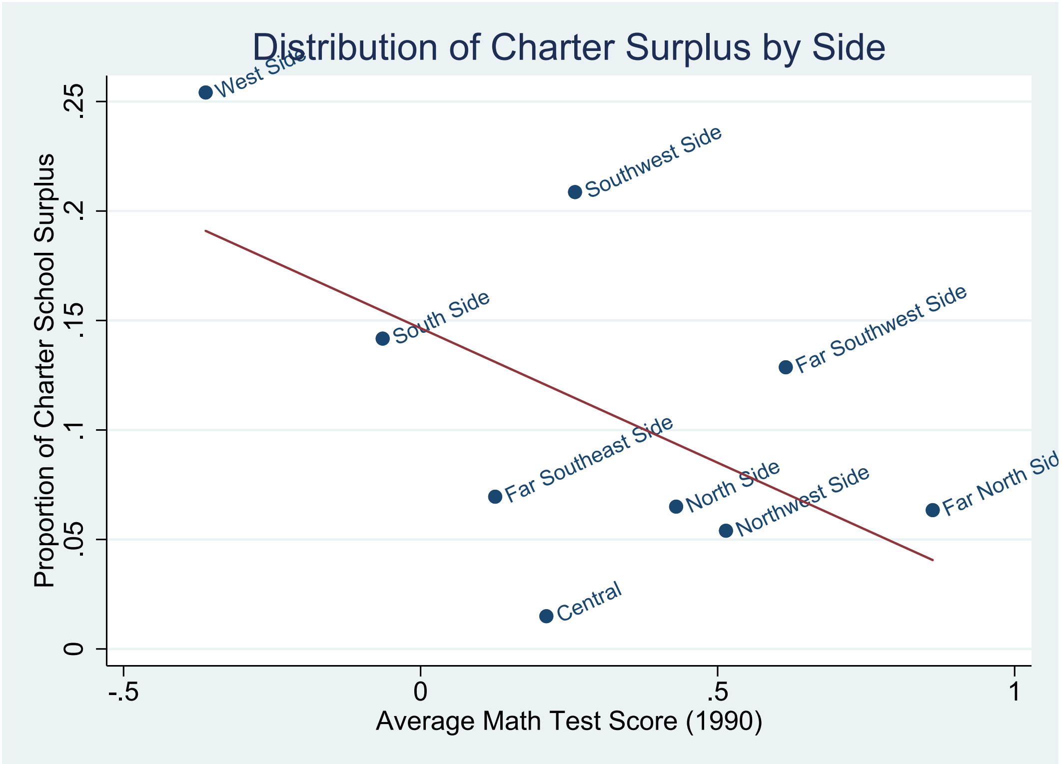

Figure 3.4: Graph of the relationship between the proportion of consumer surplus from charter schools accrued to each Side and the average math test score in that Side. The average math test score is the average standardized math test score for school-grades in each Side in 1990. The red line displays the fitted values of a regression of proportion of consumer surplus on average math test score.

the most charter school entry but had the second- and third-lowest welfare per school-grade. By the same token, the Southwest Side had the second-highest number of school-grades and the fourth-highest welfare per school-grade. The Far Southwest Side is an outlier among the 9 Sides. It is one of the top 4 in terms of consumer surplus proportion because its charter schools are high quality. It had the second highest welfare per school, but only the 4th most charter schools. The North Side and Far Southeast Sides had similar quantity of charter school entry to the Far Southwest Side but their welfare per school measures were among the lowest of the nine Sides.

To summarize, disadvantaged neighborhoods realized the most benefits of charter school entry because charter schools entered those neighborhoods more frequently. In the next

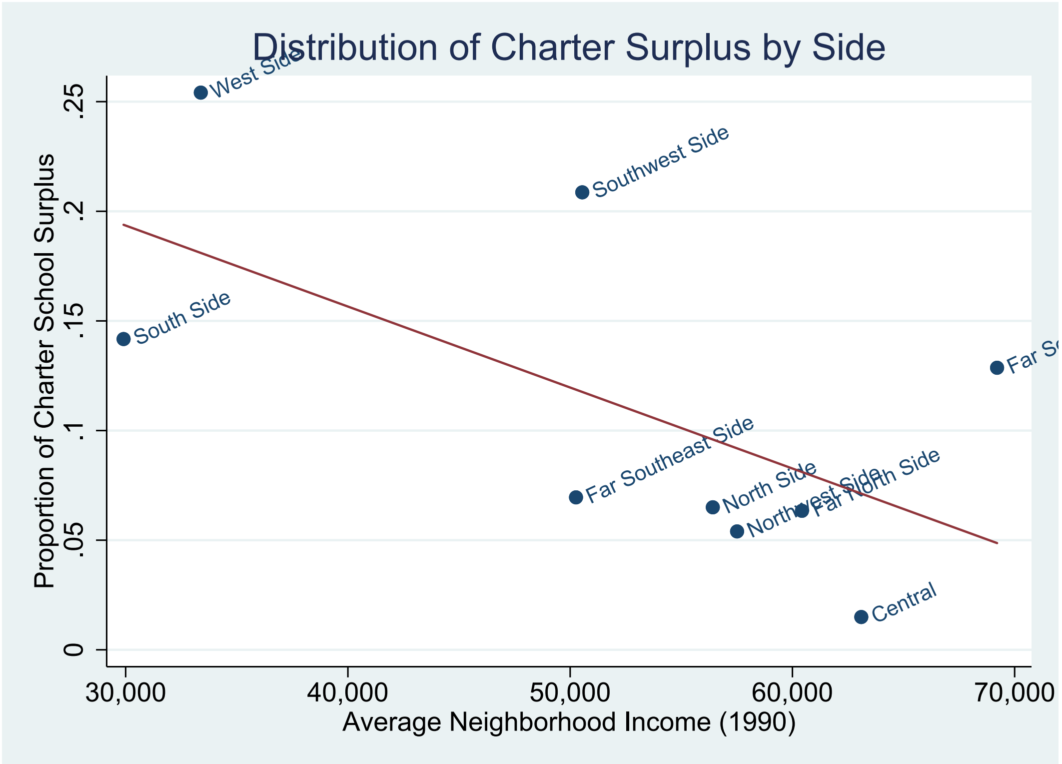

Figure 3.5: Graph of the relationship between the proportion of consumer surplus from charter schools accrued to each Side and the average median income in each Side. To calculate average income in 1990, I take the average median income over the census tracts in each Side from the 1990 U.S. Decennial Census. The red line displays the fitted values of a regression of proportion of consumer surplus on 1990 income.

section, I calculate the total dollar value of consumer surplus of charter school entry in Chicago and compare it to the cost savings that CPS realizes from operating the charter sector.

3.5.3 Aggregate Benefits and Costs

Converting Consumer Surplus to Dollars

In the market-specific analyses of the previous section, I measure the proportion of consumer surplus that accrued to each geographic market, using utils as the unit of measure of consumer surplus. In this section, I aim to measure aggregate benefits. Therefore, I need to calculate

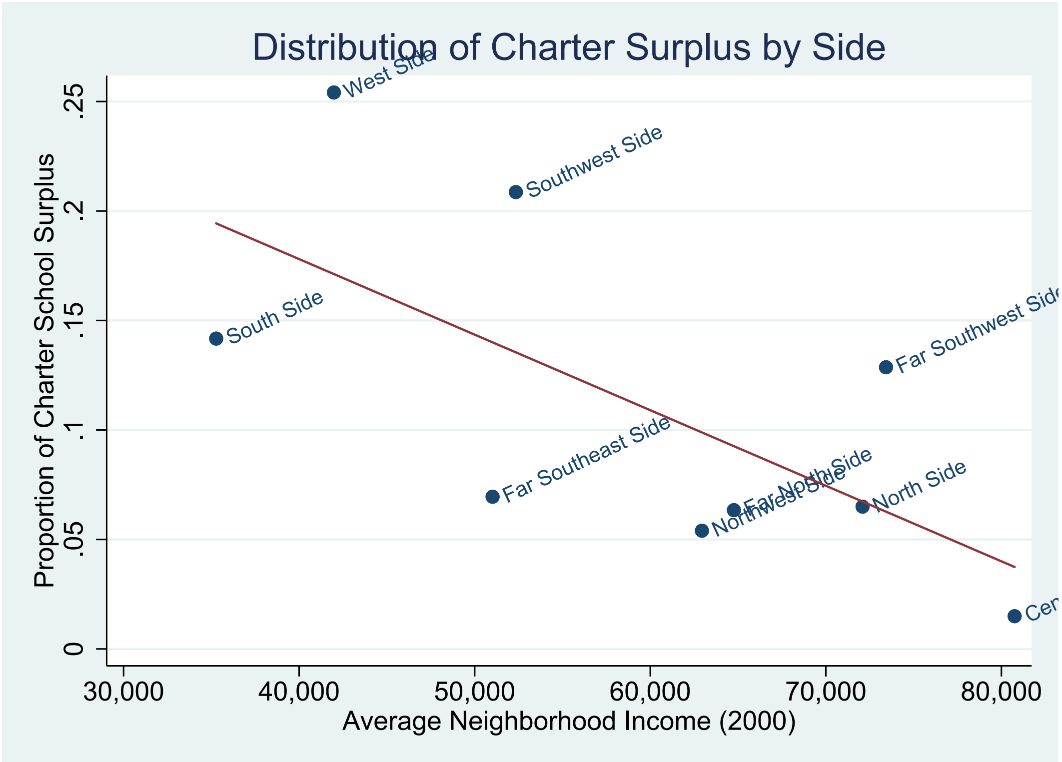

Figure 3.6: Graph of the relationship between the proportion of consumer surplus from charter schools in each Side and the average median income in each Side. To calculate average Side income in 2000, I take the average median income over the census tracts in each Side from the 2000 U.S. Census. The red line displays the fitted values of a regression of proportion of consumer surplus on 2000 income.

consumer surplus in dollars. To do so, I present an estimate of α, which is necessary to calculate consumer surplus using Equation 3.6.

The $\frac{1}{\alpha}$ term in Equation 3.6 converts consumer surplus from utils to dollars. This coefficient measures the utility decrease associated with an increase in the price paid, and, thus, a decrease in income. This results in an estimate of the marginal utility of income $\frac{\partial U}{\partial Income}$.[23] To estimate the relationship between utility and income in the Chicago school market, I regress my estimates of δ_{jg}, measured in utils, on average tuition paid at Catholic schools. I use the following regression:

23. In many cases, the estimate of α is the absolute value of the coefficient on a price variable directly estimated in the utility function. I do not use this method because I lack comprehensive tuition data.

Cumulative Welfare and Welfare per School				
Side	Welfare (Utils)	Count of School-Grades	Welfare per School	Proportion of Total Welfare
Central	3,040	62	49.04	1%
North Side	13,213	225	58.72	6%
Far North Side	12,890	94	137.13	6%
Northwest Side	10,977	134	81.92	5%
West Side	51,667	905	57.09	25%
South Side	28,815	463	62.24	14%
Southwest Side	42,423	537	79.00	21%
Far Southeast Side	14,137	234	60.41	7%
Far Southwest Side	26,155	236	110.83	13%

Table 3.13: Statistics that summarize the cumulative welfare that charter schools created during 1998-2013.

$$\hat{\delta}_{jg} = \beta_0 + \alpha AverageTuition_{jg} + \nu_{jg} \tag{3.8}$$

where $\hat{\delta}_{jg}$ are my estimates of the mean value of grade g at school j and $AverageTuition_{jg}$ is the average tuition paid in grade g and school j. I calculate $AverageTuition_{jg}$ at Catholic schools using the Tuition Data and demographic data on family size. I construct $AverageTuition_{jg}$ by calculating a weighted average of each school's one-, two-, three-, four-, and five-child prices. For the weights, I estimate the distribution of family size at each school using Census data on family size at the Census-Block-Group level.

By construction, an estimate of α in Equation 3.8 has the unit of measure necessary to convert consumer surplus from utils into dollars. $\hat{\alpha}$ represents utils per dollar and dividing by this term converts consumer surplus into dollars. However, under what conditions is it appropriate to use $\hat{\alpha}$ in order to assign a dollar value to the consumer surplus that charter schools created? This regression describes how in Chicago, the prices of school-grades are related to the utility of attending those school-grades. Therefore, if schools use additional revenue to increase the utility-increasing inputs at their schools, then this measure of α is likely to be appropriate. For example, spending on tuition that increases the quality of teachers or the availability of activities and sports programs would increase the utility of a particular school. If schools use extra tuition revenue for utility-inducing inputs, then we expect tuition to be positively related to utility; *i.e.*, $\hat{\alpha} > 0$. Table 3.14 contains the OLS estimate of α. An additional \$1,000 dollars in average tuition paid is associated with an increase in utility of 0.935.[24]

	OLS
	Delta
Average Tuition Paid (\$1000s)	0.935
	(0.215)*
Grade Fixed Effects	Yes
N	629
R-squared	0.038

* p<0.10, ** p<0.05, *** p<0.01

Table 3.14: OLS Regression of the estimated school-grade fixed-effect parameter "Delta" $\hat{\delta}_{jg}$ on the average tuition paid at Catholic schools grades 1 to 8. The average tuition paid is the list price of tuition less the average discount awarded. The average discount is calculated using a weighted-average of the two-, three-, four-, and five-child prices. For the weights, I estimate the distribution of family size in the block group of each Catholic school.

Using the model, I calculate the dollar value of the consumer surplus created by charter schools. This consumer surplus reflects the utility that students enjoyed from having additional, and potentially better, schools in their menu of options. Using Equation 3.7, I calculate for each year and geographic market the change in consumer surplus that was achieved when charter schools were added to students' choice sets in Chicago. Table 3.15 contains summary figures of the surplus calculations. Total surplus associated with charter schools during the sample period was over \$217.5 million, approximately \$44 per student ever enrolled in any sector. My model calculates that in 2012-2013, charter schools created

24. Contrast this to the effect on utility of an exogenous increase in tuition. If nothing about a school changes, but it increases tuition, utility would decrease and we would expect $\hat{\alpha} < 0$.

\$37.1 million of consumer surplus, which is \$138 per student and \$1,319 per charter student. Charter school entry created considerable benefits for families. These welfare calculations combine two benefits: the benefit of having more school choices and benefits attributable to the quality of the charter schools. In the next section, I attempt to separate these two sources of benefit.

Total Surplus and Surplus per Student

Total Surplus: 1998-2013	Surplus per Student: 1998-2013	Total Surplus per Student: 2013	Total Surplus per Charter Student: 2013
\$217,451,085	\$44	\$138	\$1,319

Table 3.15: Estimates of the consumer surplus due to charter school entry in Chicago. See Equation 3.7.

More schools or more charter schools?

In logit demand models, a portion of the consumer surplus can be attributed simply to having more choices. The idiosyncratic ϵ_{ijg} causes this well-known feature. To determine whether more choices drive the welfare change or whether charter schools themselves increase welfare, I calculate an alternative welfare estimate that compares choice sets of equal size, $\Delta CS_i'$. I use this alternative welfare calculation to estimate how much consumer surplus would change if the public or private sectors had provided schools in the same locations that charter schools entered.

In the main welfare estimate I compare the "Full" choice set J_A with charter schools to a "Counterfactual" choice set without charter schools J_{CF}. In the alternative welfare estimates in this section, I compare the same Full choice set to a different "Alternative" choice set. The Alternative choice set has the same number of schools as the Full choice set, and in both sets the schools are in the same locations. However, in the case of the charter schools in the Alternative choice set, I replace the parameter δ_{jg} with that of the average public school in the student's Side of residence, $\bar{\delta}_{public}$. This choice set approximates the surplus that would accrue if the public sector had provided new schools in the same locations where charter schools entered. This welfare calculation eliminates the surplus associated solely with the location of schools and the number of schools in the choice set by isolating the surplus associated with the difference between the school-grade fixed effects of charter schools and the average public school.

I also calculate $\Delta CS_i''$, defined similarly, but replace δ_{jg} with $\bar{\delta}_{private}$, which is the average δ_{jg} of private schools in a student's Side of residence. I summarize the two Alternative welfare calculations below.

$$\Delta CS_i' = CS_i^{J_A} - CS_i^{J_A}\Big|_{\delta_{jg}^{charter}=\bar{\delta}_{public}} \tag{3.9}$$

$$\Delta CS_i'' = CS_i^{J_A} - CS_i^{J_A}\Big|_{\delta_{jg}^{charter}=\bar{\delta}_{private}} \tag{3.10}$$

Table 3.16 summarizes the Alternative welfare amounts. Columns 1 and 2 contain calculations of $\Delta CS_i''$ and $\Delta CS_i'$, respectively. According to the Alternative welfare calculations, charter entry provides approximately \$60 million less consumer surplus relative to a world in which the private sector provided schools at the same locations. Column 2 of Table 3.16 shows that charter school entry created approximately \$216 million less in consumer surplus than would have been created if the public school sector had opened in the same location. Bearing in mind these calculations, CPS's decision to open new schools through the charter sector may seem puzzling. However, CPS does not capture the consumer surplus that my model measures. Rather this surplus accrues to students and families. As I show in the next section, CPS decreases its costs by diverting students from the traditional public sector to the charter sector, which is one explanation why CPS opens new schools through the charter sector.

Consumer Surplus with Equal Size Choice Sets

Replacing Charter Delta with Average Private School in Charter School's Side	Replacing Charter Delta with Average Public School in Charter School's Side
-$59,273,088	-$215,857,423

Table 3.16: This table presents the alternative consumer surplus calculations described in Section 3.5. The first column contains calculations of Equation 3.10. These are estimates of the consumer surplus gain. A choice set with charter schools is compared to a choice set of the same size, and I replace the delta parameter of charter schools with the average private school delta parameter in that charter school's geographic market. The second column contains calculations of Equation 3.8. Charter schools are compared to a choice set of the same size, and I replace the delta parameter of charter schools with the average public school delta parameter in that charter school's geographic market.

Effect of Charter Sector on CPS Costs

As enrollment in the charter sector grows, CPS's expenditures change in two ways. First, to fund charter schools, the Illinois Charter Law requires that CPS pay charter schools a per-student "tuition." Second, CPS needs to educate fewer students, and this produces numerous cost savings that result from operating fewer facilities, buying fewer materials, and hiring fewer employees. In this section, I investigate two types of cost savings. First, I study the cost savings that are formulaically related to enrollment — those from hiring fewer staff. Second, I study cost savings related to operating and capital costs. Although the latter source of savings is not formulaically related to enrollment, it represents opportunities for cost savings that have arisen due to the existence and growth of the charter sector.

Average Cost of Instruction

To calculate the cost savings in 2012–2013, I would ideally observe CPS's total costs at their current enrollment level and their total costs if they had to educate 28,109 fewer students, which was the level of enrollment in charter schools in 2012-2013. Since I do not observe this experiment, I use CPS's budget books to estimate how much CPS would save if their enrollment decreased by 28,109 students. To do this, I calculate three versions of what I call the average cost of instruction (ACI). The first version is a base version, and each subsequent version adds additional costs. All three versions of ACI include per-student costs in expenditure on budget categories which covary strongly with the level of enrollment. Therefore, they represent an estimate of CPS's change in cost with respect to a change in enrollment.

ACI_1 is CPS's ACI assuming that their only instruction costs are teacher salaries.[25] In school year 2012-2013, CPS spent \$1.89 billion (\$4,686 per student) on salaries of regular teachers.[26] To calculate ACI_2, I add pension and medical benefits that CPS pays to teachers. Each year CPS pays into its pension fund an amount equal to 7% of current teachers' salaries.[27] In FY2013, these payments totaled \$134.1 million (\$332 per student).[28] I estimate that in 2012–2013 CPS paid approximately \$270.7 million (\$670 per student) in medical benefits to teachers.[29] In total, ACI_2, is equal to \$5,689.

To construct ACI_3, I add CPS's expenditure on school support staff to ACI_2. These are non-teacher employees who work in schools, such as security guards and school clerks.

25. The expenditure on teacher salaries directly increases with enrollment. In 2012-2013, CPS used a formula to allocate the budget for teacher positions to schools. The formula mandated a 28:1 pupil-to-teacher ratio in grades 1-3 and a 31:1 pupil-to-teacher ratio in grades 4-8. See the CPS FY2013 budget book, p.159.

26. This category includes salary expenditures (not including benefits) on full-time regular teachers, principals, guidance counselors and other teachers with specific duties, such as special education or bilingual instruction. This figure does not include salary expenditures related to employing teachers — for example, payment for extended day teachers, overtime, and substitute teacher salaries. In 2012-2013 CPS spent \$31.7 million in these categories.

27. See `http://cps.edu/finance/FY14budget/pages/pensions.aspx`

28. This figure only includes payments according to current teachers' salaries. CPS has also made "catch-up" contributions to the pension fund because the fund not being 100% funded. These payments began in FY2014, after the sample period.

29. CPS's budget book does not disaggregate medical benefits by employee type. In total, CPS spent \$587.9 million on medical benefits. I assume that CPS paid 76% of that to teachers. I arrive at 76% by dividing total regular teacher salary expenditures by the sum of regular teacher and educational support staff salary.

I estimate that CPS's total cost of school support staff in 2012-2013 was \$32.2 million, implying a per-student cost of \$1,151.[30] Combining educational support staff with teacher salary and benefits yields ACI_3, which is \$6,841 per student.

Figure 3.7 summarizes CPS's per-student costs under ACI_3 by budget category and compares them to the per-student tuition cost of \$6,070. ACI_3 is 113% of the charter school per-student tuition cost, while ACI_1 and ACI_2 cover 74% and 94%, respectively, of that cost. In other words, ACI_1, ACI_2, and ACI_3 produce the following total cost savings of educating 28,109 fewer students: \$131.7 million, \$159.9 million, and \$192.3 million, respectively. In comparison, the total charter school tuition payment for 28,109 students is \$171.1 million.

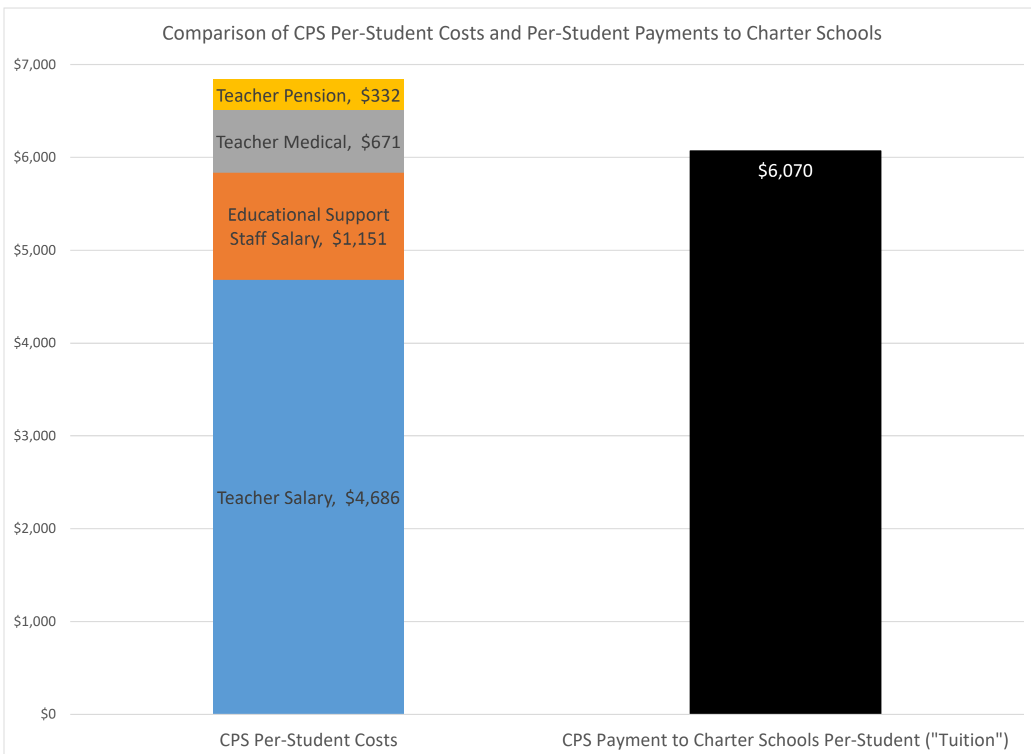

Figure 3.7: Comparison of costs of instruction and CPS tuition payment to charter schools.

All three estimates of ACI almost certainly underestimate the cost savings that the

30. CPS employed 16,475 school educational support staff in 2012-2013. 13,014 (79%) of these were employed at schools and the remaining 3,461.2 (21%) occupied city-wide student support positions. On average, educational support staff earned a salary of \$35,691.

charter sector generates. ACI_1 and ACI_2 only include payments to teachers, and by CPS policy the number of teachers increases as the number of students increases. Even with these conservative estimates, ACI_1 implies cost savings that cover the vast majority of charter tuition payments, while cost savings using ACI_2 covers 94% of charter school tuition payments. ACI_3, the highest of the three versions, still probably underestimates the cost savings. Even if we used only one-third of the educational support staff salaries used to calculate ACI_3, the cost savings implied by ACI_3 would cover the charter school tuition costs. Furthermore, the estimates of ACI do not include costs from other budget categories. In the next section, I illustrate the cost savings from two important categories: operating an capital costs.

Operating and Capital Costs

The analysis above does not include costs from numerous other budget categories. CPS's cost savings on facilities provide a salient example. Below, I analyze two additional sources of potential cost savings related to facilities. These cost savings are not formulaically related to charter enrollment, but they represent opportunities for cost savings that have arisen because of the existence of the charter sector.

First, CPS defrays its costs on existing school buildings by leasing space to charter schools. Of the 51 elementary charter schools listed in CPS's budget book in 2012-2013, 16 leased space in buildings that CPS owns. All of these schools paid no rent or a nominal rent of $1. However, in all but one of these cases the charter schools agreed to pay or share the operating costs of the buildings such as janitorial services, utilities, and information technology services. In the remaining case, the charter operator and CPS agreed to alternative compensation. The University of Chicago agreed to provide educational services to CPS public schools near University of Chicago charter campuses.[31]

While CPS does not have data on what charter schools pay for these operating costs, one

31. CPS posts their leases involving school properties on their website. See `http://propertyleases.cps.edu/ViewLeases.aspx`

estimate of CPS's benefit from these agreements comes from Betty Shabazz Charter High School's agreement to share space with DuSable, a traditional public high school. In 2008-2009, Shabazz agreed to pay CPS $1,722 per student to cover its operating expenses, which is 23% of the charter high school tuition rate.[32] This particular number may overestimate the actual cost savings since it includes the implied benefit of the charter school avoiding transaction costs of securing vendors. However, this illustrates that CPS can enjoy significant cost savings from leasing or sharing space in its buildings to charter schools.

Second, due to decreased enrollment in the district, CPS has been able to close schools and sell the buildings that housed those schools. Here, I present figures on cost savings that CPS has enjoyed from closing schools, and discuss how much of those savings can be attributed to the growth of the charter sector.

To assess the amount of savings from closed buildings, I use data and policy documents from CPS's 2013 closures, in which CPS closed 49 elementary schools. I focus on the 2013 closures because there are several CPS policy documents and spreadsheets related to this event. These documents make it clear that "underutilization," too many seats for the level of enrollment, was the primary criterion CPS used for closing schools. For example, marketing materials consistently argued that the closures were necessary because CPS had too many seats for its level of enrollment and that almost 140 schools were "more than half empty." Moreover, CPS's official guidelines specified underutilization as the main criterion for closing a school. Indeed, the schools they closed reflected these policies. Among the 49 schools CPS closed in 2013, the average utilization was 46%.[33]

These closures produced sizable cost savings for CPS. As of this writing CPS has closed and sold 23 of these 49 schools. The sales alone have garnered $31.2 million.[34] Even more

32. Source: `http://propertyleases.cps.edu/ViewLeases.aspx`

33. See e.g., `http://cps.edu/About_CPS/Policies_and_guidelines/Pages/2013GuidelinesforSchoolActions.aspx`

34. Source: `http://www.chicagoreporter.com/what-happened-to-the-closed-school-in-your-neighborhood/#attucks`

than that, CPS has avoided \$290.8 in capital costs of maintenance and updates of those buildings, generating total savings of \$322 million.[35]

Underutilization of CPS schools was the main factor that lead them to close and sell 23 schools in 2013. How much does removing 28,109 students from CPS impact utilization? To move the average fully-utilized school from full utilization to 46% utilization, the average utilization of a closed school in 2013, requires a decrease in enrollment of 328 students.[36] At this rate, Removing 28,109 students from the district is enough to move 73 average schools from full utilization to a utilization in danger of closure. There were 47 schools at or below 46% utilization that CPS considered for closure in 2012-2013 and 60% of them closed. Based on these back-of-the-envelope calculations, I conclude that the a decrease in enrollment equivalent to 2012–2013 charter sector enrollment would have at least a small impact on the decrease in utilization in CPS that lead to the mass closings in 2013. Nonetheless, a small proportion of \$322 million represents significant cost savings.

3.5.4 Discussion of Benefits and Costs

The model calculates that charter school entry created a sizable consumer surplus for families in Chicago. Most of this consumer surplus accrued to disadvantaged neighborhoods — a phenomenon that I show is due to increased charter school entry in those areas rather than to higher-quality charter schools choosing those areas This begs the question of why CPS operates a charter sector and does not open additional traditional public schools. More schools creates more utility for students and my estimates suggest that CPS schools would provide more utility on average than charter schools have. First CPS does not directly capture the consumer surplus created when a new school opens. Second, as I show, diverting

35. Source: `http://cps.edu/About_CPS/Policies_and_guidelines/Pages/qualityschools.aspx`

36. At the time, CPS considered a school building underutilized if its enrollment was less than 80% of its "ideal capacity," which is equal to 30 times the number of classrooms in the building. According to CPS data, the average CPS elementary school building had 23.8 classrooms, implying an average ideal capacity of 714 students.

students from the charter sector to the public sector generates cost savings for CPS. These facts together explain why the charter sector grew during the sample period, providing considerable consumer surplus to families. Thus, even if by opening more schools CPS could provide more consumer surplus than the charter sector, it would not do so because CPS does not capture that consumer surplus and would have to pay more to operate the new schools themselves.

3.6 Conclusion

A large literature shows that charter schools can help students raise their test scores. Economists have argued that charter schools especially help disadvantaged students in urban neighborhoods. In a case study of Chicago, I document that charter schools entered in neighborhoods that had low income and low test scores. These entry patterns are consistent with a simple model that predicts that it is relatively easy for charter schools to attract students in areas that have poor schooling options. To further develop the conclusions from the case study, I estimate a utility model for schools and calculate the total consumer surplus that can be attributed to charter school entry during the period of 1998–2013. I find that consumer surplus disproportionately accrued to neighborhoods that had low income and test scores. My analyses show that this phenomenon was due to more charter entry into these neighborhoods rather than schools that provided more utility. Furthermore, I show that operating the charter sector has decreased CPS's labor, materials, and capital costs. Together, my findings suggest that school districts can provide welfare gains to families in their district and decrease their costs by not only expanding schooling options but by allowing charter schools to enter disadvantaged neighborhoods.

CHAPTER 4

DATA DESCRIPTION

4.1 Summary of Data Sources

4.1.1 School Data

I assemble a dataset that includes grade-level enrollment and school location for the universe of schools in Chicago between 1992 and 2013, a period that includes data before and after the first charter schools entered in Chicago in 1997-1998. To create this dataset, I combine a variety of sources. For traditional public schools, I use grade-level enrollment and school addresses from the NCES Common Core from 1992 to 2013. The NCES makes these data available to the public. See `https://nces.ed.gov/ccd/pubschuniv.asp`

No such public dataset exists for charter schools, so I combine publicly available data and information from archived Illinois Charter Annual Reports.[1] I use charter school enrollment and location data from the CPS Racial and Ethnic Survey for the years 2004 to 2013. For 1998 to 2003, I manually compile the data from ISBE Charter Annual Reports.

Similarly, for private schools there is no publicly available dataset that contains annual grade-level enrollment and location.[2] For private schools, I obtained the necessary data via the Freedom of Information Act (FOIA). Through FOIA, the Illinois State Board of Education provided me with grade-level enrollment and school location from 1992 to 2013.[3]

1. NCES and ISBE data contain data on charter schools, but they do not always disaggregate the data by charter campus within a charter network.

2. I considered the Private School Survey (PSS). My data provide two main advantages over the PSS. First, my data are annual, allowing me to observe year-to-year changes in enrollment. Second, the data contain school location back to 1992. Before 2002, the PSS location data is unreliable.

3. ISBE has similar files that are publicly available, but they do not contain grade-level enrollment and the earliest year they offer is SY2004.

4.1.2 Tuition Data

I construct a cross-sectional dataset of tuition data by school-grade. As a starting point, I begin with the list of all private schools open in the 2015-2016, according to the ISBE School Data.. I call this set of schools the 2016 Private Schools.

I collected tuition figures for each of the school-grades in each of 2016 Private schools. The process consisted of two stages. The first stage was in May 2017, and the second stage was in September 2017. During the first stage, I visited the website of each of the 2016 Private schools and recorded the annual per-student tuition rate and any sibling discounts that the school offered. I record the 2017-2018 tuition rates, and if the school had not posted their 2017-2018 tuition, then I recorded the 2016-2017 tuition rate. During the second stage, I revisited each of the websites of the 2016 Private Schools. If available, I updated schools' tuition values to the 2017-2018 figures. During both stages, if the tuition rates were not available on the website, then I contacted the school by e-mail and phone and conducted Internet research to obtain their most recent tuition rates.

4.1.3 1990-1997 Digitized Test Scores

Annually, the Chicago Tribune published a report summarizing test scores for Chicago Public School students. The report varies slightly by year, but always includes Reading and Math test scores for grades 3, 6, and 8. To use these test score data, I digitized the articles and transcribed the data into spreadsheets.

4.1.4 CPS Zone Data

I obtain the student-level CPS Zone Data via FOIA. These data contain for each student in school years 2015-2016 and 2016-2017, the students' zoned school and the student's actual school of attendance.

4.1.5 Chicago Transit Authority Train Route Shapefiles

I downloaded geographic coordinates of public train stops from the the City of Chicago data portal (`https://data.cityofchicago.org/Transportation/CTA-List-of-CTA-Datasets/pnau-cf66`). At the time of download, the train stops had not changed since before the beginning of my sample period, so I use the current train maps without any loss of information.

4.1.6 U.S. Decennial Censuses

I use selected variables from the 1990, 2000, and 2010 Decennial Censuses. In both years, I use Summary File 1, accessed through Social Explorer.

- For 1990, see `https://www.socialexplorer.com/tables/C1990`
- For 2000, see `https://www.socialexplorer.com/tables/C2000`
- For 2010, see `https://www.socialexplorer.com/tables/C2010`

4.1.7 Simulated Student Location Data — 2010 Decennial Census

To estimate the model in Section 3.3, I utilize locations of students' residences. Because I do not have actual student location data, I simulate student location data with the 2010 U.S. Census. The 2010 U.S. Census contains counts of school-age residents by age at the Census block level. I assume each student in the 2010 U.S. Census lives at the geographic centroid of her block. This yields a dataset of student locations for each school-age resident.[4]

4.1.8 CPS Zone Maps

I assign each student in the simulated dataset to zoned schools using shapefiles that outline CPS 2009-2010 attendance area boundaries. I access these shapefiles via the City of Chicago

4. I assume the geographic distribution of students is the same in each year of my sample period.

Data Portal.[5]

4.2 Creating Analysis Dataset of Grade-Level Enrollment and School Location

For both Chapter 2 and 3, I use grade-level enrollment data that includes detailed school location. These data are essential for the analyses. In the next three sections I describe how I create the grade-level enrollment data for each sector: private, public, and charter. For each sector, I describe quality control, document data sources, document key features of the data, and describe how I convert the raw data into my analysis dataset.

4.2.1 Private Schools

Overview

In response to a FOIA request, the Illinois State Board of Education (ISBE) provided me with raw files that contain enrollment by school-grade for all Illinois private schools. These files vary in format, but they always contain the following variables: region, school code, school name, address, city, zip code, and grade-level enrollment. Using the ISBE Raw Files, I construct a panel of grade-level enrollment and location of private schools in Cook County from 1991-1992 to 2015-2016.

In this appendix, I describe how I transform the ISBE raw files into my analysis dataset. I organize this process into five steps:

1. Initial Cleaning

5. See,

- For elementary schools: `https://data.cityofchicago.org/Education/Chicago-Public-Schools-Elementary-School-Attendanc/sra3-5rba`
- For middle schools: `https://data.cityofchicago.org/Education/Chicago-Public-Schools-Middle-School-Attendance-Bo/btx6-zt6f`

2. Validate and Standardize School Addresses

3. Geocode Address Variables

4. Assign Unique Identifier

5. Create Enrollment Variable

Each step involves quality control and documentation of the data. In the following sections, I describe each of these steps.

Initial Cleaning

As an initial cleaning step, I edit the raw files.

1. Edit 12 observations that contain spreadsheet formatting errors.

2. Restrict the sample to schools located in Cook County.

3. Restrict the sample to schools that are not primarily Special Education. Specifically, if the ISBE "Level" variable is equal to "S," then I drop the observation.

Validate and Standardize School Addresses

After the initial cleaning, I validate and standardize addresses. I use software called ZP4[6] to access the United States Postal Service (USPS) database to validate and standardize addresses. Using ZP4, I send each address to the USPS database for validation and standardization. Then, the ZP4 application returns whether the address has a match in the USPS database. If it does not have a match, ZP4 returns a detailed set of error codes describing why the application could not find a match in the database. If the address has a

6. Companies and universities, including the University of Chicago, have used the ZP4 application to standardize and validate addresses for bulk mailing. Users can obtain the ZP4 application from the Semaphore Corporation. See, `http://www.semaphorecorp.com/zp4/zp4.html`.

match, the ZP4 will, if necessary, standardize the address to match the USPS's Coding Accuracy Support System (CASS). For example, if the input address is "SUITE A 123 MAIN STREET" then the standardized address may be "123 MAIN ST APT A." Specifically, I validate and standardize address in three steps:

1. I create a list of each unique combination of address, city, state, and 5-digit zip code in the raw ISBE files.
2. I load this list of addresses into the ZP4 database.
3. The ZP4 database returns the following information: standardized address, standardized city, standardized zip code, and error code (if applicable).

Of the 1,562 addresses from the raw input file, 62 (4%) return an error indicating that the street or the address cannot be found.

Geocoding

After using ZP4 to standardize addresses, I use the Texas A & M University Geocoding Service (TAMU) to geocode the standardized addresses.[7] TAMU geocoding assigns latitude, longitude, and census tract to each address and produces variables describing the quality of the geocoding. Of the 1,200 Street Address, City, and ZIP Code combinations, TAMU geocodes 1,131 (94%) with the highest quality match precision. For these 1,131, I rely on the TAMU-generated latitude, longitude, and census tract variables I geocode the remaining 69 addresses according to the following process.

1. If the TAMU geocoding variables are missing, I use the geography variables from the ZP4 application if the following conditions are true:
   (a) ZP4 recognizes the address without error

7. See `Seehttp://geoservices.tamu.edu/Services/Geocode/`

(b) ZP4 geocodes the address without error

2. I identify post office box addresses

3. I manually inspect address and assign longitude and latitude using Google Maps

Step 1 produces geography variables for nine additional observations. Step 2 identifies 29 post office boxes. I replace their geography values as missing. Step 3 identifies valid addresses. For these, I acquire latitude longitude using Google Maps and census tract using the FCCs Census Block Conversion API. The resulting dataset contains matched latitude, longitude, and census tract to 1,173 of 1,200 total addresses in the raw files. Table 4.1 below summarizes the sources of geography variables.

Table 4.1: Geocoding Sources

Source	Count	Percentage
Texas A & M Geocoding	1,129	94.0%
Google Maps and FCC API	35	2.9%
Missing Post Office Box	22	1.8%
ZP4	9	0.8%
Missing Post Office Box	5	0.4%

Assign Unique School Identifier

In the raw files, ISBE included information that uniquely identifies schools within each school year. However, this information is not always sufficient to track schools over time. In this section, I describe how I create a unique identifier that tracks schools over time. The ISBE raw files contain three variables that identify schools:

1. Two-digit Region of Education (ROE) Code,

2. Three-digit School Code,

3. One-letter code that indicates the Level of the school: elementary ("X"), high school ("Y") or both ("Z").

Within each year of my data, there are no duplicates with respect to these three variables. However, upon inspection of the data, I find instances where schools' identifying information changed over time. Thus, I am not able to use ROE Code, School Code, and Level to track schools over time. Below, I describe how I create a unique identifier variable that tracks schools over time.

1. Assign consistent ROE Code

   The ISBE assigned new ROE Codes to some schools in 2011. ISBE provides a crosswalk that maps 1992-2010 ((pre-2011) ROE Codes to 2011-present (post-2011) ROE Codes for each affected school (ROE Crosswalk). As a first step, I assign pre-2011 observations their corresponding post-2011 ROE Code.

2. Create RCLZ Variable

   After, assigning consistent ROE Codes, I create an ID variable RCLZ by concatenating Region Code, School Code, Level, and ZIP Code. Within each year, this variable uniquely identifies the data. That is, there are no duplicate RCLZs within a year. However, RCLZ does not necessarily uniquely identify schools in all cases. Some schools change either Region Code, School Code, Level, or ZIP Code over time. In order to identify these cases, I perform three checks.

   Check 1: RCLZs associated with multiple School Names I find 32 RCLZs associated with multiple school names. Upon inspection, I conclude that each of these represents one school.[8]

   Check 2: School Names associated with multiple RCLZs

   I find 160 School Names associated with multiple RCLZs. I divide these into four main categories:

8. See Appendix "RCLZs associated with multiple school names" for a summary. Available upon request.

1. School Names associated with multiple Levels and only one Region Code, School Code, and ZIP Code (8 cases)

2. School Names associated with multiple Region Codes and multiple Levels, but only one School Code, and ZIP Code (10 cases)

3. School Names associated with multiple ZIP Codes, and possibly multiple Levels, School Codes, and Region Codes. (140 cases)

4. School names associated with multiple School Codes, and only one Region Code, ZIP Code, and Level (2 cases)

- I conclude that all School Names in Category 1 represent one school. I assign the School Name its first RCLZ in ascending order. 1 school switched from a unit school to an elementary school. 2 schools switched from an elementary to school to a unit school. 5 schools switched two or more times between elementary and unit school

- I conclude that School Names in Category 2 represent one school. I assign the School Name its first RCLZ in ascending order.

- For School Names in Category 3, in order to conclude whether they represent one school, I visited school websites and called school offices to investigate whether these represent a school that moved or whether multiple schools exist with the same name. In cases where the School Name represents one school, I assign the School Name its first RCLZ in ascending order. In the cases where multiple schools have the same School Name (e.g., St Paul located in Skokie and St. Paul located in Chicago), I edit the School Name so that each school has its own name.

- I conclude that School Names in Category 4 represent one school. I assign the School Name its first RCLZ in ascending order.

See Appendix Section "School Names associated with multiple RCLZs" for a brief description of each School Name that is associated with multiple RCLZs and how I edit their observations.

Check 3: Multiple Schools with same address. I found 20 addresses associated with multiple schools (Table 4.2)

Enrollment Variable

In this section, I describe three issues relevant to how I construct the grade-level enrollment variable for my analysis dataset: left-censoring, cell size, and special education (SPED) enrollment. Below, I summarize these issues. The conclusion of this section contains a step-by-step description of how I create the grade-level enrollment variable given these issues.

First, In the raw files, the ISBE left-censors enrollment values in order to protect the identity of students. That is, for any cell in a spreadsheet, it will replace a value less than ten with the value "< 10." In these cases, I impute values.

Second, in most raw files, the cell-size is enrollment at the school-grade level. However, in some spreadsheets, the data are more granular, either by grade-gender or grade-race-gender. In spreadsheets with more granular cell sizes, there are more left-censored values. For example, it is more likely that there is a school that has less than ten male eight graders than less than ten eighth graders of any gender.

Third, in each spreadsheet, the enrollment variables contain some SPED enrollment. Depending on the year, the enrollment variable includes either ungraded SPED enrollment only or both ungraded and graded SPED enrollment. In the "SPED Enrollment" section below, I document the status of SPED in the enrollment variables and describe how I create the grade-level enrollment variable consistently over time.

Left Censoring

ISBE left censored enrollment values in all but two of the spreadsheets ISBE provided me.

Table 4.2: Treatment of multiple Schools with same address.

Address	Description
1015 W. Golf Road	Kripa Montessori took over for Montessori Learning Center.
1025 W. Lake St	St. Paul Lutheran and Walter Lutheran are separate schools that have inhabited this address.
118 N. Central	Circle Rock Preparatory and Circle Rock Academy are the same school. .
1143 W. 63rd St	CS Academy and Academy II split. CS Academy II remained at this address.
1501 N Oakley	Josephinum Academy and Josephinum High School.
16511 S. Park Avenue	Apostolic Kingdom and Protestant Reformed Christian have both inhabited this address.
2867 S. Throop St	St. Barbara Elementary and St. Barbara High School at same address
30 E 112th Place	Vivian Summers Alternative High School changed its name to Vivian E. Summers Child Development Prep.
3130 W. 87th St	Luther High School South and Luther High School South Assoc., and Luther Math Science and Arts are the same school.
3210 Dundee	Sager Solomon Schechter School has middle and high school at same building. The middle school closed in 2011 while the high school remained open
337 E 107th St	Albert J Shegog Christian Academy and Park Vernon Academy have both inhabited this address. I have found no evidence they are affiliated
400 23rd Avenue	True Vine Christian Academy and Divinity Christian Academy have both inhabited this address.
418 W Touhy Avenue	Park Ridge Montessori and Montessori Academy of Illinois.
4215 W West End Avenue	Bethel Christian School and Bethel-LCA Christian are the same school.
4700 Oakton Ave	Gan Ketan Montessori and Torah Montessori have both inhabited this address

Table 4.3: Treatment of multiple Schools with same address (cont.)

Address	Description
501 Bellwood	Living Word Christian Academy occupies this address in 2002 and onward. St. Simeon occupies this address from 1992-2001
5700 W Berteau	Luther North High School and Luther High School North are the same school.
59 W North Blvd	Latin School of Chicago and Latin School of Chicago Upper are both affiliated with The Latin School
5946 S. Prairie	The Hunter Lab Academy and Hunter Bolden Academy are open at the same time and at the same address. I have no evidence they are separate schools.
74 Park Drive	Glenview New Church School is a continuation of Immanuel Church School. Glenview New Church school website indicates it was founded in 1895.
900 E 54th S	St. Jude The Apostle consolidated along with other schools into Christ Our Savior Catholic School.
9301 Gross Point	Two different Schechter schools shared building.
6416 S Washtenaw Ave.	Hope Lutheran with New Hope Lutheran are the same school.

In Table 4.4, I summarize how ISBE handles small enrollment values in each spreadsheet.

Cell Size of Enrollment Variables

ISBE provided spreadsheets containing variables describing grade-level enrollment for each year of 1992 to 2015. The cell size of enrollment variables differs by year. The 1992-2001, 2007-2011, and 2013-2016 spreadsheets contain columns for total grade-level enrollment. The 2002-2006 spreadsheets and 2012 spreadsheet contains two columns for each grade: one for male enrollment and one for female enrollment. These spreadsheets do not contain a column that contains only total grade enrollment. See Table 4.5.

Table 4.4: Description of how ISBE codes small values of enrollment.

Spreadsheet(s)	Description of how ISBE coding.
1992-2008	Zero coded as "-". Values less than ten and greater than zero coded as "<10".
2009 Elementary Enrollment	Zero coded as "-". Values less than ten and greater than zero coded as "<10". The total enrollment cell sums race-level enrollment cells, treating cells less than ten as zero.
2009 Secondary Enrollment	Zero coded as "-". Values less than ten and greater than zero coded as "<10". The total enrollment cell sums race-level enrollment cells, treating cells less than ten as zero.
2010 Elementary Enrollment	Zero code as 0. No left-censoring.
2010 Secondary Enrollment	Zero coded as "-". Values less than ten and greater than zero coded as "<10". The total enrollment cell sums race-level enrollment cells, treating cells less than ten as zero.
2011-2012	Zero coded as "-". Values less than ten and greater than zero coded as "<10".
2013	Zero code as 0. No left censoring.
2014-2016	Zero coded as "-". Values less than ten and greater than 0 coded as "<10".

Table 4.5: Summary of cell size grade-level enrollment variables in ISBE Raw Files.

Year	Grade-level enrollment cell-size
1992-2001	Grade
2002	Grade-Gender
2003	Grade-Gender
2004	Grade-Gender
2005	Grade-Gender
2005	Grade-Gender
2006	Grade-Gender
2007	Grade
2008	Grade
2009	Grade
2010	Grade
2011	Grade
2012	Grade-Gender
2013	Grade
2014	Grade
2015	Grade
2016	Grade

Table 4.6: Special Education Data Status by dataset.

Year	Enrollment include SPED?	Separate ungraded SPED?	Separate graded SPED?
1992-2001	Yes, both ungraded and graded	Yes	Yes
2002	Yes, both ungraded and graded	Yes	Yes
2003	Yes, ungraded only	Yes	No
2004	Yes, both ungraded and graded	Yes	Yes
2005	Yes, both ungraded and graded	Yes	Yes
2005	Yes, both ungraded and graded	Yes	Yes
2006	Yes, both ungraded and graded	Yes	Yes
2007	Yes, both ungraded and graded	Yes	Yes
2008	Yes, ungraded only	Yes	Yes
2009	Yes, ungraded only	Yes	Yes
2010	Yes, ungraded only	Yes	Yes
2011	Yes, ungraded only	Yes	Yes
2012	Yes, ungraded only	Yes	Yes
2013	Yes, ungraded only	Yes	No
2014	Yes, ungraded only	Yes	No
2015	Yes, ungraded only	Yes	No
2016	Yes, ungraded only	Yes	No

SPED Enrollment

In each spreadsheet, the enrollment variables contain some SPED enrollment. Depending on the year, the enrollment variable includes either ungraded SPED enrollment only or both ungraded and graded SPED enrollment. In Table 4.6, I document the SPED status of the enrollment variables. The sped status of the enrollment variables informs how I make an enrollment variable that is uniform across years.

How I Construct Grade-Level Enrollment Variables for Analysis

The three issues I describe above guide how I construct the grade-level enrollment variable for my analysis dataset. I first impute left-censored cells. Then, for each year, I sum the relevant variables to create grade-level enrollment. I describe this process in detail below. The process creates enrollment variables that are uniform over time.

Impute Left-Censored Cells

The ISBE did not left-censor cells in two raw files: the file that contains enrollment for elementary schools in 2010 and the file that contains enrollment for all schools in 2013. Using these two files, I calculate four empirical distributions that help me impute enrollment in files where ISBE left-censored the enrollment variables.

1. Empirical distribution of grade-level Elementary Enrollment conditional on grade-level Elementary Enrollment being greater than zero and less than ten. (Source: Combined 2010 and 2013 files)

2. Empirical distribution of grade-level Secondary Enrollment conditional on grade-level Secondary Enrollment being greater than zero and less than ten. (Source: 2013 File)

3. Empirical distribution of Pre-K Graded SPED Enrollment conditional on Pre-K Graded SPED Enrollment being greater than zero and less than ten. (Source: 2010 File)

4. Empirical distribution of Elementary Graded SPED Enrollment conditional on Elementary Graded SPED Enrollment being greater than zero and less than ten. (Source: 2010 File)

For each left-censored cell in the ISBE raw files, I assign an imputed value by drawing values with probabilities according to one of these empirical distributions.[9]

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9. Below I describe the exact process for creating these empirical distributions.

1. Import source data

2. Keep the N observations where the enrollment variable of interest is less than 10 and greater than

Table 4.7: Formulas for Creating Grade-Level Enrollment.

Case	Rule
Secondary Special Education Enrollment <10	Impute Value using Empirical Distribution #4.
Enrollment variable reported by gender	Draw value according to empirical distribution. Divide drawn value by 2. Round resulting value to the nearest integer.
Enrollment variable reported by gender and race	Replace cell with enrollment value equal to 1.

In most cases, the four empirical distributions above provide the imputed value that I need. In some cases, I do not have an empirical distribution for the exact value I need to impute. In Table 4.7 below, I list these cases, and the rule I use to assign an imputed value.

---

zero.

3. For each integer greater than zero and less than 10, count the number of times I observe each integer, n_i, where i in [1,9].
4. For each integer i in [1,9], calculate $p_i = n_i/N$.
5. The values p_1, , p_9 establish a probability mass function that assigns an empirical probability of observing enrollment value i conditional on i in $[1, 9]$. When I impute values for left-censored cells, I draw imputed values with probabilities according to this probability mass function.

Grade-level enrollment variable

I construct grade-level enrollment variables that include ungraded enrollment and do not include graded SPED enrollment. Using grade-level enrollment with graded special education enrollment allows me to use the provided total enrollment variables as-is for years 2003 and 2008-2016. In the remaining years, I calculate grade-level enrollment by subtracting graded SPED enrollment from the provided grade-level enrollment variable.[10]

4.2.2 Public Schools

I use publicly available datasets from the National Center for Education Statistics (NCES) and Chicago Public Schools (CPS) to create the dataset that contains enrollment and school location for traditional public schools (TPS), that is, public schools that are not charter schools.

In this section, I describe the data sources and how I convert the raw files to the analysis dataset.

Data Sources

I use two data sources. The NCES Common Core files contain enrollment, student location, and a unique identifier, ISBE ID, for all public schools. I also use the CPS School Files. The school files contain two unique identifiers of schools: ISBE ID and "unit." I use the CPS School Files to create a unit-ISBEID crosswalk. With the crosswalk, I am able to match the NCES data data to other data sources that contain information about CPS schools.

Creating the Analysis Dataset

10. I considered two alternative measures of enrollment: 1) grade-level enrollment excluding any type of SPED and 2) grade-level enrollment including both types of SPED. Graded special education enrollment is not available in all years, and, thus, option #2 is impossible. Alternative measure 1 is possible. However, I prefer my chosen method since I can use the grade-level enrollment variables as provided for years 2003 and 2008 to 2016. When I use the variables as provided, I do not have to subtract possibly imputed values of graded SPED enrollment. This reduces measurement error.

Table 4.8: Formulas for Creating Grade-Level Enrollment.

Raw File	Formula for grade-level enrollment
1992	Grade-Level Enrollment - Graded SPED
1993	Grade-Level Enrollment - Graded SPED
1994	Grade-Level Enrollment - Graded SPED
1995	Grade-Level Enrollment - Graded SPED
1996	Grade-Level Enrollment - Graded SPED
1997	Grade-Level Enrollment- Graded SPED
1998	Grade-Level Enrollment - Graded SPED
1999	Grade-Level Enrollment - Graded SPED
2000	Grade-Level Enrollment - Graded SPED
2001	Grade-Level Enrollment - Graded SPED
2002	Grade-Level Enrollment - Graded SPED
2003	Grade-Level Enrollment
2004	Grade-Level Enrollment - Graded SPED
2005	Grade-Level Enrollment- Graded SPED
2006	Grade-Level Enrollment - Graded SPED
2007	Grade-Level Enrollment - Graded SPED
2008	Grade-Level Enrollment
2009	Grade-Level Enrollment
2010	Grade-Level Enrollment
2011	Grade-Level Enrollment
2012	Grade-Level Enrollment
2013	Grade-Level Enrollment
2014	Grade-Level Enrollment
2015	Grade-Level Enrollment
2016	Grade-Level Enrollment

1. Using the CPS School Files, I create a unit-ISBEID crosswalk. The CPS School Files contain publicly available information about CPS schools. This crosswalk is unique by ISBEID. There are ISBE IDs that are associated with multiple Unit IDs.

2. I import the NCES Common Core Public Files.

3. I assign unit to each case using the unit-ISBEID crosswalk. There are 212 observations across 62 ISBE IDs that do not have a matching unit

4. I drop charter schools and other school-years where the enrollment variables is missing.

Dropping Charter Conversions

There are eight schools that have been charter schools and non-charter schools in different years. I treat these eight schools as charter schools. I include them in the charter school data, and drop them from the public enrollment file. See Section "Charter Conversions." The charter school data contain enrollment and location for these schools.

Unit-ISBEID Crosswalk

I create a Unit ID to ISBE ID crosswalk in order to match the grade-level enrollment file to other CPS and ISBE data sources. There are some ISBE IDs that are associated with multiple Unit IDs. I assign them the minimum of their multiple Unit ID values. This mismatch does not affect any of the matching underlying any of my analyses.

4.2.3 Charter Schools

Below I describe the process for creating charter school enrollment by year. I use multiple sources of data to construct a panel of the enrollment and school location for each charter schools. I also document cases of charter school conversions, which I treat as charter schools. Finally, for a small set of charter branches, I impute grade-level enrollment for 1998–2003, since it is unavailable from either of my data sources. I document these below.

Process for creating charter school enrollment

1. Using the CPS School Files, I create a dataset that maps unit ID to a charter indicator. I assign the charter indicator equal to 1 if the unit ID is ever identified as a charter in the school files.

2. Using the CPS School Files, I create a dataset that maps school address to each unit in all years.

3. Using the CPS School Files and the unit-schlid crosswalk, I create a crosswalk that assigns a unit to each schlid.

4. Using the CPS Race and Ethnicity Survey Files, I create a dataset that maps school-level enrollment to each unit in school years 1999-2000 to 2012-2013.

5. In each year, I identify which charter schools were open. For school years 1997-1998 to 2004-2005, I manually create the Charter Grades offered by charter school 1998-2005 spreadsheet. All of the units in this spreadsheet are charter schools. Each row represents a unit in a year. The columns are grade indicators equal to one if the charter offers that grade in a year. To create this spreadsheet I rely on ISBE Annual Charter reports and CPS School Board Meeting notes. For school years 2005 to 2013, I use Day 20 Enrollment files from CPS. Day 20 enrollment files represent CPSs official count of enrollment from the 20th day of school. These files contain enrollment by grade. Using the charter indicator and unit-schlid crosswalk (See Steps 1 and 3), I assign each unit a charter indicator. I review each school and manually edit the charter indicator if necessary. See Section "Charter conversions."

6. I drop cases where the charter indicator is equal to zero.

7. Using the dataset described in step 2, I assign address to each unit in all years.

8. Using the dataset described in step 4, I assign enrollment to each unit in school years 1999-2000 to 2012-2013.

9. The CPS Race and Ethnicity Survey Files do not have enrollment for school years 1997-1998 or 1998-1999, the first two years of charter entry. To assign enrollment to charter schools open in these years, I rely on the 2004 ISBE Charter Annual Report. For three schools I interpolate enrollment. See Enrollment Interpolation for Chicago International Charter School branches in 1997-1998 and 1998-1999.

10. Using Texas A&M's geocoding API, I assign latitude, longitude, and census tract to each address.

Charter Conversions

The following schools converted to charters, usually from contract schools. I classify them as charters.

- Unit 2025: Academy for Global Citizenship Elementary School converted from contract to charter school. First year as charter: 2010-2011. See 2009-2010 - 2010-2011 ISBE Charter Annual Report and CPS Board Report 11-0323-EX5.

- Unit 2055: Kwame Nkrumah opened as a contract school in SY2009. Converted to charter starting in 2011-2012. See 2009-2010 / 2010-2011 ISBE Charter Annual Report.

- Unit 4371: Catalyst - Circle Rock. Contract from 2008-2010. 2011 and after: Charter. See http://www.prnewswire.com/news-releases/16-public-charter-schools-open-in-illinois-102562159.html

- Unit 6650: Frazier was contract 2013 and prior and charter 2013-2014 and after. See 2013-2014 / 2014-2015 ISBE Charter Annual Report.

- Unit 8053: Chicago Talent Development Charter High School converted from a contract school to a charter school in the 2010-2011 school year. See 2009-2010 / 2010-2011 ISBE Charter Annual Report.

- Unit 8058: Epic Academy. Opened as a charter in SY2011. Was previously a contract school. See 2009-2010 / 2010-2011 ISBE Charter Annual Report.

- Unit 8096: Urban Prep Wests application was approved in the Fall of 2009 for the school to occupy Charter status beginning in the 2010-2011 school year. See 2011-2012 / 2012-2013 ISBE Charter Annual Report.

- Unit 7710: I assign KIPP Chicago Youth Village Academy as a charter school because it is associated with a charter network. See http://chicagoreporter.com/cps-schools-opened-and-closed-year/ and CPS Board Report 06-0222-EX9.

Enrollment Interpolation for Chicago International Charter School branches in 1997-1998 and 1998-1999

For school years 1999-2000 to 2012-2013, I use the CPS Race and Ethnicity Survey Files to assign enrollment to schools. For 1997-1998 and 1998-1999, I assign enrollment using figures from the 2004 ISBE Charter Annual Report if available. Chicago International Charter school has three branches under its charter during these school years. ISBE only reports enrollment aggregated at the charter level. For these three schools, I linearly interpolate enrollment. I summarize these cases in Table 4.2.3.

4.3 Compiling the Tuition Data

4.3.1 Data Collection

I construct a cross-sectional dataset of tuition data by school-grade. As a starting point, I begin with the list of all private schools open in the 2015-2016, according to the ISBE School Data, the same source that I use for both Chapter 2 and Chapter 3. I call this set of schools the 2016 Private Schools.

I collected tuition figures for each of the grades in each of 2016 Private schools. The

Table 4.9: Enrollment Interpolation

Year	Unit	School Name	Enrollment	Enrollment Source
1999	1105	NORTH LAWNDALE	86	2004 ISBE Charter Annual Report
1998	1121	YOUTH CONNECTIONS	1013	2004 ISBE Charter Annual Report
1999	1121	YOUTH CONNECTIONS	1475	2004 ISBE Charter Annual Report
1998	1720	ACT	132	2004 ISBE Charter Annual Report
1999	1720	ACT	155	2004 ISBE Charter Annual Report
1998	1780	ACORN (NUESTRA)	100	2004 ISBE Charter Annual Report
1999	1780	ACORN (NUESTRA)	117	2004 ISBE Charter Annual Report
1998	1960	PERSPECTIVES	117	2004 ISBE Charter Annual Report
1999	1960	PERSPECTIVES	130	2004 ISBE Charter Annual Report
1998	2420	CICS LONGWOOD	789	Imputed
1999	2420	CICS LONGWOOD	960	Imputed
1999	3060	NORTH KENWOOD	113	2004 ISBE Charter Annual Report
1998	4220	CICS PRAIRIE	253	Imputed
1999	4220	CICS PRAIRIE	282	Imputed
1999	4520	SHABAZZ	266	2004 ISBE Charter Annual Report
1998	4910	CICS BUCKTOWN	598	Imputed
1999	4910	CICS BUCKTOWN	598	Imputed
1998	5320	TRIUMPHANT	160	2004 ISBE Charter Annual Report
1999	5320	TRIUMPHANT	170	2004 ISBE Charter Annual Report
1999	5810	OCTAVIO PAZ	527	2004 ISBE Charter Annual Report

process consisted of two stages. The first stage was in May 2017, and the second stage was in September 2017. During the first stage, I visited the website of each of the 2016 Private schools and recorded the annual per-student tuition rate and any sibling discounts that the school offered. I record the 2017-2018 tuition rates, and if the school had not posted their 2017-2018 tuition, then I recorded the 2016-2017 tuition rate. During the second stage, I revisited each of the websites of the 2016 Private Schools. If available, I updated schools' tuition values to the 2017-2018 figures. During both stages, if the tuition rates were not available on the website, then I contacted the school by e-mail and phone and conducted Internet research to obtain their most recent tuition rates.

4.3.2 Merging the Tuition Data with Demand Estimation Results

Section 3.5 contains regressions of the estimates of the school quality parameter $\hat{\delta}$ on tuition rates. This assigns a dollar value to the utility associated with school quality. In order to run this regression I merge the tuition data with the demand parameter estimates. There are five schools in the tuition data without a corresponding $\hat{\delta}$: Intercultural Montessori, Altus Academy, Gateway Montessori School, and Urban Prairie Waldorf School. All of these schools opened after the last year in my School Data sample (2012-2013), therefore, this mismatch is expected, and does not affect the analyses.

CHAPTER 5

CONCLUSION

Charter schools have successfully educated disadvantaged students in numerous school districts. Charter schools exist in 43 states and the District of Columbia.[1] Moreover, all of the twenty-five most populous urban areas in the United States have a charter school program.[2] An extensive literature shows that charter schools can raise the test scores of their students. Furthermore, we know that charter schools that serve low-SES students often are successful while those that serve more advantaged students often are not.[3]

In this dissertation, I investigate numerous aspects of the charter sector. In Chapter 2 I study two issues related to the supply of charter schools.

First, I show that in Chicago charter schools entered disadvantaged neighborhoods that had poor schooling options, many public students, a relatively weak Catholic sector, and available public transportation. Visual evidence clearly shows that charter schools preferred to enter neighborhoods that had these characteristics, and descriptive regressions quantify these relationships. That is, in Chicago, charter schools entered exactly the neighborhoods where the literature has shown they can be successful. There are at least two explanations for these entry patterns. First, a study of CPS's policies shows that the CPS officials who chose which charters to approve preferred schools that planned to serve "at-risk" students. Second, a simple model in which charter schools maximize their potential demand predicts that charter operators would choose disadvantaged neighborhoods where existing schooling options are weak and public transportation is prevalent.

Second, I test whether charter entry affected Catholic school enrollment at the neigh-

1. National Alliance for Public Charter Schools

2. Source: U.S. Census Bureau's July 1 2016 population estimates.

3. Serving disadvantaged students, however, is not a sufficient condition for a charter school to be successful. Among schools that serve disadvantaged student, schools that employ "No Excuses" educational practices typically have success while schools that do not employ these practices often do not.

borhood level. I find that if charter school entry crowded out Catholic school enrollment then the effect was likely small. Some districts open charter sectors in order to supply disadvantaged areas with additional schooling options. If the charter sector displaces existing catholic schools then charter school entry's potential benefits would be muted

Chapter 2 looks at one large urban school district, and future studies will help determine whether these entry patterns generalize to other school districts. Although the predictions in the conceptual framework hold generally, the design of school choice programs could vary across cities, which would change the observed entry patterns. The results of this study can inform future policy discussions about charter schools. The current discussion often focuses on "charter caps," or constraints on the number of charter schools allowed in a district. However, future discussions may focus on identifying the neighborhoods and and types of students that charter schools should serve.

Chapter 3 builds on the analyses in Chapter 2. I estimate a utility model for schools and calculate the total consumer surplus that can be attributed to charter school entry during the period of 1998–2013. I find that consumer surplus disproportionately accrued to neighborhoods that had low income and test scores. Furthermore, I show that operating the charter sector has decreased CPS's labor, materials, and capital costs. Together, my findings suggest that school districts can provide welfare gains to families in their district and decrease their costs by expanding schooling options and by targeting the neighborhoods where new schools will be most successful.

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APPENDIX A

APPENDIX TO “NEIGHBORHOOD DETERMINANTS OF CHARTER SCHOOL ENTRY”

A.1 1990 Math Score

In Section 2.6, I measure neighborhood school quality with ”Average Math Test Score.” In this section, I describe how I create Average Math Test Score.

On November 1, 1990, the Chicago Tribune published a report summarizing test scores for the 1989-1990 school year. The report included IGAP Math, Reading, and Writing scores grades 3, 6, and 8. I create Math Score with the following process

1. Create z-scores of 1989-1990 math scores
2. Assign each school to a Community Area using address information from NCES Common Core of data.
3. Create Community Area Weighted Averages of z-scores for each measure, weighting by grade-level enrollment.

A.2 Median Income

Neighborhood income as an important control variable in a charter school's entry decision. Specifically, my proxy for I_n is median income in 1990, the most recent U.S. Decennial Census prior to charter school entry. Neighborhood income could proxy for many characteristics. First, neighborhood income is correlated the price of land, which would determine where charters schools enter. Unsurprisingly, 1990 neighborhood average income and 1990 neighborhood average rent paid are positively correlated ($\rho = 0.82$). Second, neighborhood income will be correlated with parental involvement in the local public schools volunteer organizations and PTA. Thus, neighborhood income represents a portion of school inputs not measured directly by, but correlated with, test scores. Indeed, AMTS and median income are also highly correlated. ($\rho = 0.72$). Finally, neighborhood income represents residents' ability to pay for Catholic schools and other private schools. Using school data from 1992, Catholic enrollment share is positively correlated with 1990 median income ($\rho = 0.43$). In conclusion, neighborhood income represents at least three factors that will decrease the demand for an entering charter school. Further, neighborhood income is correlated with Catholic school presence, test scores, and land prices.

Table A.3 contains my main results using Median Income in 1990 instead of Average Math Test Score. Median Income is also negatively related to charter school entry. Median Income is not significant in the multivariate regression whereas Average Math Test Score is. This is likely because the Transportation Index and Median Income are more strongly correlated than Average Math Test Score and Transportation Index. Average Math Test Score provides more explanatory power of charter school entry conditional on the Transportation Index.

A.3 Cohort Value Added

To check the robustness of the Average Math Test Score measure, I create additional test score data from archived Chicago Tribune reports from 1991, 1993, 1994, 1995, and 1996.

From the additional test score data, I create a cohort math value-added measure for each school using three 6th grade cohorts from 1993, 1995, and 1996. I run the following regression.

$$MathTest_{s,6,t} = \alpha MathTest_{s,3,t-3} + \gamma_t + \theta_j + \epsilon_{s,g,t}$$

I divide the school-grade fixed effect θ_j by 3 to create a one-year value added measure.

This measure is highly correlated with Average Math Test Score ($\rho = .90$), ensuring that Average Math Test Score is a credible measure of neighborhood school quality. Using the Cohort Value-Added measure instead of Average Math Test Score yields similar results to those in Table 2.3. See Table A.2.

I also checked Average Math Test Score and Value-Added against a 2-year simple growth rate of standardized math score using the 1996 6th grade cohort. This is positively correlated with both measures, but weakly ($\rho = .14$ and $\rho = .24$ respectively).

A.4 Transportation Index

I create the Transportation Index with the following process:

1. Identify the Census blocks in each Chicago Community Area (CCA)

2. Count how many train stops are within 2 miles of the centroid of each census block.

3. Calculate average block-level train-stop count in each CCA

4. Create the CCA-level Transportation Index by standardizing the averages in Step 3.

The higher the Transportation Index, the more accessible it is to public transportation.

A.5 Pre-Sample-Period Public School Location and Quality

One might be concerned that distance between public and private schools is mediated by public school quality. If in 1997, before charter entry, private schools grouped near public schools based on public school quality, then the effects of quality and presence of schools will be difficult to separate.

To investigate this, I assign each public school in 1996 into a quality quintile and study whether distance to a private school varies across quality quintiles. See Figure A.2. I find no difference across quality quintiles. Low quality schools are equally as likely as high quality schools to have a private school nearby. While, this does not rule out schools grouping together based on a school or neighborhood characteristics, the analyses support including school quality measures in the regressions in Section 2.6.2.

A.6 Additional Visual Evidence

In Figure A.1, I showed the relationship between Average Math Test Score and charter entry. As a robustness check, I conduct the same analysis with reading scores instead of math scores. See Figure A.3 contains a neighborhood map of Chicago where the neighborhood are colored by the average reading scores of the school-grades in each neighborhood. The blue squares indicate the locations of charter campuses in 2003. Charter schools overwhelmingly entered neighborhoods where the schools had low test scores. Of the nineteen charter campuses open in 2003, fourteen campuses were in neighborhoods in the bottom two quintiles in average reading score. This map provides further evidence of the charter schools opening in neighborhoods where the existing public schools were poor.

A.7 Additional Catholic Sector Analyses

In Section 2.6.2, I concluded that if charter school entry negatively affected Catholic sector enrollment, the effect was likely small. In this section, I provide additional analyses to investigate the issue.

A.7.1 Exclude Zeros and include all neighborhoods

Table A.4 contains regressions like those in estimates of Equation 2.4 and Equation 2.5 for the sample that includes all neighborhoods and excludes observations in which Catholic enrollment is zero. The qualitative conclusions from these results do not differ from the main results.

A.7.2 Log Enrollment

Figure A.5 contains estimates of 2.3 where the dependent variable is log enrollment. The qualitative conclusions from these results do not differ from the main results.

Table A.1: This table shows coefficient estimates from four OLS regressions. The unit of observation is a Chicago Community Area (CCA). In each regression, the dependent variable is an indicator variable equal to 1 if a charter school ever located in that CCA during 1998-2003. I create CCA-level demographic variables by aggregating Census tract-level and school-level data.

	(1)	(2)	(3)	(4)
Public Enrollment 1997 (1000s)	0.045***			0.029**
	(0.013)			(0.013)
Median Income 1990 (1000s)		-0.008***		-0.004
		(0.003)		(0.003)
Transportation Index			0.157***	0.105**
			(0.049)	(0.049)
Constant	0.040	0.679***	0.286***	0.344*
	(0.084)	(0.142)	(0.049)	(0.180)
Observations	77	77	77	77
R^2	0.15	0.10	0.12	0.23

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: This table shows coefficient estimates from four OLS regressions. The unit of observation is a Chicago Community Area (CCA). In each regression, the dependent variable is an indicator variable equal to 1 if a charter school ever located in that CCA during 1998-2003. I create CCA-level demographic variables by aggregating Census tract-level and school-level data.

	(1)	(2)	(3)	(4)
Public Enrollment 1997 (1000s)	0.045***			0.032**
	(0.013)			(0.013)
Math Value Added		-0.020***		-0.013**
		(0.005)		(0.005)
Transportation Index			0.157***	0.063
			(0.049)	(0.052)
Constant	0.040	0.311***	0.286***	0.120
	(0.084)	(0.048)	(0.049)	(0.091)
Observations	77	75	77	75
R^2	0.15	0.19	0.12	0.29

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: This table shows coefficient estimates from four OLS regressions. The unit of observation is a Chicago Community Area (CCA). In each regression, the dependent variable is an indicator variable equal to 1 if a charter school ever located in that CCA during 1998-2003. I create CCA-level demographic variables by aggregating Census tract-level and school-level data.

	(1)	(2)	(3)	(4)
School-Age Residents 1990 (1000s)	0.023**			0.011
	(0.010)			(0.010)
Average Math Test Score		-0.255***		-0.194**
		(0.069)		(0.074)
Transportation Index			0.157***	0.105**
			(0.049)	(0.052)
Constant	0.133	0.344***	0.286***	0.257***
	(0.083)	(0.051)	(0.049)	(0.090)
Observations	77	76	77	76
R^2	0.07	0.16	0.12	0.22

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: OLS. In all models, sample excludes neighborhoods with zero Catholic enrollment. Sample does not exclude never treated neighborhoods. Column 1 displays estimates from a regression of Catholic enrollment on an indicator equal to one if a charter school exists in a neighborhood-year. Columns 2 displays estimates from a regression of Catholic enrollment on dummies for years since first charter school entry. The excluded category is year 0 and before. Year 0 is the school year prior to first charter school entry.

	(1) All	(2) All
Charter Indicator	-105.422***	
	(22.845)	
Charter Indicator, Year 1		-71.002*
		(36.534)
Charter Indicator, Year 2		-93.770**
		(36.751)
Charter Indicator, Year 3		-103.436***
		(36.969)
Charter Indicator, Year 4		-118.246***
		(37.165)
Constant	984.045***	840.576***
	(64.885)	(66.025)
Observations	832	832
R^2	0.97	0.97
Year Fixed Effects.	Yes	Yes
Neighborhood Fixed Effects	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

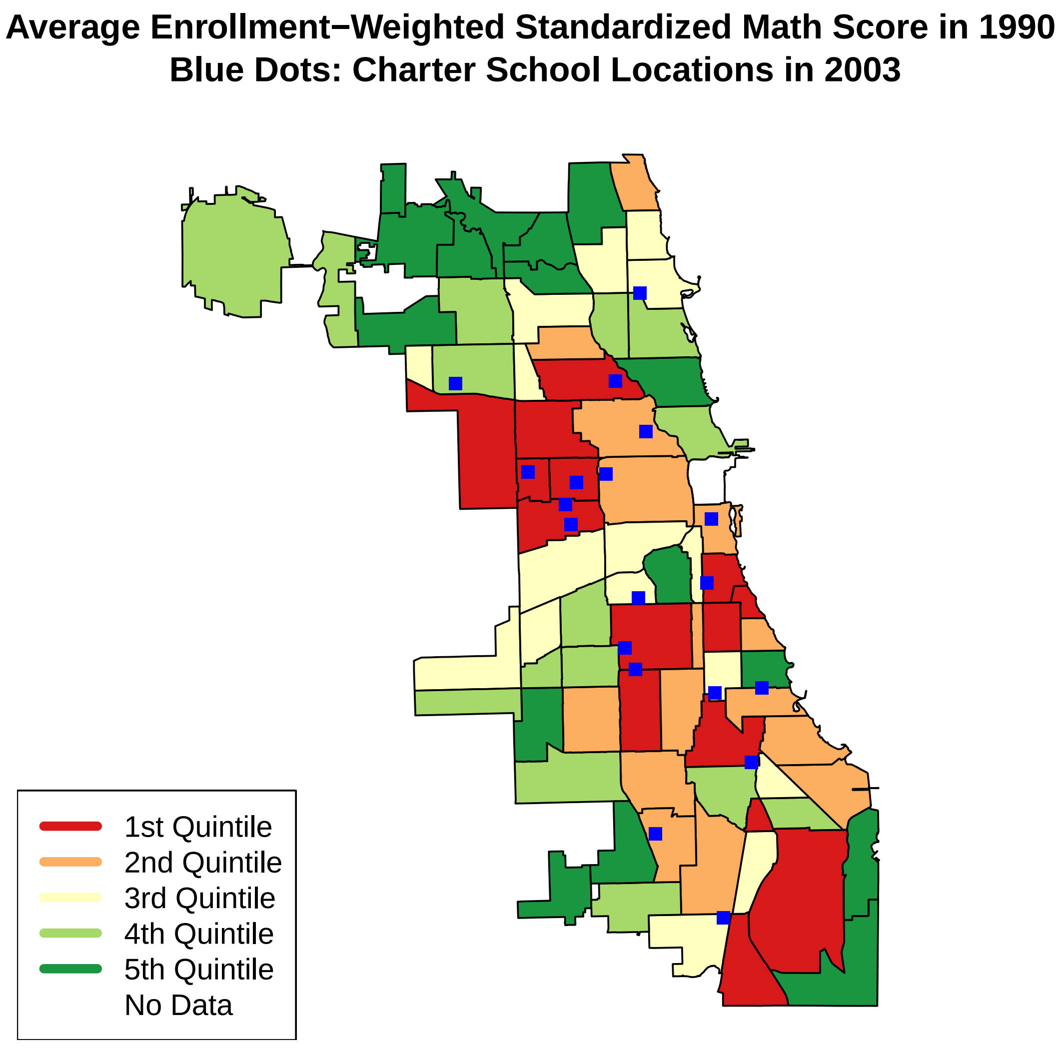

Figure A.1: Map of charter school campuses in 2003 (Blue Squares). Colors indicate the quintile of the Chicago Community Area's average 1990 math test score. "1st Quintile," *e.g.*, indicates the lowest test score neighborhoods.

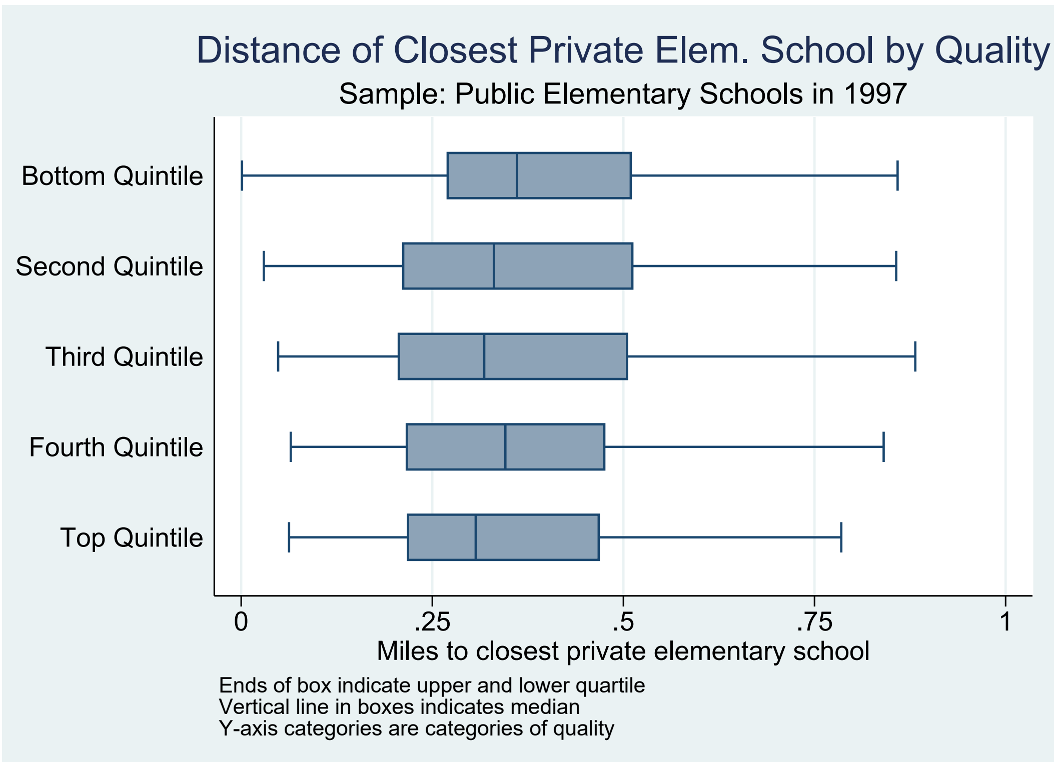

Figure A.2: Proximity of closest private school by quintile of public school quality. The unit of observation is a public elementary school open in 1997. I divide the schools into quintiles by quality. The bars display the distribution how distance of nearest private schools.

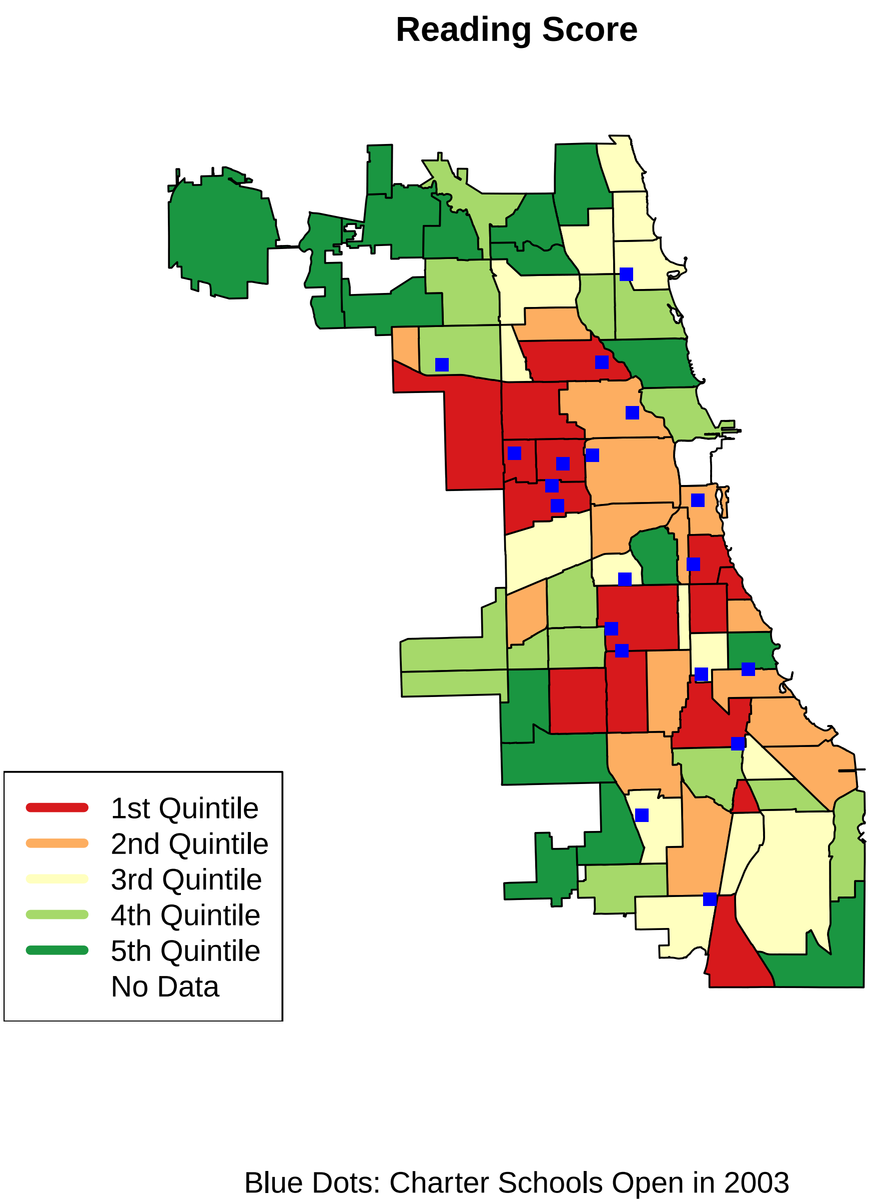

Figure A.3: Map of charter school campuses in 2003 (Blue Squares). Colors indicate Chicago Community Area's average 1990 reading test score. "1st Quintile," *e.g.*, indicates the lowest test score neighborhoods.

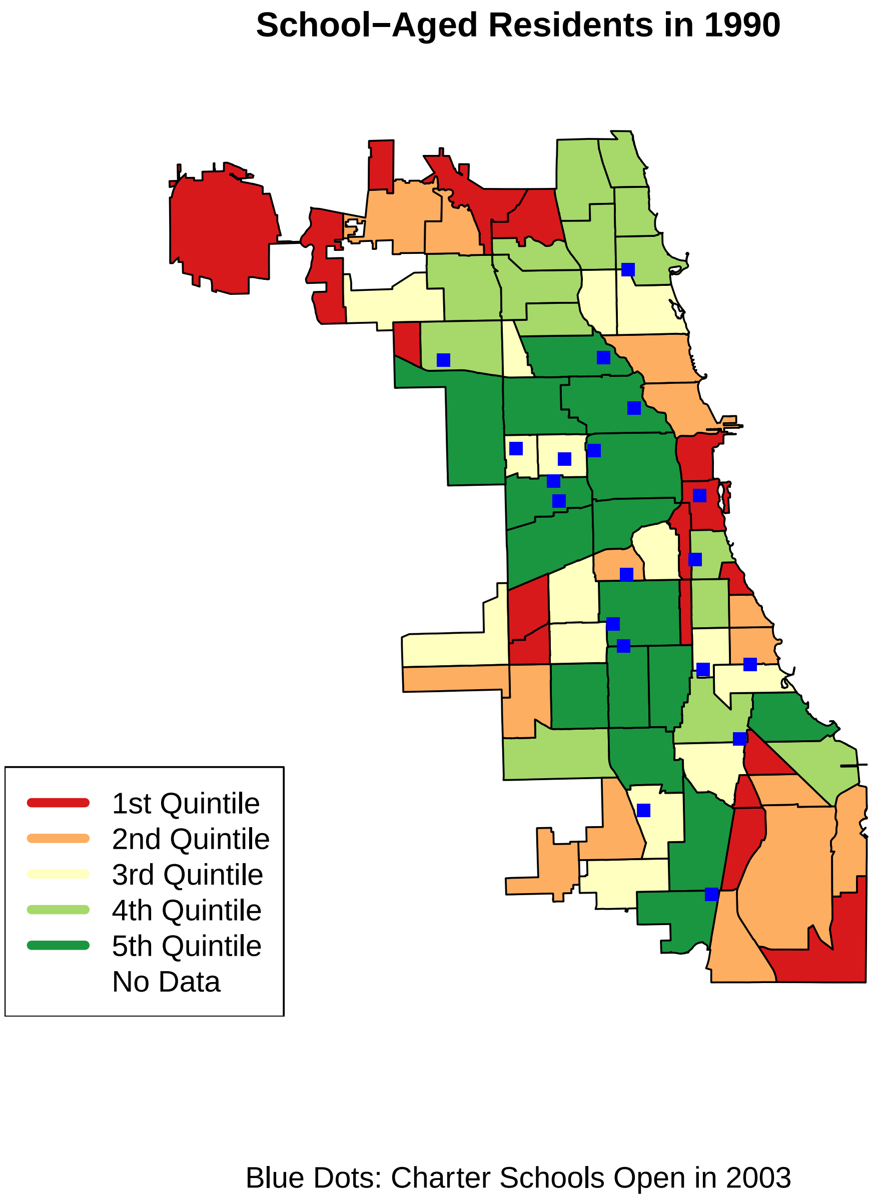

Figure A.4: Map of charter school campuses in 2003 (Blue Squares). Colors indicate Chicago Community Area's quintile of school-age residents according to the 1990 Census. "1st Quintile," *e.g.*, indicates the lowest income neighborhoods.

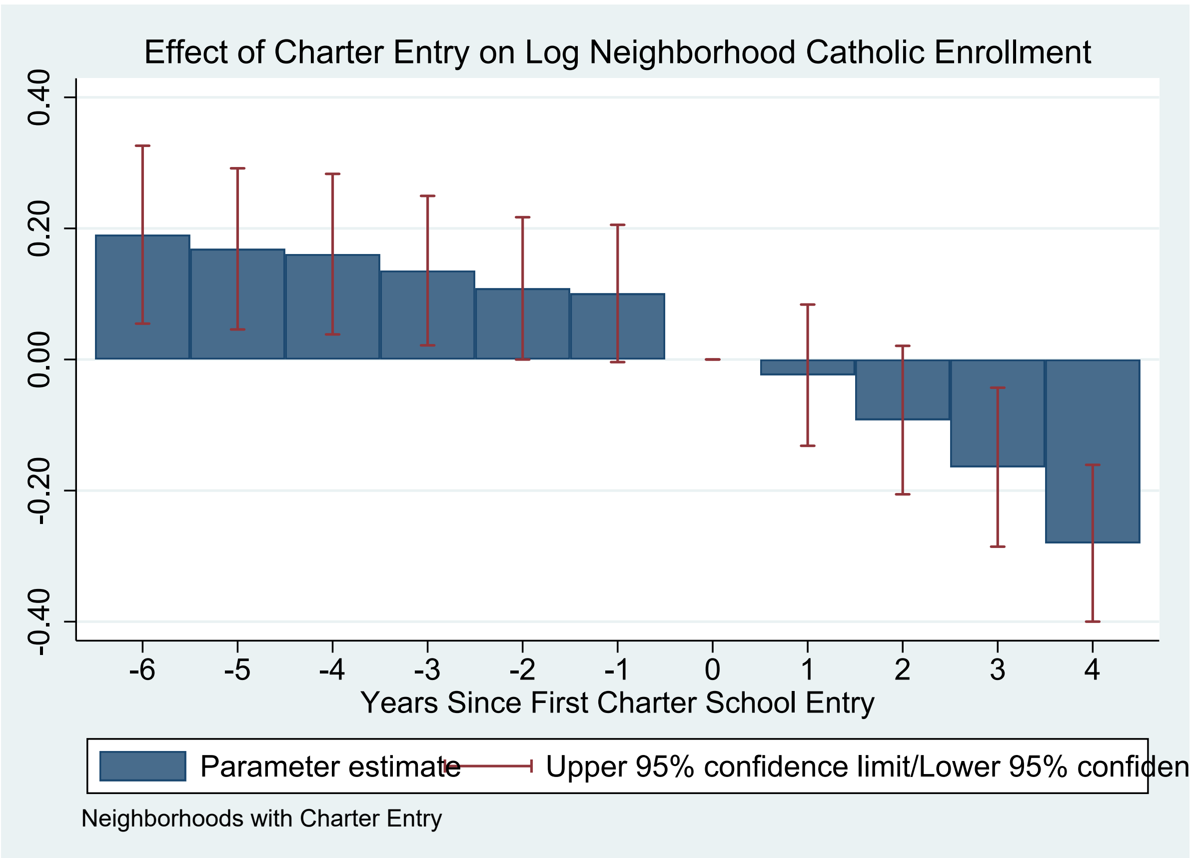

Figure A.5: The effects of first charter school entry on neighborhood Catholic enrollment. The figure shows the effect of first charter school entry on log Catholic enrollment by year. Bars represent coefficients from the event study specification in Equation 2.3. Whiskers represent 95% confidence interval. I restrict the analysis to neighborhoods that ever experienced charter school entry in the years in a chosen analysis window. The analysis window is $l \in [-6, 4]$ where l is the years since first charter school entry. There are jumps in charter campus entry in 1998, 2004, and 2009. The analysis window includes 6 years prior and 4 years following each of these years.

APPENDIX B

APPENDIX TO “THE AGGREGATE AND DISTRIBUTIONAL WELFARE EFFECTS OF CHARTER SCHOOL ENTRY”

B.1 Model Estimation Procedure

I describe the model estimation in three steps. First, in Section B.1.1 I describe the data I use to create the inputs for the estimation. Second, in Section B.1.2 I describe the moments. Third, in Section B.1.3 I describe how the procedure uses the moments to estimate the model parameters.

Note that I estimate the model separately for each grade. I assume students choose among school-grades within their Side of residence. Therefore, I calculate enrollment shares within a Side for each school-grade.

B.1.1 Data and Inputs

In this section, I provide an overview of the inputs to the model estimation procedure. I outline the datasets I use, and the measures I create with the datasets.

To estimate the model I use the following data sources:

- **Simulated Student Location Data and CPS Zone Maps**:
  - I create the Simulated Student Location Data using the 2010 U.S. Decennial Census. The 2010 Decennial Census contains U.S. Census Block of residence and age for each Chicago resident. I use the age variable to assign each student to a grade. I assume each resident lives at the centroid of her block, which yields a dataset in which a row is a student and a column is the (simulated) geographic coordinates of her residence. From the student geographic coordinates, I calculate

d_{ijg}, the distance between a student's simulated residence and each school in her Side.

- The 2010 CPS Zone Map contains the boundaries of attendance areas for all schools that served grades 1-8 in Chicago in 2010. Using the Simulated Student Location Data, I assign each student to an attendance zone on the basis of her grade and geographic location. Then, I assign each student in the Simulated Student Location Data to a zoned school. Lastly, I calculate the variable $d^{z\prime}_{ijg}$, which is the distance between student i's zoned school and school-grade jg.

- I use the Simulated Student Location Data and the 2010 CPS Zone Map to calculate two objects that I use in the estimation:

  1. s_{jgt}: model-predicted enrollment shares for each school-grade in a Side-year. Since I assume Type 1 Extreme Value errors in the utility function, I follow Berry (1994) to calculate the model-predicted enrollment shares:

$$s_{jgt}\left(\delta_{jg}, \gamma_g, \rho_g\right) = \frac{1}{I}\sum_{i=1}^{I} s_{ijg} = \frac{1}{I}\frac{\exp(\delta_{jg} - \gamma_g d_{ijg} + \rho_g z_{ijg})}{\sum_{jg=1}^{J_g}\exp(\delta_{jg} - \gamma_g d_{ijg} + \rho_g z_{ijg})} \quad \text{(B.1)}$$

     where s_{ijg} is the probability that student i will attend school-grade jg and J_g is the set of schools that offer grade g.[1] I use s_{jgt} to construct the Share Moments. See Section B.1.2.

  2. $\tilde{d}^{z}_{ijg}$: the model-predicted distance the between zoned-school and the school of attendance, conditional on attending public school for student i in grade g. This measure is defined as the following:

1. If a school-grade is not open in year t, then then s_{jgt}=0 for that year. Similarly, if a student lives in a different Side than a school, her probability of attending that school is zero.

$$\tilde{d}^z_{ijg} = \frac{\sum_{l=1}^{J_{lg}} s_{ilg}\left(\delta(\gamma_g), \gamma_g\right) d^{z\prime}_{ilg}}{\sum_{l=1}^{J_{lg}} s_{ilg}}.$$

The right-hand side is the average expected distance traveled to school conditional on attending a public school-grade lg in the set of public school-grades J_{lg}. The numerator $\sum_{l=1}^{J_{lg}} s_{ilg}\left(\delta(\gamma_g), \gamma_g\right) d^{z\prime}_{ilg}$ is the expected distance traveled to public school-grades for student i in grade g. The denominator is the probability of attending any public school for student i in grade g. I use this measure to construct the Distance Moment. See Section B.1.2.

- **School Data**: The school data contains enrollment and detailed location for each school-grade in Chicago during the period 1992-2013. I use these data to calculate S_{jgt}, which is the empirical enrollment share for grade g in school j in year t. I use S_{jgt} to construct the share moments. See Section B.1.2.

- **CPS Zone Data**: These data contain each CPS student's zoned school and the student's actual school of attendance for school years 2015-2016 and 2016-2017. I use these data to calculate $\bar{d}^z_g$, the empirical average distance between a student's zoned school and school of attendance for students in grade g. I use $\bar{d}^z_g$ to construct the Distance Moment. See Section B.1.2.

B.1.2 Moments

To estimate the parameters I use a method of moments procedure. In this section, I describe how I construct the moments. Note that I estimate the model separately for each grade. For each grade, I use a set of share moments (Equation B.2) and one distance moment (Equation B.3).

The Share Moments

For each school-grade, I calculate $s_{jg}\left(\delta_{jg}, \gamma_g, \rho_g\right)$, the average annual *model-predicted* share of grade g in school j, and S_{jg}, the average annual *empirical* market share of grade g in school j.

I estimate the model separately for each grade. Therefore, for a given grade g, the estimation uses J_g share equations, one for each school that offers grade g. Specifically, Equation B.2 defines the Share Moments:

$$s_{jg}\left(\delta_{jg}, \gamma_g, \rho_g\right) - S_{jg} = 0, \quad jg = 1, ..., J_g \tag{B.2}$$

where

$$\begin{aligned} s_{jg}\left(\delta_{jg}, \gamma_g, \rho_g\right) &\equiv \frac{1}{T}\sum_{t=1992}^{2013} s_{jgt}\left(\delta_{jg}, \gamma_g, \rho_g\right) \\ &\textit{and} \\ S_{jg} &\equiv \frac{1}{T}\sum_{t=1992}^{2013} S_{jgt} \end{aligned}$$

I define $s_{jgt}\left(\delta_{jg}, \gamma_g, \rho_g\right)$ in Equation B.1.

The Distance Moment

The distance moment helps identify γ_g, the travel cost parameter. Specifically, I compare *model-predicted* distance between public student i's zoned school and her school of attendance $\bar{\tilde{d}}_g^z$ to the *empirical* version of the same measure $\bar{d}_g^z$. Equation B.3 defines the Distance Moment:

$$\bar{\tilde{d}}_g^z - \bar{d}_g^z = 0 \tag{B.3}$$

Using the CPS Zone Data, I calculate the empirical distance between public student i's zoned school and her school of attendance, and I take the average to construct the empirical moment:

$$\bar{d}_g^z \equiv \frac{1}{I} \sum_{i=1}^{I} d_{ig}^z \tag{B.4}$$

To create the model-predicted counterpart I use Simulated Student Location Data:

$$\bar{\tilde{d}}_g^z \equiv \frac{1}{I} \sum_{i=1}^{I} \left(\frac{\sum_{l=1}^{J_l} s_{ilg} \left(\delta(\gamma_g, \rho_g), \gamma_g, \rho_g\right) d_{ilg}^{z\prime}}{\sum_{l=1}^{J_l} s_{ilg}} \right). \tag{B.5}$$

The right-hand side is the average expected distance traveled to school conditional on attending a public school-grade lg in the set of public school-grades J_{lg}. The numerator $\sum_{l=1}^{J_{lg}} s_{ilg} \left(\delta(\gamma_g), \gamma_g, \rho_g\right) d_{ilg}^{z\prime}$ is the expected distance traveled to public school-grades for student i in grade g. The denominator is the probability of attending any public school for student i in grade g.

The Zone Moment

For the zone moment, I compare the model-predicted share of students that attend their zoned school $\tilde{z}_g$ to its empirical counterpart $\bar{z}_g$, which I calculate using CPS Zone Data.

$$\tilde{z}_g \left(\delta_{jg}, \gamma_g, \rho_g\right) - \bar{z}_g = 0 \tag{B.6}$$

B.1.3 The Estimation Procedure

For each grade, the model estimation procedure follows these steps:

1. Solve for the vector of mean utilities $\delta_{jg}(\gamma_g, \rho_g)$ that equates the share moments

$$s_{jg}\left(\delta_{jg}, \gamma_g, \rho_g\right) - S_{jg} = 0, \quad jg = 1, ..., J_g \tag{B.7}$$

$\delta_{jg}(\gamma_g, \rho_g)$ is defined implicitly as the value that sets the observed shares equal to the model-predicted shares. I solve for $\delta_{jg}(\gamma_g, \rho_g)$ using the contraction mapping outlined by Berry, Levinsohn, and Pakes (1996).

2. Define the objective function $G(\gamma_g, \rho_g)$. The objective function uses the Distance Moment and the Zone Moment:

$$G(\gamma_g, \rho_g) = \begin{bmatrix} \tilde{\bar{d}}_g^z\left(\delta_{jg}, \gamma_g, \rho_g\right) - \bar{d}_g^z \\ \tilde{z}_g\left(\delta_{jg}, \gamma_g, \rho_g\right) - \bar{z}_g \end{bmatrix}$$

3. Find the pair $[\gamma_g,\ \rho_g]$ that minimizes the objective function $G(\gamma_g, \rho_g)$.

B.2 Geographic Market Definition

In Section 3.3.1, I present summary statistics of the distance traveled to school, the proportion of students who attend school outside of their geographic market, and the proportion of students who attend their zoned school. In this appendix, I examine the heterogeneity of these measures across geographic markets. In general, the within-market trends reflect the aggregate trends presented in Section 3.3.1. I find some exceptions in the geographic markets that have relatively low populations of students.

Table B.1 shows that depending on the grade, between 13% and 18% of students attended a school outside of their Side of residence. Table B.2 displays the percentage of students who attend a school outside of their Side of residence by Side of residence and grade. The overall pattern apparent in Table B.1 exists in almost all grade-Sides. Three grades in the Central Side are an exception. In the 6th through 8th grades in the Central Side, more students attend a school outside of the Central Side than in the Central Side. These Side-grade observations represent a small section of students (0.5%) in Chicago. Overall, 90% of students live in a Side where over 75% of the students attend school in their own Side.

Percent of Students Attending Zoned School by Grade

	1	2	3	4	5	6	7	8
%	60%	61%	62%	61%	60%	59%	56%	56%
N	57,304	58,582	61,944	58,106	55,792	56,436	54,781	53,246

Table B.1: The proportion of students who attend their zoned school by grade. Source: 2015-2016 and 2016-2017 CPS Zone Data.

Table 3.4 shows that the distance between the zoned school and the school of attendance is slightly larger for students in older grades than for students in younger grades. Examining this measure by Side shows why the difference exists and why it is small. The upper panel (Panel A) of Table B.4 displays the average distance between the zoned school and the school of attendance by grade and Side of residence for students who attend school in their own Side. In some Sides, older students travel farther to school (North, Far North, Northwest, South, and Far Southwest) while in others there is no difference (Central, West, Southwest, and Far Southeast). Therefore, some Sides have small differences while others have none, which explains why the aggregate trend is a small difference.[2]

Table B.1 shows that younger students generally are more likely to attend their zoned school than older students. To shed light on the aggregate figures, I investigate in this section the proportion of students who attend their zoned school within each Side. Table B.5 displays the proportion of students who attend their zoned school by grade and Side of residence. On the Central, North, Far North, Northwest, and South Sides, the proportion of seventh and eighth graders who attend their zoned school is less than that of first through sixth graders. In the remaining Sides, the proportion is approximately constant across grades. Therefore,

2. The lower panel (Panel B) of Table B.4 includes only students who attend a school outside of their Side.

within each Side the pattern of zoned school attendance is similar across Sides.

To investigate what drives the overall distance measures, I show in Table B.3 the distance between the zoned school and the school of attendance for students who do not attend their zoned school. These figures show that among students who do not attend their zoned school, older students travel slightly farther to school than younger students. Table B.6 displays the same analyses broken down by Side. The aggregate trend appears in all Sides except the Central and North Sides.

In conclusion, in the analyses presented in Section 3.3.1, there is some heterogeneity across Sides. However, in the majority of cases, the within-market trends reflect the aggregate trends.

B.3 Population Change

For the demand estimation, I assume that the geographic distribution of students is the same in each year of my sample period. If the geographic distribution of students changed over time, this could bias the estimates of the model parameters. In this section, I discuss the potential for this bias and present population change by Side between 2000 and 2010.

The extent of measurement error depends on how population change manifests itself in observed market shares. For example, if the population density around a school increases and a school's enrollment share increases, my model will assume that this school became more attractive. However, population density near the school could increase for reasons that have nothing to do with the school. Similarly, if an area of the city becomes depopulated and a school loses enrollment, my model will attribute this change not to a demographic change but to the school being less attractive.

My concern here is not population change *per se* but the possibility that some areas of the city change more than others. To investigate how much the population distribution changes over time in Chicago, I document population change in geographic markets. Table B.7

displays population change by Side in Chicago from 2000 to 2010. During this period, Chicago's population decreased by 7%, losing over 200,000 people. In the North, Far North, Southwest, and Far Southwest Sides, the population change was similar to the aggregate change. The Central Side, which comprises the Loop, Chicago's central business district, and two bordering CCAs, was the only Side that added residents during this time period. Population decline was higher than the citywide trend in three Sides: South, West, and Far Southeast.

If I were to further investigate whether some neighborhoods experienced more population change than others, I would look at higher resolution data on population change in Chicago. However, even with the most granular of data, it would be impossible to determine whether population change was due to demographic shifts or to a change in school attractiveness.

One could improve on the measurement of student locations by using the 1990 and 2000 decennial censuses, but there still would be unmeasured changes in population density between 1990 and 2000 and between 2000 and 2010. Based on the current analysis, I conclude that there could be measurement error of the school-grade fixed effect because of changes in population that my model assumes are prompted by changes in attractiveness.

B.4 Outside Options

Table B.8 displays the outside option schools for each grade and Side. For each grade and Side, I choose the outside option school that fits the following criteria:

- Has the largest enrollment among schools within its grade and Side in year 2013
- Has zoned students (i.e., not a charter school or a magnet school)
- Open during all years of the sample period

B.5 Standard Errors

In this section, I describe how I calculate standard errors for the parameters estimates. I follow Cameron and Trivedi (2005) and I adapt their notation. The sample GMM objective function is

$$\frac{1}{N}\sum_{i=1}^{N} G_i(\widehat{\theta}) = 0 \tag{B.8}$$

The matrix of standard errors is

$$\frac{1}{N}\left(\widehat{B}\widehat{S}\widehat{B}\right)^{\frac{-1}{2}} \tag{B.9}$$

where

$$\widehat{B} = \frac{1}{N}\sum_i^N \frac{\partial G_i}{\partial \theta}\bigg|_{\widehat{\theta}} \tag{B.10}$$

$$\widehat{S} = \frac{1}{N}\sum_i^N G_i(\widehat{\theta})G_i(\widehat{\theta})' \tag{B.11}$$

$$\tag{B.12}$$

In my case $\theta = [\delta, \gamma, \rho]$, the objective function minimizes the distance between the model-predicted and empirical version of the distance between student i's zoned school and their school of attendance.

$$G(\delta_{jg}\gamma_g, \rho_g) = \begin{bmatrix} G_1(\delta_{jg}\gamma_g, \rho_g) \\ G_2(\delta_{jg}\gamma_g, \rho_g) \end{bmatrix} = \begin{bmatrix} \bar{\tilde{d}}_g^z\left(\delta_{jg}, \gamma_g, \rho_g\right) - \bar{d}_g^z \\ \tilde{z}_g\left(\delta_{jg}, \gamma_g, \rho_g\right) - \bar{z}_g \end{bmatrix}$$

where the components of $G(\delta_{jg}\gamma_g, \rho_g)$ are as defined in Section B.1. In my case, the $\hat{b}$ and $\hat{S}$ matrices are the following:

$$\widehat{B} = \begin{bmatrix} \frac{\partial G_1(\delta_{jg}\gamma_g,\rho_g)}{\partial \gamma_g} & \frac{\partial G_1(\delta_{jg}\gamma_g,\rho_g)}{\partial \rho_g} \\ \frac{\partial G_2(\delta_{jg}\gamma_g,\rho_g)}{\partial \gamma_g} & \frac{\partial G_2(\delta_{jg}\gamma_g,\rho_g)}{\partial \rho_g} \end{bmatrix}$$

$$\widehat{S} = \frac{1}{N}\sum_{i}^{N} G_i(\delta_{jg}\widehat{\gamma_g,\rho_g}))G_i(\delta_{jg}\widehat{\gamma_g,\rho_g}))'$$

		Percent of Students Attending School in Different Side (%) and Total Number of Students per side (N) by Grade							
		1	2	3	4	5	6	7	8
Central	%	32%	33%	36%	40%	42%	63%	65%	66%
	N	1,107	1,035	1,038	970	890	761	744	774
North Side	%	30%	30%	30%	31%	34%	35%	41%	42%
	N	4,871	4,952	5,028	4,760	4,552	4,674	4,863	4,656
Far North Side	%	8%	8%	8%	8%	8%	10%	15%	16%
	N	7,590	7,565	7,672	7,335	7,045	7,193	7,137	7,095
Northwest Side	%	7%	7%	6%	6%	6%	6%	7%	8%
	N	6,278	6,476	6,790	6,632	6,410	6,219	5,705	5,489
West Side	%	11%	12%	12%	12%	13%	14%	15%	15%
	N	12,002	12,357	13,112	12,204	11,610	11,905	11,299	10,943
South Side	%	19%	19%	19%	19%	21%	22%	24%	25%
	N	5,284	5,401	5,871	5,203	4,981	5,159	5,000	4,792
Southwest Side	%	7%	7%	7%	7%	8%	7%	8%	9%
	N	11,141	11,617	12,537	11,710	11,450	11,573	11,296	10,871
Far Southeast Side	%	15%	14%	14%	15%	15%	13%	12%	12%
	N	5,226	5,327	5,739	5,271	4,975	5,041	4,720	4,575
Far Southwest Side	%	20%	21%	19%	20%	20%	20%	23%	22%
	N	3,805	3,852	4,157	4,021	3,879	3,911	4,017	4,051

Table B.2: The proportion of students that attend a school outside of their Side by Grade and Side. Source: 2015-2016 and 2016-2017 CPS Zone Data.

	Average Distance Travelled to School, Students Attending Non-Zoned School Within Side of Residence							
	1	2	3	4	5	6	7	8
Mean	1.33	1.34	1.36	1.38	1.38	1.36	1.37	1.39
N	15,150	14,985	15,500	14,677	14,279	14,572	14,623	14,146

Table B.3: The average distance traveled in miles for students who attend a non-zoned school in their Side of residence. Source: 2015-2016 and 2016-2017 CPS Zone Data.

Panel A: Attending a school in same Side: Distance between zoned school and school of attendance

		1	2	3	4	5	6	7	8
Central	Mean	0.12	0.11	0.12	0.11	0.11	0.19	0.12	0.14
	N	756	694	667	584	520	285	257	264
North Side	Mean	0.30	0.29	0.28	0.30	0.34	0.36	0.39	0.38
	N	3,414	3,464	3,514	3,268	3,027	3,033	2,882	2,692
Far North Side	Mean	0.35	0.36	0.37	0.37	0.36	0.38	0.43	0.43
	N	6,976	6,925	7,059	6,753	6,473	6,501	6,040	5,965
Northwest Side	Mean	0.22	0.20	0.20	0.20	0.22	0.22	0.32	0.34
	N	5,858	6,051	6,375	6,253	6,000	5,817	5,286	5,060
West Side	Mean	0.65	0.64	0.64	0.64	0.65	0.61	0.63	0.64
	N	10,634	10,893	11,531	10,700	10,049	10,179	9,624	9,250
South Side	Mean	0.58	0.57	0.57	0.62	0.63	0.65	0.68	0.72
	N	4,288	4,355	4,768	4,189	3,948	4,031	3,812	3,591
Southwest Side	Mean	0.31	0.29	0.28	0.28	0.30	0.29	0.31	0.33
	N	10,369	10,830	11,641	10,907	10,588	10,709	10,349	9,924
Far Southeast Side	Mean	0.42	0.42	0.38	0.42	0.43	0.44	0.40	0.39
	N	4,452	4,570	4,918	4,498	4,243	4,363	4,145	4,022
Far Southwest Side	Mean	0.29	0.31	0.29	0.31	0.32	0.32	0.34	0.32
	N	3,032	3,059	3,369	3,223	3,101	3,117	3,101	3,140

Panel B: Attending a school in different Side: Distance between zoned school and school of attendance

		1	2	3	4	5	6	7	8
Central	Mean	4.96	5.27	5.20	5.30	5.14	5.29	5.84	6.01
	N	351	341	371	386	370	476	487	510
North Side	Mean	3.73	3.80	3.76	3.78	3.83	3.87	3.53	3.49
	N	1,457	1,488	1,514	1,492	1,525	1,641	1,981	1,964
Far North Side	Mean	5.40	5.64	5.19	5.21	5.27	5.04	3.73	3.53
	N	614	640	613	582	572	692	1,097	1,130
Northwest Side	Mean	2.50	2.53	2.62	2.62	2.83	2.97	3.02	3.44
	N	420	425	415	379	410	402	419	429
West Side	Mean	5.36	5.44	5.33	5.24	5.57	5.17	5.20	5.32
	N	1,368	1,464	1,581	1,504	1,561	1,726	1,675	1,693
South Side	Mean	4.78	4.81	4.56	4.60	4.85	4.51	4.62	4.90
	N	996	1,046	1,103	1,014	1,033	1,128	1,188	1,201
Southwest Side	Mean	4.88	4.83	4.52	4.48	4.67	4.60	4.63	4.72
	N	772	787	896	803	862	864	947	947
Far Southeast Side	Mean	4.10	4.26	4.26	4.19	4.26	4.38	4.44	4.49
	N	774	757	821	773	732	678	575	553
Far Southwest Side	Mean	4.12	4.04	3.93	4.17	4.07	3.71	4.02	3.90
	N	773	793	788	798	778	794	916	911

Table B.4: The average distance between zoned school and school of attendance by grade, Side, and whether student attends school outside of their Side. Source: 2015-2016 and 2016-2017 CPS Zone Data.

		Percent of Students Attending Zoned School (%) and Total Number of Students per side (N) by Grade							
		1	2	3	4	5	6	7	8
Central	%	59%	58%	57%	53%	52%	30%	28%	27%
	N	1,107	1,035	1,038	970	890	761	744	774
North Side	%	54%	55%	55%	53%	49%	48%	42%	41%
	N	4,871	4,952	5,028	4,760	4,552	4,674	4,863	4,656
Far North Side	%	71%	71%	71%	71%	71%	67%	62%	62%
	N	7,590	7,565	7,672	7,335	7,045	7,193	7,137	7,095
Northwest Side	%	75%	76%	77%	78%	76%	76%	67%	67%
	N	6,278	6,476	6,790	6,632	6,410	6,219	5,705	5,489
West Side	%	48%	49%	50%	50%	48%	48%	47%	47%
	N	12,002	12,357	13,112	12,204	11,610	11,905	11,299	10,943
South Side	%	49%	49%	50%	49%	47%	45%	42%	41%
	N	5,284	5,401	5,871	5,203	4,981	5,159	5,000	4,792
Southwest Side	%	67%	69%	69%	69%	68%	69%	67%	66%
	N	11,141	11,617	12,537	11,710	11,450	11,573	11,296	10,871
Far Southeast Side	%	60%	60%	63%	60%	60%	61%	64%	65%
	N	5,226	5,327	5,739	5,271	4,975	5,041	4,720	4,575
Far Southwest Side	%	60%	59%	61%	60%	60%	59%	57%	58%
	N	3,805	3,852	4,157	4,021	3,879	3,911	4,017	4,051

Table B.5: The proportion of students who attend their zoned school by grade and Side. Source: 2015-2016 and 2016-2017 CPS Zone Data.

		Average Distance Travelled to School by Side, Students Attending Non-Zoned School Within Side of Residence							
		1	2	3	4	5	6	7	8
Central	Mean	0.88	0.84	0.99	0.94	0.97	0.99	0.61	0.66
	N	104	93	80	66	57	56	50	57
North Side	Mean	1.36	1.36	1.34	1.32	1.34	1.35	1.34	1.32
	N	763	742	730	751	778	807	837	780
Far North Side	Mean	1.57	1.61	1.66	1.65	1.63	1.51	1.62	1.61
	N	1,552	1,530	1,578	1,531	1,444	1,650	1,604	1,600
Northwest Side	Mean	1.10	1.10	1.10	1.14	1.17	1.13	1.18	1.23
	N	1,160	1,112	1,134	1,109	1,105	1,115	1,450	1,391
West Side	Mean	1.41	1.44	1.47	1.49	1.46	1.42	1.42	1.44
	N	4,902	4,802	4,983	4,591	4,435	4,409	4,287	4,104
South Side	Mean	1.47	1.44	1.50	1.55	1.54	1.52	1.54	1.58
	N	1,693	1,710	1,809	1,664	1,615	1,712	1,691	1,638
Southwest Side	Mean	1.11	1.08	1.08	1.08	1.15	1.14	1.18	1.19
	N	2,895	2,866	3,033	2,837	2,787	2,746	2,757	2,744
Far Southeast Side	Mean	1.40	1.41	1.42	1.42	1.45	1.51	1.47	1.51
	N	1,342	1,360	1,327	1,327	1,270	1,279	1,117	1,026
Far Southwest Side	Mean	1.18	1.23	1.20	1.26	1.25	1.23	1.26	1.26
	N	739	770	826	801	788	798	830	806

Table B.6: The average distance traveled in miles by students who attend a school in their Side of residence that is not their zoned school. Source: 2015-2016 and 2016-2017 CPS Zone Data.

Population Change by Geographic Market in Chicago		
Side	Population Change	% Change
Central	32,449	33%
North	-14,426	-5%
Far North	-34,379	-7%
Northwest	-7,251	-3%
West	-56,496	-11%
South	-41,502	-14%
Southwest	-25,389	-6%
Far Southeast	-40,019	-15%
Far Southwest	-13,405	-7%
Total	-200,418	-7%

Table B.7: Changes in population by Side in Chicago between 2000 and 2010. The percentage changes are the raw change divided by the 2000 population. Sources: 2010 U.S. Decennial Census and Rob Paral.

	Outside Options by Grade and Side							
	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5	Grade 6	Grade 7	Grade 8
Central	Ogden	Ogden	South Loop	South Loop	Ogden	South Loop	South Loop	South Loop
North Side	Reilly	Reilly	Monroe	Reilly	Monroe	Monroe	Monroe	Monroe
Far North Side	Hibbard	Hibbard	Haugan	Armstrong	Haugan	Armstrong	Albany Park	Armstrong
Northwest Side	Falconer	Lloyd	Lloyd	Falconer	Falconer	Lyon	Lyon	Hanson Park
West Side	Cardenas	Cardenas	Gary	Gary	Gary	Gary	Gary	Gary
South Side	Carnegie	Healy	Healy	Healy	Healy	Healy	Healy	Healy
Southwest Side	Eberheart	Sawyer	Shields	Shields	Sawyer	Eberhart	Sawyer	Sawyer
Far Southeast Side	Gallistel	Gallistel	Gallistel	Gallistel	Gallistel	Gallistel	Dixon	Addams
Far Southwest Side	Stevenson	Stevenson	Stevenson	Stevenson	Stevenson	Stevenson	Stevenson	Stevenson

Table B.8: Outside option for each grade and Side. Each outside option school 1) is open in every year in the sample period, 2) has zoned students, and 3) in 2013 had the largest enrollment among school-grades in its Side.