Essays on the Economics of Education

by

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Abstract

This dissertation consists of three essays in the economics of education. The first chapter uses Boston charter school admissions lotteries to estimate the effects of charter enrollment on special needs students' classification and achievement. Charter schools remove special needs classifications and move special education students into more inclusive classrooms at a rate over two times higher than traditional public schools. Despite this reduction in special needs services, charters increase special needs students' test scores, likelihood of meeting a high school graduation requirement, and likelihood of earning a state merit scholarship. Charters benefit even the most disadvantaged special needs students: those with the lowest test scores and those who receive the most services at the time of lottery. Non-experimental evidence suggests that the classification removal explains at most 26 percent of the achievement gains for special needs students and has no detrimental effect. The results show that special needs students can achieve gains without the traditional set of special needs services in the charter environment.

The second chapter, coauthored with Sarah Cohodes and Chris Walters, studies whether schools that boost student outcomes can replicate their success at new campuses. We analyze a policy reform that allowed effective charter schools in Boston to replicate their school models at new locations. Estimates based on randomized admission lotteries show that replicate charter schools generate large achievement gains on par with those produced by their parent campuses. The average effectiveness of Boston's charter middle school sector increased after the reform despite a doubling of charter market share.

The third chapter uses experimental evidence in two Boston charter schools to estimate the effect of a math and English Language Arts tablet educational program. I find that the personalized learning technology can substantially increase test scores, narrowing the math black-white achievement gap by up to 22% if implemented well. Correct implementation of technology matters: one study site had low technology usage and had noisy, null results. Students of varying ability experience similar effects – suggesting that the targeting of student's learning gaps promotes gains. This paper demonstrates the ability of technology to enhance student learning if students spend enough time with the educational technology. More work is needed to identify optimal amount of time for learning programs and the relative effectiveness of different education technology.

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This thesis is lovingly dedicated to them.

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Chapter 1

Special Education and English Language Learners in Boston Charter Schools: Impact and Classification

1.1 Introduction

Schools spend over twice as much per pupil educating special education students and English Language Learners (ELLs) compared to other students (e.g. Hayes et al. (2013); Chambers, Parrish, and Harr (2004)). Yet in Massachusetts special needs students have achievement gaps at least double the size of the low-income and black-white achievement gaps. Urban, high poverty districts have large and growing special needs student populations: fifty percent of Boston Public School students have either a special education or ELL status. Despite special needs students' increasing prevalence, higher costs, and low academic achievement, little causal evidence exists for which school models and practices serve them well.

Lower enrollment rates of special needs students in charters compared to district schools have led to the common perception that charters underserve special education and ELL students (Government Accountability Office, 2012; Boston Globe Editorial Board, 2015; Massachusetts Teachers Association, 2015). Critics question whether charter schools have the capacity to provide special needs services because charters lack the economies of scale of traditional public school districts. These concerns call into question whether the growing evidence that urban charters generate gains for lottery applicants, particularly for low-performing students, extends to special needs students. Perhaps urban charters' remarkable achievement gains are generated in part by a tendency to focus on non-special needs students.[1]

[1] A growing literature documents lottery-based evidence that urban charter schools generate large gains in Boston, Chicago, Denver, and New York (Angrist, Pathak, and Walters, 2013; Abdulkadiroğlu et al., 2011; Hoxby and Rockoff, 2004; Hoxby, Kang, and Murarka, 2009; Dobbie and Fryer, 2013; Angrist et al., 2016; Walters, 2014; Abdulkadiroğlu

This paper provides the first lottery-based estimates of charter enrollment's effect on special needs students' classification and academic outcomes. To conduct this analysis, I collected lottery records from 30 Boston elementary, middle, and high school charters which account for 89 percent of Boston charter school enrollment.[2] The data includes over 7,500 special needs applicants: the first charter lottery sample large enough to study special needs students. I also investigate the role of classification, school quality, and school practices in generating charter achievement effects.

Special needs classification, a process managed by individual schools, legally obligates schools to provide services and accommodations to help special needs students succeed academically. Lottery-based estimates show that charter enrollment nearly doubles the likelihood that a student in special education at the time of the lottery loses this classification. Moreover, charters remove ELL classifications three times as often. Charters are also three times more likely than traditional public schools to move special education students into general education classrooms. These classification changes happen at the beginning of the school year following the lottery and therefore cannot be attributed to learning gains.

Although charter enrollment reduces time spent receiving services and exposure to special needs teachers, lottery-based estimates show that Boston charters generate large achievement gains for their special needs students. These gains are similar to those made by non-special needs students in charter schools. Charters also significantly increase the likelihood that special needs students meet a key high school graduation requirement, become eligible for a state merit scholarship, and take an AP exam. Special education students in charters score on average 115.7 points higher on the SAT than their traditional public school counterparts.

Charters generate academic gains even for the most disadvantaged charter applicants. Special needs students who scored in the bottom third on their state exams in the year of the lottery experience gains of over 0.24 standard deviations in math. English Language Learners with the lowest baseline scores have the largest English exam gains. Students with the most severe needs at the time of the lottery – special education students who spent the majority of their time in substantially separate classrooms and ELLs with beginning English proficiency – perform significantly better in charters than in traditional public schools.

Next I use non-experimental methods to explore explanations for the academic effects. Evidence from multiple endogenous variable estimation finds that classification removal and increased inclusion have weak positive effects on test scores. The weak positive correlation between individual charter schools' classification removal effects and special needs achievement gains supports this finding. At the same time, charter practices that predict gains for general education students also predict gains for special needs students.

This paper contributes to the effectiveness of special needs classification and practices literature. Earlier research on ELL classification and bilingual education finds mixed effects (Chin, Daysal, and Imberman, 2013; Pope, 2016; Matsudaira, 2005; Robinson-Cimpian and Thompson, 2015). Hanushek,

et al., 2015).

[2]The sample expands upon the 11 Boston charter schools included in Angrist, Pathak, and Walters (2013) by incorporating charter elementary schools, adding nine additional charter middle and high schools, and extending the sample to include the 2011-12 through 2014-15 school years.

Kain, and Rivkin (2002) find that special education classification boosts math outcomes by analyzing students who move in and out of special education programs, but these movements are not random.[3]

The next section provides background on Boston charter schools, discusses the special needs classification process, and describes the data analyzed here. Section 3 details my empirical strategy and reports the effect of charter enrollment on special needs classification. Section 4 reports the academic effects of charter enrollment and Section 5 investigates mechanisms. The final section concludes.

1.2 Background and Data

1.2.1 Boston's Charter Sector

Massachusetts uses a rigorous charter authorization and monitoring process. Since the state first allowed charters in 1995, it has unauthorized 21 schools (Massachusetts Department of Elementary and Secondary Education, 2016). The state also restricts charter spending to 18 percent of the state and local annual school budget for low performing districts. Boston nearly reached this cap in the 2015-16 school year with over 17 percent of Boston students enrolled in charter schools. In 2016, the state legislature debated raising the charter cap and failed to reach a compromise, a civil rights lawsuit contended that the cap limited students' access to quality education, and citizens will vote on a ballot initiative to raise the cap on charter enrollment.

Massachusetts urban charters are characterized by the prevalence of No Excuses pedagogy (Angrist, Pathak, and Walters, 2013). This approach utilizes strict discipline, a long school day and year, selective teacher hiring, frequent testing, high expectations, teacher feedback, data-driven instruction, and tutoring (Thernstrom and Thernstrom, 2003; Carter, 2000). Past studies have documented a strong positive relationship between the use of No Excuses practices and charter school gains for the average lottery applicant in both NYC and Boston (Dobbie and Fryer, 2013; Angrist, Pathak, and Walters, 2013), but little is known about the effect of these practices on special education and ELL students specifically.

1.2.2 Special Needs Classification Processes

The special education classification process begins when a parent, teacher, or school staff requests an evaluation for a student. This can happen at any grade or age. After a request, the district or a private psychologist conducts an evaluation. The school holds a meeting with the parent(s) to decide the student's classification. If the student is classified, the school develops an Individualized Education Program (IEP) that details the supports the student will receive. Students are designated to full, partial, or substantial separate classroom inclusion. Students in full inclusion spend less than 21%

[3]Other work focuses on how financial incentives affect special education classification (Cullen, 2003; Kubik, 1999). Cullen and Rivkin (2003) overviews the classification incentives and stratification in school choice programs.

of their time outside of the general education classroom. Partial inclusion students spend between 21% to 60% of their time in a separate setting, and substantially separate students spend over 60% of their time receiving special education services. Schools are required to re-evaluate students' classification and level of services every three years.

Massachusetts public schools survey the parent(s) of all new students, including those coming from within the same district, to identify students whose primary language at home is not English.[4] Once identified, these students take an English Proficiency exam. A licensed ELL teacher or administrator interprets the test to decide whether the student will be classified as ELL and to determine the set of services they will receive. Every Spring, ELL students take a state standardized English proficiency exam, and their teachers and ELL specialists evaluate their results to reconsider their ELL status and services.

Schools aim to improve English language ability of ELL students so that they no longer need the ELL classification and services. This goal of removing classification does not exist for special education students; rather, schools aim to provide the proper set of supports to enable the child succeed academically.

1.2.3 Classification Incentives

The financial and accountability incentives for special needs classification go in opposite directions and impact charters more than traditional public school districts. The state and local school funding formula in Massachusetts does not include special education enrollment to discourage over-classification. As a result, the formula disincentivizes special education classification due to higher costs for special education services. The funding formula includes lagged ELL enrollment, but districts face financial disincentives to classify students if the costs of services exceed additional funding. Smaller school districts, including charter school districts, face relatively larger disincentives because of economies of scale for providing special needs services.

Accountability incentives encourage schools to properly classify special needs students. The state inspects schools for proper identification of special needs and provision of services. The state accountability system considers the outcomes of special needs students in addition to overall student performance, which incentivizes providing the proper set of services for this group of students to succeed academically.[5] Charter schools face higher accountability standards and the threat of de-authorization, so these incentives affect charters more acutely than traditional public schools.

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[4]The survey is offered in 28 languages and administered by specially trained professionals (including teachers, principals, and guidance counselors). The training aims to detect if families falsely report English proficiency.

[5]This might also incentivize over-classification to increase the performance of special education students as a whole. The state inspections and financial disincentives counter this incentive.

1.2.4 Data and Sample

To study the effect of charter attendance for special needs students, this paper uses the admissions lotteries of 30 Boston elementary, middle, and high charter schools from the 2003-04 to 2014-15 school years. These schools account for 89 percent of Boston charter entry grade enrollment in 2012-13. Schools are excluded from the study if they closed,[6] declined to participate,[7] had insufficient records,[8] did not have any oversubscribed lotteries,[9] or serve alternative students.[10] Appendix Table A1 describes the schools and application cohorts in the sample.

I match lottery records to state administrative education data for detailed student demographics, enrollment, and outcomes. This data provides both baseline characteristics of students from the time of the lottery and post-lottery outcomes. It includes special education status, disability type, and level of classroom inclusion for special education students and ELL status, native language, and test scores on the annual English proficiency exam for ELLs. I categorize ELL students as beginning, intermediate, or advanced English proficient using their English proficiency exam scores and state guidelines for the amount of services to provide ELLs. I study students with special needs classifications at the time of the lottery because special needs status can change over time. Throughout the paper, mentions of special education and ELL students refer to those with baseline classifications. Similarly, analysis by level of inclusion or English proficiency refers to baseline characteristics. More details about the data and matching procedure appears in the Data Appendix.

This paper's main analysis estimates the impact of charter school attendance on academic outcomes for students by their pre-lottery special needs status. As a result, applicants who are not enrolled in Massachusetts public schools the year of the lottery are excluded because they do not have a pre-lottery special needs status. This excludes 95.4% of pre-k applicants and 70.7% of kindergarten applicants. These excluded applicants are used to investigate the effect of attending a charter school on special needs initial classification.

1.2.5 Representation of Special Needs Students

Until recently, special needs students have been underrepresented among students applying to and attending charters. In 2010, the Massachusetts state legislature passed a law that required charter schools to increase efforts to recruit and retain special education and ELL students. Figure A1 shows that the special education application gap has narrowed for both middle and high school. In Spring

[6]Uphams Corner Charter School closed in 2009. Fredrick Douglas Charter School and Roxbury Charter High School both closed in 2005.

[7]Kennedy Academy for Health Careers (formerly Health Careers Academy) and Helen Davis Leadership Academy (formerly Smith Leadership Academy) declined to participate

[8]Boston Renaissance and Dudley Street Neighborhood Charter School had insufficient records.

[9]UP Academy Dorchester opened in 2013-14 and did not have an oversubscribed lottery.

[10]Boston Day and Evening Academy Charter serves alternative students, including those who are overage for high school, dropouts, and students with behavioral and attendance issues. In addition to serving a different population than the other Boston charters, Boston Day and Evening Academy uses rolling admissions instead of a lottery, making the school not appropriate for this paper's empirical strategy.

2004, 22.1 percent of BPS students in 4th and 5th grades had a special education status. Comparatively, only 17.0 percent of charter applicants in those grades had a special education status. By the Spring 2014 lottery, the prevalence of special education students in middle school charter lotteries was similar to BPS: 21.6 and 23.1 percent respectively. The gap also closed for high school, with 20.3 percent of applicants with a special education status in charters, compared to 19.5 percent of BPS 8th graders. Gaps in enrollment have also narrowed. Figure A1 shows that gaps between BPS and charters remain in middle school special education enrollment in entry grades, but special education students are overrepresented in 9th grade in charters.[11]

Gaps in ELL application and enrollment rates in BPS compared to charters were historically larger, but they have also narrowed. Figure A2 shows that in Spring 2004, ELL students were almost three times more prevalent in BPS than in charter middle and high school lotteries. In the past decade, ELLs have become more prevalent in BPS, and the gap has closed. By Spring 2014, ELLs have similar prevalence in BPS and charters: 24 percent in each for high school and 30 and 27 percent respectively for middle school.

Differences between the application and enrollment trends result from parental choices in response to other school options and the sibling lottery preference. Figures A1 and A2 show that the enrollment gaps have reversed for special education students in high school. The trends are noisier for ELL students, but the middle school ELL enrollment gap has almost halved from 18.0 percent at its peak in 2007 to 9.3 percent in 2014. Similarly, the high school ELL enrollment gap has halved from 9.5 percent in 2009 to 4.3 percent in 2014. Because ELL students were historically underrepresented in charters, the sibling lottery preference means that ELL students have a lower likelihood of getting a charter offer compared to non-ELL students. This likely contributes to the current ELL enrollment gap.

By Spring 2014, students across the pre-lottery levels of special education classroom inclusion and English language proficiency are, for the most part, similarly represented in charter lotteries and BPS as shown in Figures A3 and A4. Small gaps remain for substantially separate inclusion students in middle school and high school and for beginning English speakers in high school.[12]

[11] I do not display the application and enrollment trends for elementary school charters because a low proportion of pre-k and kindergarten charter applicants have a pre-lottery special needs status.

[12] Students with developmental delay are slightly over-represented in middle school charter lotteries. Students with autism and intellectual disabilities are slightly underrepresented in middle school charter lotteries relative to BPS. For the past ten years, there has been similar representation for students with physical, health, sensory, neurological, communication, and multiple disabilities in middle school lotteries. Students with learning disabilities have been similarly represented in middle school lotteries since Spring 2009.

Students with learning disabilities are over-represented in high school charter lotteries relative to BPS. Students with autism and developmental delay are slightly underrepresented in high school charter lotteries. All other disability types were similarly represented in high school charter lotteries compared to BPS by Spring 2014. Over the past ten years, students with physical, health, sensory, neurological, and multiple disabilities have been similarly represented in high school charter lotteries and in BPS.

Students who speak Haitian Creole have been similarly represented in charter lotteries and BPS for the past ten years. Chinese speaking students remain underrepresented in charter lotteries. Spanish speaking students historically were underrepresented in lotteries and now apply to charters at similar rates as their prevalence in BPS.

Subsidized lunch status students were historically underrepresented in charter lotteries, but became similarly represented in middle school charter lotteries by Spring 2011 and in high school lotteries by Spring 2006.

Further information about application trends for these subgroups is available at the request of the author.

1.3 Classification

1.3.1 Empirical Framework

I use charter lottery offers as instruments to estimate the causal effect of attending charter schools in a two-stage least squares setup. The second-stage equation links charter school attendance with outcomes as follows:

$$y_{igt} = \alpha_t + \beta_g + \sum_j \delta_j d_{ij} + X_i'\theta + \tau C_{igt} + \epsilon_{igt} \tag{1.1}$$

where y_{igt} is the outcome of interest for student i in grade g in year t. The terms α_t and β_g represent outcome year and grade effects. The d_{ij} are dummy variables for all combinations of charter school lotteries (indexed by j) present in the sample (henceforth referred to as experimental strata). These experimental strata control for the fact that the set of school applications determines the probability of receiving an offer. Baseline demographic characteristics from the year of the lottery, represented by vector X_i, include gender, race, subsidized lunch status, ELL, special education, and a female-minority interaction.

The treatment variable, C_{igt}, equals one if the student enrolled in a charter any time following the lottery and until the time schools reported special needs classification.[13] For models testing charter effects on college preparation measures and high school graduation, C_{igt} indicates charter enrollment between the lottery and the test or graduation date. Standard errors are clustered on the school, grade, and year of the outcome. The parameter τ captures the causal effect of charter school enrollment. I estimate the model separately for each baseline special needs status: special education, ELL, and non-special needs.

When estimating the math or English exam effects, C_{igt} represents years spent in a charter from the time of the lottery to the the test date. Students take exams in grades 3 through 8 and grade 10, so elementary and middle school applicants who appear in multiple testing grades contribute multiple observations to the estimation. To account for this, the standard errors, ϵ_{igt}, are clustered on the unique student identifier in addition to the school, grade, and year of the test. For math and English test results, the parameter τ estimates the causal effect of a year of charter school attendance.

I use two instruments for charter attendance: whether a student receives a random offer on the day of the lottery (immediate offer) or whether a student receives an offer from the randomly-ordered waitlist (waitlist offer). Z_{1i} is equal to one if the applicant received an immediate offer to attend a charter and zero otherwise. Z_{2i} designates whether the applicant received a waitlist offer. Appendix Table A1 details the schools and application cohorts with immediate and waitlist offers.

The first stage equation for the instrumental variables estimation is:

[13]Students for whom C_{igt} equals zero enroll in non-charter public schools, including traditional public schools, pilot schools, exam schools, and innovation schools. For simplicity, I refer to this group by the most common type: traditional public schools.

$$C_{igt} = \lambda_t + \kappa_g + \sum_j \mu_j d_{ij} + X_i'\Gamma + \pi_1 Z_{1i} + \pi_2 Z_{2i} + \eta_{igt}, \tag{1.2}$$

where π_1 and π_2 capture the effects of receiving immediate or waitlist offers on charter attendance. Like the second-stage equation, the first stage includes year and grade effects, experimental strata dummies, and baseline demographic controls.

Because they are randomly assigned, charter offers are likely to be independent of student background and ability within experimental strata. The pre-lottery demographics and test scores are similar for offered and non-offered students, as shown in Columns (3) and (4) of Table 1. Differences in baseline characteristics by offer status are small, mostly statistically insignificant, and the p-values from joint tests are high. The subset of students with baseline special needs also have comparable characteristics across offer status, as seen in Columns (6) and (7) for special education and Columns (9) and (10) for ELL.

Differences between charter applicants and Boston Public School (BPS) students are documented in the first two columns of Table 1. Lottery applicants are less likely to have a special education status than BPS students. The charter applicant pool has a smaller proportion of substantially separate and full inclusion special education students and similar rates of partial inclusion students. The two populations have similar rates of ELL students (though as discussed above, this is not historically true). All levels of English proficiency are more represented in charter applicants than in BPS students. Lottery applicants have slightly higher baseline test scores compared to BPS students (0.042 and 0.093 standard deviations in math and English respectively). The baseline test score positive selection for special needs students ranges from 0.08 standard deviations to 0.21 standard deviations.

Special needs applicants have substantially lower baseline test scores on average than the full lottery applicant pool as described in Columns (5) and (8) of Table 1. This achievement gap is large, particularly for special education students. Compared to the full lottery applicant sample, the baseline math scores are 0.595 standard deviations lower for special education students and 0.329 standard deviations lower for ELL students. The special needs achievement gaps are larger for baseline English scores.

1.3.2 Special Needs Classification

Receiving a lottery offer increases the time spent in charters and the likelihood of enrolling in a charter. These first stage estimates, which are strong for both special and non-special needs students, appear in Table A2. Special needs middle school applicants with immediate and waitlist offers spend over a year and 0.66 years longer respectively in charters compared to those without offers. Elementary and high school special needs applicants who receive offers also spend substantially more time in charters. Immediate and waitlist offers also boost the likelihood that special needs students will enroll in charters one year after the lottery by over 58 and 35 percentage points respectively. The first stage for charter enrollment does not equal one because some students with offers elect to go to traditional public schools and some students without offers ultimately enroll by moving off of a waitlist after our data was collected.

Charters remove special needs classifications and move special education students to more inclusive settings at the time of enrollment[14] at a higher rate than traditional public schools. Column (2) of Table 2 shows that relative to their counterparts who attend traditional public schools, elementary and middle school special education charter students are 19.0 and 16.1 percentage points more likely to have their special education classification removed.[15] Middle school charters even remove special education status from students with more severe disabilities: students from substantially separate classrooms are 14.0 percentage points less likely to keep their special education status in a charter compared to a traditional public school. Charter high schools change classifications of incoming special education students at a similar rate to traditional public high schools.[16]

Charters move elementary and middle school special education applicants to more inclusive classrooms over 29 percentage points more often than traditional publics, a pattern documented in Column (10) of Table 2. This means that students spend more time in a general education classroom and less time receiving services outside of the mainstream classroom. Middle school charters move students across all ranges of need to more inclusive settings. For elementary schools, charters move students with the most severe needs to full inclusion classrooms (see Column (4) and (8) of Table 2). Overall, high school charters do not move special education students to more inclusive settings at significantly higher rates, but they are 47.0 percentage points more likely to move partial inclusion classroom students to a full inclusion or general education classroom.

In all school levels, charters remove ELL status at the time of enrollment at a substantially higher rate than traditional public schools. Ninety percent of elementary ELL applicants who enroll in traditional public schools remain ELL by the following fall, but as shown in Table 3, 19.8 percentage points fewer elementary school ELL applicants maintain their ELL classification in charters. Compared to traditional public schools, applicants to charter middle and high schools are respectively 32.8 and 37.4 percentage points less likely to keep their ELL classifications. Students with intermediate and advanced English proficiency drive the differences in classification. In both types of schools, those with beginning English proficiency rarely have their ELL classification removed at the time of enrollment.

Furthermore, charters classify new enrollees to Massachusetts public schools as special needs less often than traditional public schools. New students in pre-k and kindergarten do not have pre-lottery special needs classifications. Only 1.4 percent of applicants who attend a traditional public school become classified as special education at the time of enrollment.[17] Attending a charter leads to an

[14]Data is collected on October 1st. Given this short time span, schools likely do not have sufficient time to alter the initial classification given at the time of enrollment before the reporting date.

[15]I consider students to have their classifications removed if they had a classification the year of the lottery, have no classification on the October 1st following the lottery, and continue to have no classification for the next two years. Students who have their classification removed and then reinstated are coded as keeping their classification. I follow the same practice for changes in classroom inclusion.

[16]Applicants from substantially separate classrooms are substantially less likely to remain classified as special education in a charter high school. It is surprising that students receiving special education services for more than 60% of the time prior to the lottery would transition to receiving no services. The effect fades away in the 2009-10 through 2013-14 school years.

[17]The state actively recruitments students with special needs for early intervention pre-k that starts at age 3. Therefore,

even lower special education classification rate close to zero (see Column (2), Panel A of Table 2). The difference comes largely from fewer students receiving full inclusion status in charters (see Column (8), Panel A of Table 2).[18] Traditional public schools designate 63.7 percent of non-native English speakers, the potential candidates for ELL services, as ELL. The rate is 26.1 percentage points lower in charters (see Panel A of Table 3). These classification and inclusion effects appear to persist for two years, as shown in Tables A3 and A4, though with less precision.[19]

1.3.3 Explanations for Classification Removal and Increased Inclusion Effects

Learning gains cannot justify the classification differences because the special needs status changes occur at the beginning of the school year following the lottery. At this point, schools have not had time to generate substantial learning gains. The differential special needs classification for new pre-k and kindergarten students implies that charters have a lower preference for classification compared to traditional public schools. Massachusetts law requires schools to assess the English proficiency of all incoming non-native English speaking students. Therefore, schools assess all incoming ELLs, but charters remove ELL classification 3.1 times more often than traditional public schools. This supports the idea that charters have lower preference for classification.

Unlike English language proficiency, Massachusetts does not require schools to assess all new enrolled students for special education needs. Because schools do not evaluate each student, factors other than schools' classification preferences could contribute to different classification practices. Better transfer of student records, which include special education information, between BPS district schools compared to between BPS district schools and charter schools plays a major role in special education classification changes.

As a result, charters learn of special needs classifications from voluntary parental reporting before they receive school records.[20] The initial reliance on parental reporting could contribute to fewer students maintaining their special education classifications in charters. A survey conducted by the Massachusetts Department of Elementary and Secondary Education that resulted from this study

a large portion of students who qualify for special education services at a young age already have a classification at the time of the lottery.

[18]Analogous analysis of initial classification for new students could not be conducted on middle and high school applicants because few students have no special education classification at application and then become classified after the lottery.

[19]The time of enrollment and two years after the lottery sample sizes are different because data from the most recent lottery is included in the former, but not the latter, and some students attrit from the sample if they move out of state or to private school. The estimates for the Fall after the lottery are similar in magnitude and significance if the sample is restricted to those who appear in the data after two years.

[20]Starting in late Fall 2012, the Massachusetts Department of Elementary and Secondary Education began using a new data reporting system called Edwin Analytics. This system aims to make student data accessible to their schools in a more efficient and timely manner. The charter schools began using this system at varying times. Even with the new system, charter schools rarely have the special education classification information of their students before the school year started. For students that notify the school of a special education status, charter schools report difficulty getting important documentation about students' special education needs and services including their evaluations and Individualized Education Programs (IEPs).

found that the most common reason for special education classification removal was parent(s) not disclosing.[21] The reasons why parents decline reporting special education status could include stigma, individual preferences, not knowing their child received special education services, assuming the school received the records, and not understanding what special education means. Additionally, parents can refuse their child's special education classification. Parental refusal of special needs status could differ in charters compared to traditional public schools.

The data transfer issues and differences in parental reporting and preferences likely contribute to the increased use of inclusion in charter schools. Charters' preference for high levels of special education inclusion, often cited in charter schools' annual reports, likely also play a role in higher levels of inclusion. Additionally, the relatively smaller size of charter schools make it less likely for them to have the economies of scale to provide substantially separate and partial inclusion services to students compared to traditional public schools.

1.3.4 Special Needs Inputs and Implications of Special Needs Reclassification

Students who have their special needs status removed have substantially different educational experiences than those that remain classified. Schools are only legally obligated to provide special education or ELL services to students with special needs classifications. Therefore, the higher rate of classification removal in charter schools likely results in baseline special needs students receiving fewer special education and ELL services. Additionally, students who are moved to more inclusive classrooms spend less time receiving services. Classification differences likely contribute to the large differences in special needs educational inputs between charter and BPS.

Students who enroll in charters experience lower special education and ELL staff-to-student ratios (Columns (4) and (6) of Table A5). Lottery applicants who enrolled in BPS have roughly 1.9 special education and 1.5 ELL staff per 100 students. Enrolling in a charter school exposes lottery applicants to 1.1 fewer special education staff and 1.3 fewer ELL staff per 100 students. Lower counts of special needs teachers drives the lower special needs staff-to-student ratio in charters.

Despite charters having fewer classified special needs students, they employ mostly similar proportions of special needs specialists[22] and content support teachers.[23] The similar rates of specialists in

[21]The survey investigated all cases of special education classification removal in the 2012-13 through 2014-15 school years. All sample charters participated. Forty-nine percent of the cases cited parent(s) not disclosing. The other reasons include unknown (12 percent), record error (12), student found ineligible for services after lottery by BPS (8), student transferred out of charter soon after enrolling (7), parent declined services (7), student determined ineligible by charter (3), and charter gave services later in the year (2).

[22]Special needs specialists include special education and ELL directors who oversee service provision, special education diagnosticians, therapists, and counselors.

[23]Content support teachers coach teachers in how to better serve those with special education needs or limited English proficiency in the classroom or teach alongside another teacher, providing additional attention and differentiation. They could more broadly help students without special education or ELL statuses who might also benefit from the additional attention or a more accessible learning environment. In particular, these interventions could help students with baseline special education and ELL statuses who had their classification removed.

charters and traditional public schools suggest that either specialists work with students who remain classified more intensively or that they also serve students without special needs classifications.

Charters also spend 44 percent less on special education instructional spending compared to BPS (shown in Table A6).[24] See Table A6 for detailed BPS and charter school expenditure and grant information.

1.4 Academic Effects

Charter enrollment leads to two effects for special needs students: higher likelihood of classification removal and exposure to the charter school environment. The charter school environment and classification removal could have complementary or opposing effects. The high academic and strict behavior standards common in Boston charter schools could leave special needs students behind or motivate them to meet higher expectations. Special needs students could thrive in a more inclusive classroom environment or fall behind without the specialized services they previously received.

Prior research suggests no effect or limited gains from ELL classification removal (Chin, Daysal, and Imberman, 2013; Pope, 2016; Matsudaira, 2005) except Robinson-Cimpian and Thompson (2015) who estimate a negative effect on when lower ability ELLs marginally qualify for classification removal. To the best of my knowledge, no causal evidence exists for special education classification removal.

In this section, I present causal estimates the effect of charter enrollment on special needs' students outcomes which bundles the two treatments of classification removal and charter environment. In Section 6, I estimate the academic effects of classification removal and the charter environment.

1.4.1 Charter School Effects

Charter school attendance has large positive effects for math and English state exam scores for special needs students. Table 4 documents the large and statistically significant gains for elementary, middle, and high school special needs applicants. A year of charter attendance increases math test scores by over 0.240 standard deviations for middle and high school special education applicants and by 0.309 standard deviations for elementary school special education applicants. ELL students score over 0.306 standard deviations higher on math in charters relative to traditional public schools.

Charters generate English score gains of 0.177 and 0.200 standard deviations for special education and ELL middle school applicants (shown in Panel B of Table 4). Elementary special education and ELL applicants had English exam charter gains of 0.478 and 0.360 standard deviations respectively (see Panel A of Table 4). While English exam estimates for high schools are noisier, they are also positive.

[24] Districts do not report ELL specific school expenditures.

Positive charter effects are, with few exceptions, statistically similar for special needs and non-special needs students; however, point estimates for ELLs are larger and become statistically significantly different than non-special needs effects when all grade levels are pooled together.

One year of charter attendance for a special needs student narrows the special needs achievement gap. Most notably, after one year in a charter, ELL charter students score higher on the math exam than non-special needs students in traditional public schools for elementary and high school (seen by adding Columns (3) and (4) of Table 4 and comparing to the non-special needs traditional public school mean in Column (5)). The larger gap between special education and non-special needs students narrows substantially as well. With one year of charter enrollment, the special education gap for math decreases by 27 percent for middle and high school students and by 48 percent for elementary school students. Charter attendance also narrows the gap for English, though by a lower proportion.

The ordinary least squares (OLS) estimates (shown in Table A7) have comparable estimates to the two-stage least squares. This suggests that the OLS is unbiased. Therefore, there is not significant selection into complying with the results of the lottery: accepting a charter offer if it is received and not attending a charter if the student does not receive an offer.

The reduced form or intent to treat estimates (shown in Table A8) also have comparable estimates to the two-stage least squares. Therefore, even without accounting for lottery compliance, randomly assigned charter offers have a strong positive relation to test scores.

The effects of charter attendance accumulate in the first two years and then level off. The first year of charter attendance generates gains of 0.397 and 0.457 standard deviations in math for special education and ELL middle school applicants respectively (see Figure A5, Panel B). The charter enrollment effect nearly doubles for special education students and grows by 1.6 times for ELLs in the second year (see Figure A5, Panel C). After the third year, the charter effects stabilize: effects in the second and third years are comparable (see Figure A5, Panel D).[25]

The annual English proficiency exam – which schools use to reevaluate ELL students' classification and services – also suggests that charter schools improve English skills for ELLs. Attending a charter makes students less likely to take the English proficiency exam because charters remove ELL status at higher rates than traditional public schools (see Column (2) of Table A9). Charters likely remove classification from the ELLs with relatively higher English proficiency: leading to negative selection. Therefore if traditional public schools and charters have the same effect on English language proficiency, charters would have a negative effect on English proficiency scores. Instead, charter students perform similarly or significantly better compared to traditional public school students: suggesting positive charter effects on English proficiency (see Column (4) of Table A9).

Charters also have positive effects on longer-term outcomes that likely have a strong, lasting link to human capital and future earnings through educational attainment. Panel A of Table 5 shows that charter special education and ELL students are 24.4 and 36.7 percentage points respectively more likely to reach a key high school graduation requirement: reaching proficiency on the 10th grade math

[25]This analysis focuses on middle school applicants because they take the state standardized exam in the three years following the lottery. The test schedule for elementary and high school applicants does not lend itself to this analysis.

and English exams.[26] Students who do not meet this requirement need to fulfill remedial coursework to graduate. Therefore, fulfilling this requirement keeps students on the path towards high school graduation and enables them to take more college preparation courses.

Charters also boost the likelihood that special education students and ELL students will become eligible for the Adams state merit college scholarship by 11.3 percentage points and 28.7 percentage points each. The Adams Scholarship awards free tuition to Massachusetts public universities based on 10th grade math and English exams and has stricter conditions than the proficiency graduation requirement.

Evidence in Panel B of Table 5 suggests that charter enrollment has positive effects on college preparation exams for special needs students. Special needs charter and traditional public school students take the SAT at similar rates, but charter enrollment leads special education students to score 115.3 points higher on the SAT. Special education and ELL students are 36.3 and 40.3 percentage points more likely to take at least one AP exam in charters compared to in traditional public schools. However, there is no significant effect of charter enrollment on scoring a 3 or higher, which is required to earn college credit. Columns (7) and (8) of Table 5 show the effects across special needs status are not statistically significantly different.

Charter enrollment dramatically lowers the likelihood that special education and ELL students will graduate high school in four years by 36 percentage points (see Panel C of Table 5). Given the gains in reaching the proficiency graduation requirement, this is surprising. However, special needs students are similarly likely to graduate within five years in charters than in traditional public schools. Special needs students in charters and traditional public schools also have similar five-year high school dropout rates. Angrist et al. (2016) suggest that students could take longer to graduate from charters because they need additional time to meet charters' rigorous graduation requirements or because they choose to save money by remaining in high school for an additional year rather than seeking remediation at a community college.

1.4.2 Heterogeneity

Charters generate test score gains for even the most disadvantaged special needs students. Panel A of Table 6 shows gains of 0.256 standard deviations in math for special education students with the highest need. Students with less severe needs, those who apply from partial and full inclusion classrooms, also experience gains of 0.328 and 0.269 standard deviations respectively. English exam gains for special education students are positive and of similar magnitude across level of inclusion, but they are imprecise for substantially separate and partial inclusion students.

Those with the lowest level of English proficiency experience math and English test score gains of over 0.400 standard deviations in charters as seen in Panel B of Table . Charters also generate math and English test score gains for ELLs with intermediate and advanced English proficiency.

[26]This requirement is called Competency Determination.

Baseline test scores provide an alternative approach to analyze whether charters benefit the neediest students. Column (2) of Table 7 shows that the bottom third of special education students, as measured by their combined pre-lottery math and English exams, score 0.255 standard deviations higher in math and 0.189 in English in charter schools. Column (4) shows that charters also have positive effects for the bottom third of ELLs. While the higher-baseline performing students also experience charter gains, the bottom third of ELLs experience the largest gains for English. The cumulative distribution functions (CDFs) for treated and untreated charter compliers in Figure A5 show charters boost student performance across the test score distribution.

Charter gains are strongest for those with specific learning disabilities, which are the most common disability type among charter applicants (see Table A10).[27] The estimates for other types of disabilities were imprecise. Charters generate significant math and English gains for ELLs who speak Spanish and Haitian Creole, the most common native languages of applicants after English (shown in Table A11). While the other native languages are not prevalent enough to estimate alone, ELLs who speak a language other than Spanish or Haitian Creole experience significant gains in math.

1.5 Mechanisms

1.5.1 Classification Removal and School Environment

Do the academic gains documented above stem from general charter school practices that affect all attendees or from classification removal and increased inclusion? Legal requirements and best practices operate under the assumption that special needs students need services and accommodations to succeed. Does charter classification removal and increased inclusion help or hinder special needs students?

The similar charter achievement effects for special needs and non-special needs students suggest that general charter school practices have a consistent effect for both groups. However, the similar effect sizes could mask differences in the mechanisms that led to the gains. For example, positive effects of general charter school practices for special needs students could outweigh negative effects of the classification changes.

[27]Federal law 34 C.F.R. §§300.7 and 300.541 defines specific learning disability as "a disorder in one or more of the basic psychological processes involved in understanding or in using language, spoken or written, that may manifest itself in an imperfect ability to listen, think, speak, read, write, spell, or to do mathematical calculations, including conditions such as perceptual disabilities, brain injury, minimal brain dysfunction, dyslexia, and developmental aphasia." Of the lottery applicants with a special education status, 40% of them have a specific learning disability. The severity of learning disabilities varies across lottery applicants: at the time of the lottery, thirty-seven percent come from a full inclusion classroom, 44% from partial inclusion, and 19% from substantially separate classrooms.

1.5.1.1 Empirical Strategy

To answer these questions, I estimate the effect of classification removal and increased inclusion in charters and in traditional public schools and the effect of charter enrollment holding classification constant. This estimation requires quasi-random variation in charter enrollment and in student reclassification in charters and in traditional public schools. Unlike the lottery which randomly offers students seats at charters, schools non-randomly make reclassification decisions based upon students' needs.

To address this selection issue, I harness school-specific variation in reclassification rates and pre-lottery characteristics of charter applicants. I use individual charter lottery offers and the interaction of these offers with students' pre-lottery classification removal likelihood (see the Data Appendix for a detailed explanation of the index's estimation) as instruments for charter enrollment, classification removal, and the interaction of charter enrollment and classification removal.[28] [29] The individual charter lottery offers randomize not only whether students can enroll in charters, but also student exposure to different reclassification rates. The interaction of individual charter offers with students' reclassification likelihood captures variation in classification removal for similar students. In a constant effects framework, these instruments identify causal effects for charter compliers. Heterogeneous effects across the interacted characteristics make the estimates difficult to interpret (Kline and Walters, 2016; Hull, 2015; Kirkeboen, Leuven, and Mogstad, 2016).

The second stage equation links charter attendance and classification removal to test score outcomes as follows:

$$y_{igt} = \tau_1 C_{igt} + \tau_2 R_{igt} + \tau_3 C_{igt} R_{igt} + \gamma L_i + \alpha_t + \beta_g + \sum_j \delta_j d_{ij} + X_i' \theta + \epsilon_{igt} \tag{1.3}$$

where y_{igt} is the test score of student i in grade g and year t. I estimate the three endogenous variables C_{igt} (years in charter), R_{igt} (an indicator for classification removal or increased inclusion by October 1st following the lottery), and $C_{igt}R_{igt}$ (their interaction). I also control for pre-lottery reclassification likelihood (L_i), year and grade effects, experimental strata, and a vector of pre-lottery demographic characteristics. Middle school applicants have multiple observations – one for each grade in which they take the exam – so I cluster standard errors by student and the school, grade, and year of the test. I estimate each model separately for the different types of reclassification (classification removal for special education students, increased inclusion for special education students, and classification removal for ELLs) and restrict the sample to students with the corresponding baseline special needs status.

The first stage for years spent in charter can be written as follows:

[28] Abdulkadiroglu, Angrist, and Pathak (2014); Kling, Liebman, and Katz (2007); Kline and Walters (2016); Cohodes (2015) also interact site-specific indicators and baseline characteristics with random or quasi-randomly assigned offers to generate new instruments to identify models with multiple endogenous variables.

[29] Student sorting into charter schools based on classification removal rates also poses a potential threat to the use of school interactions as instruments. There is no clear evidence of this: the average predicted reclassification index of applicants is not correlated with charter special education increased inclusion effects or the charter ELL classification removal effects.

$$C_{igt} = \sum_k \rho_k Z_{ki} + \sum_k \psi_k Z_{ki} L_i + \varphi L_i + \lambda_t + \kappa_g + \sum_j \mu_j d_{ij} + X_i'\Gamma + \eta_{igt}, \tag{1.4}$$

where ρ_k represents the effect of receiving an offer, Z_{ki}, from charter school k on charter attendance and ψ_k captures the effect of a one standard deviation increase in pre-lottery reclassification likelihood, L_i, on charter attendance for students with offers at charter school k. The first stages for R_{igt} and $C_{igt}R_{igt}$ have analogous specifications. The new set of instruments yield charter effect estimates similar to the main estimates (see Columns (1) and (8) of Table 8).

1.5.1.2 Classification Removal and Increased Inclusion

Before estimating the fully saturated model with charter attendance, classification removal, and charter attendance interacted with classification removal, I estimate equation (3) with just charter attendance and classification removal as endogenous variables (see Columns (2) and (9) of Table 8). The new instruments adequately identify the endogenous variables: charter and special education classification removal have strong first stage F-statistics (all above 10). The ELL estimation has strong first stage F-statistics of 27 for classification removal and relatively weaker F-statistics for charter attendance.

Charter enrollment has similar positive effects in the double and single endogenous variable models. Special education classification removal has large positive, but noisy point estimates so I cannot rule out that classification removal has negative effects. Special needs classification removal results and special education increased classroom inclusion have similar results for the multiple endogenous variable specifications, so I only present special education classification removal estimates. ELL classification removal has a significant 0.258 standard deviation effect on English test scores and a positive point estimate for math. The over-id test rejects the constant effects model for ELL classification removal, indicating substantial effect heterogeneity across charter schools and weakening the validity of the estimates.

To address the over-id problem, I use offer status and indicator for an offer at a charter with above median historical classification removal rates as alternative instruments. This approach yields similar point estimates for ELL classification removal without the over-id problem, but with large standard errors.[30]

Next I run the fully saturated model with charter enrollment, classification removal, and the interaction of charter enrollment and classification removal. Unlike the estimates above which showed the combined effect of classification removal in charters and traditional public schools, this specification separates the two. Special education classification removal in charters has a null effect, suggesting similar positive effects of reclassification in charters and traditional public schools (see Column (3) of Table 8). The ELL fully saturated model has weak first stage F-statistics and therefore no definitive interpretation for their relative effect in charters versus traditional public schools (shown in Column (10) of Table 8).

[30]Estimates using these and other alternative instruments available at the request of the author

The noisy two-stage least squares estimates suggest that classification removal has a positive effect on special needs students' test scores. For increased precision, I estimate the Ordinary Least Squares (OLS) version of equation (3) with the same lottery applicant sample. The similarity of the OLS and two-stage least squares estimates for the effect of charter attendance on test scores and on classification removal (compare Table 4 to Table A7 and Tables 2 and 3 to Tables A12 and A13) suggests that the OLS estimates are unbiased.

OLS yields similar, but more precise estimates compared to the two-stage least squares estimation (see Columns (4) and (11) of Table 8). Holding special needs classification constant, one year in a charter boosts math and English test scores of special needs lottery applicants by 0.2 to 0.3 standard deviations on average. Classification removal increases math test scores by 0.239 and 0.166 standard deviations for special education and ELL students respectively. English test scores increase by 0.321 and 0.196 standard deviations for special education and ELL students after classification removal. Special education classification removal has a similar effect in charters and traditional public schools. For ELLs, classification removal in charters has a smaller positive effect relative to classification removal in traditional public schools.

A back of the envelope calculation reveals that classification removal can explain anywhere from 0.9 to 25.4 percent of the effect of charter enrollment on test scores. Using the OLS point estimates, I calculate the upper and lower bound of the effect of charter classification removal on scores. I scale the upper and lower bound by the charter classification removal effect: the percent of applicants who lost their classification in charters, but would have kept their classification in a traditional public school. The scaled bounds range from 0.003 to 0.063 standard deviations for special education and ELL classification removal.

The back of the envelope calculation shows that classification removal in charter schools does not fully explain the academic charter effects. Visualizations of the relationship between school and cohort-level reclassification and academic effects provide additional insight into the effect of reclassification. I estimate individual charter school cohort academic effects using the following

$$y_{igt} = \sum_t \sum_s \rho_{st} C_{igst} + X_i' \theta + \alpha_t + \beta_g + \sum_j \delta_j d_{ij} + \epsilon_{igt} \tag{1.5}$$

where y_{igt} represents student i's test score in grade $g$and year t and C_{igst} denotes the years student i spent in charter school s by year t and grade g. Similarly, I estimate individual charter cohort reclassification effects using

$$r_{igt} = \sum_t \sum_s \vartheta_{st} C_{igst} + X_i' \theta + \alpha_t + \beta_g + \sum_j \delta_j d_{ij} + \epsilon_{igt} \tag{1.6}$$

where r_{igt} indicates reclassification at enrollment for student i and C_{igst} indicates charter enrollment in the year after the lottery. I estimate equations (6) and (7) separately by baseline special needs status. Two-stage least squares estimates using individual school immediate and waitlist offers and OLS estimates yield similar results. I focus on the OLS estimates for precision.[31]

[31] Two-stage least squares estimates are available at the request of the author.

Figure 1 plots the cohort test score effects $\hat{\rho_{st}}$ against the reclassification effects $\hat{\vartheta_{st}}$. Charter school cohorts that experienced higher reclassification rates also had higher special needs student test outcomes: test score effects have a weak positive correlation with special education increased inclusion effects and ELL classification removal effects. Test score and special education classification removal effects have a positive relationship for English and an imprecise relationship for math.[32] Similar to the multiple endogenous variable results, the weak positive correlations suggest that classification removal and increased inclusion contributes positively to student growth, but cannot fully explain the charter test score gains. Therefore, school practices other than special needs classification and services play an important role.

1.5.1.3 School Quality

Charter schools that serve special needs students well also serve general education students well. Figure 2 displays the strong positive relationship between schools' special needs and non-special needs test score effects.

To contrast the relative importance of classification practices with overall school quality, I estimate a multiple endogenous two-stage least squares using charter enrollment, an index of school quality, and classification removal effects. I add the math and English two-stage least squares effects for non-special needs students from a school-level version of equation (6) to create the school quality index. The multiple endogenous variables estimations yield noisy estimates for classification removal and precisely positive estimates for school quality. Enrolling in a school with a one standard deviation higher non-special needs student test score effect boosts special education and ELL students' math scores by 0.192 and 0.332 standard deviations (see Columns (5) and (12) of Table 8). In a two-stage least squares estimation with charter, classification removal, and the school quality index, school quality remains positive and significant while classification removal is a noisy positive (see Columns (6) and (13) of Table 8). The analogous OLS estimates show that classification removal has a similar effect to one standard deviation increase in school quality for special education math and a much smaller effect for ELL math and English. School quality has a smaller effect relative to classification removal on special education students' English outcomes. This analysis show the importance of general education practices in explaining special needs' charter gains.

[32] If schools that remove classification and increase inclusion more are effective due to other practices then this exercise overstates the importance of reclassification. The relationship between non-special needs test score effects and charter school reclassification effects is small and insignificant for special education and ELL classification removal, but small, positive, and marginally significant for special education increased inclusion. Therefore, there is little evidence of other school practices correlated with classification removal and increased inclusion driving the correlation between reclassification and special needs academic effects.

1.5.2 School Practices

Special needs students who apply and do not receive charter lottery offers attend schools with markedly different characteristics. Their BPS schools have more experienced, more licensed, and higher paid teachers and spend about $1,700 more per pupil relative to the Boston charter schools (see Table 9). Over half of Boston charters have a longer school year and over 95 percent of Boston charters have a longer school day compared to BPS.[33] Tutoring programs exist in all Boston charters and about a third of charters require tutoring for all students. Boston charters commonly use no excuses practices, including high academic and behavior expectations, selective teacher hiring, frequent testing and teacher feedback, and data-driven instruction.

The set of school practices that positively correlate with charter school effectiveness for general education students also correlate with test score gains for special needs students. Column (3) of Table 9 displays the correlation between charter school special education math effects and school practices. Columns (4) and (5) display the analogous correlations for ELL and other students. An index of "No Excuses" school practices,[34] strict behavior code, longer school day, and emphasis for high expectations in academics, characteristics that Angrist, Pathak, and Walters (2013); Dobbie and Fryer (2013) find linked to overall charter gains, are also positively correlated with special education and ELL student gains.

School characteristics that do not correlate with general education student gains, expenditure per pupil, student teacher ratio, teacher licensure, teacher experience, and teacher salary, also have a null or a negative effect on special needs student outcomes. Special needs school characteristics are weakly correlated with special needs charter effects (see Panel B of Table 9).

1.5.3 Peer Composition

Charter lotteries in the bottom quartile for special needs student representation have similar academic effects as those in the top quartile (see Table A14). The similar point estimates counter the idea that charter special needs gains stem from fewer special needs students in the classroom. Lotteries with an average of 41 percent of applicants with ELL status have over 0.2 standard deviation effects. Additionally, charter cohorts with the lowest special needs representation have gains of around 0.2 standard deviations, suggesting that economies of scale cannot fully explain the charter gains. The limited evidence that special needs economies of scale correlating with academic effects further supports the importance of general school practices in explaining special needs charter gains.

[33] BPS has 180 school days and 6.5 hours in the day.

[34] The "no excuses" index includes equal weight for discussion of the following items in the annual school report: high expectations for academics, high expectations for behavior, strict behavior code, college preparatory curriculum, core values in school culture, selective teacher hiring or incentive pay, emphasis on math and reading, uniforms, hires Teach for America teachers, Teaching Fellows, or AmeriCorps members, affiliated with Teach for America alumni, data driven instruction, and regular teacher feedback.

1.6 Conclusion

Using randomized admission lotteries, this paper finds strong positive effects of Boston's elementary, middle, and high school charters for special education and English Language Learner students. Charters generate substantial gains for special needs students in math and English standardized exams, English proficiency, and college preparation outcomes. Even the most disadvantaged special needs students perform better in charter schools compared to traditional public schools.

This paper documents the proportional representation of special needs students in charter lotteries in recent years. Even those with the highest need have close to proportional representation in charter lotteries. Furthermore, charters remove special needs classifications at a higher rate than traditional public schools and move special education students to more inclusive classrooms. These differences in classification practices make the proportion of special needs students in charters appear smaller.

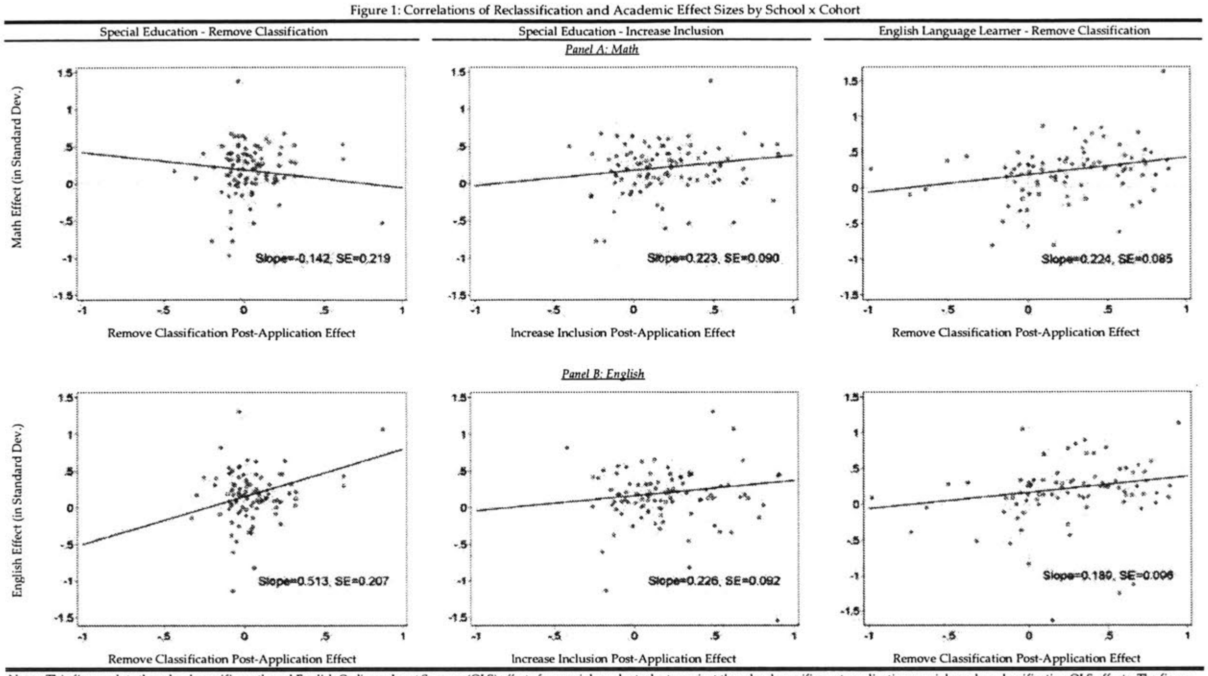
Also, charter attendance substantially decreases the special needs achievement gap. Among students attending BPS schools, special education students and ELL students score about 0.87 and 0.39 standard deviations respectively below non-special needs students in math. Since charters generate math gains of 0.268 standard deviations for special education students, one year in a charter reduces the special education achievement gap by 30.8 percent. ELL students score 0.345 standard deviations higher in charters, narrowing the ELL achievement gap by 88.4 percent.

The findings show that schools can boost special needs students' academic outcomes without the traditional set of special needs services. Frequent use of tutoring and data-driven instruction enables charters to identify and provide support to struggling students, regardless of special needs status. "No Excuses" school practices, strict behavior code, longer school day, and emphasis on high academic expectations positively correlate with charter school effectiveness for special needs and general education students.

I find no evidence that classification removal or increased inclusion lowers outcomes for students. Classification removal and increased inclusion can explain between 1 and 25 percent of the special needs achievement effects. Charter schools that generate large non-special needs student gains also generate gains for special needs students. Together, these findings imply that elements of the charter school experience that affect all students, not just those classified as having special needs, drive the positive gains for special needs students.

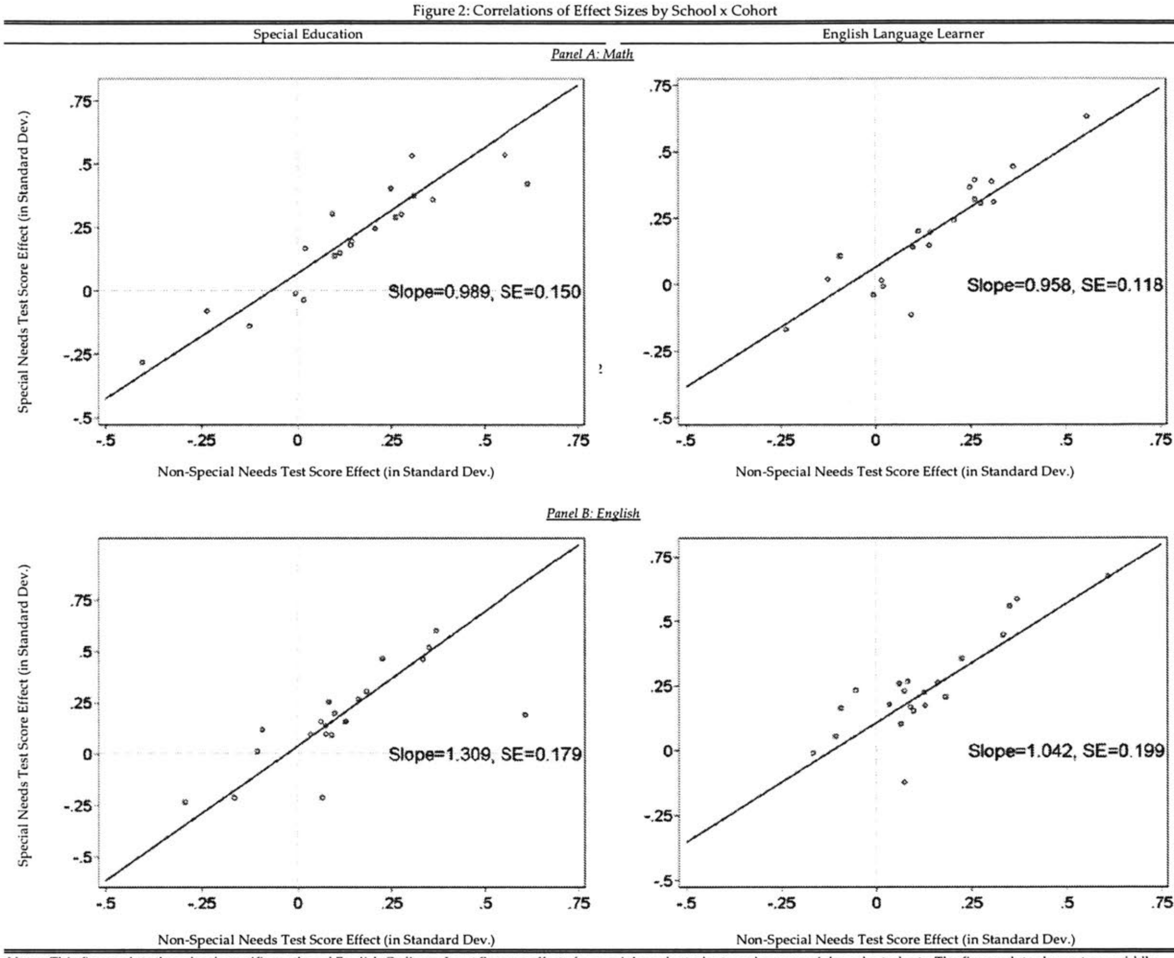
It is worth noting that the results apply to Boston charter lottery applicants. While special needs students are currently well represented in the charter lotteries, Boston charters could have different effects for the students who do not apply. By extension, my estimates may not reflect the effects of expanding the number of seats in Boston's charter sector or requiring charters to recruit more special needs students.

Figure 1: Correlations of Reclassification and Academic Effect Sizes by School x Cohort



Notes: This figure plots the school-specific math and English Ordinary Least Squares (OLS) effects for special needs students against the school-specific post-application special needs reclassification OLS effects. The figure plots elementary, middle, and high school estimates. Each dot represents a charter school application cohort. Experimental strata with samples too small to estimate are not displayed. The fitted line is the regression of the test score effect on the reclassification effect, weighted by the inverse of the average variance of the effects.

Figure 2: Correlations of Effect Sizes by School x Cohort



Notes: This figure plots the school-specific math and English Ordinary Least Squares effects for special needs students and non-special needs students. The figure plots elementary, middle, and high school estimates. Each dot represents a charter school application cohort. Experimental strata with samples too small to estimate are not displayed. The fitted line is the regression of the special needs test score effect on the non-special needs test score effect, weighted by the inverse of the average variance of the effects.

Table 1: Descriptive Statistics and Covariate Balance

	Boston Public School Students	All Lottery Applicants			Special Education at Baseline			English Language Learner at Baseline		
	Mean	Non-Offered Mean	Immediate Offer	Any Offer	Non-Offered Mean	Immediate Offer	Any Offer	Non-Offered Mean	Immediate Offer	Any Offer
Baseline Charateristics	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Female	0.480	0.503	0.010	0.001	0.342	0.012	0.013	0.482	0.006	-0.012
			(0.013)	(0.013)		(0.030)	(0.030)		(0.028)	(0.028)
Black	0.392	0.461	-0.023*	-0.017	0.477	0.005	-0.006	0.269	0.009	-0.002
			(0.013)	(0.013)		(0.031)	(0.031)		(0.025)	(0.024)
Latino/a	0.363	0.369	0.013	0.005	0.360	-0.015	-0.016	0.624	-0.035	-0.004
			(0.012)	(0.012)		(0.029)	(0.029)		(0.027)	(0.027)
Subsidized Lunch	0.753	0.749	0.002	-0.007	0.757	0.031	0.012	0.844	-0.003	0.001
			(0.011)	(0.011)		(0.024)	(0.025)		(0.020)	(0.018)
Baseline Math Test Score	-0.449	-0.407	0.016	-0.012	-1.002	-0.012	0.018	-0.736	0.017	-0.047
			(0.027)	(0.027)		(0.066)	(0.066)		(0.057)	(0.055)
Baseline English Test Score	-0.548	-0.455	-0.028	0.004	-1.214	-0.036	0.062	-0.980	-0.028	-0.003
			(0.028)	(0.028)		(0.069)	(0.068)		(0.062)	(0.060)
Special Education	0.226	0.192	0.007	-0.002	-	-	-	0.190	-0.008	0.001
			(0.011)	(0.011)	(0.003)	-	-		(0.022)	(0.022)
Substantially Separate Classroom	0.080	0.050	0.005	-0.004	0.260	0.016	-0.017	0.067	-0.021*	-0.008
			(0.005)	(0.006)		(0.025)	(0.026)		(0.011)	(0.012)
Partial Inclusion	0.056	0.057	0.008	0.002	0.296	0.021	0.014	0.059	0.015	0.011
			(0.007)	(0.007)		(0.030)	(0.030)		(0.016)	(0.015)
Full Inclusion	0.093	0.082	-0.005	-0.001	0.425	-0.035	-0.004	0.061	0.000	-0.001
			(0.007)	(0.007)		(0.030)	(0.030)		(0.014)	(0.013)
English Language Learner	0.231	0.258	-0.008	-0.003	0.254	-0.023	-0.010	-	-	-
			(0.011)	(0.011)		(0.026)	(0.026)		-	-
Beginning Proficiency	0.017	0.025	-0.006**	-0.007**	0.024	-0.007	-0.006	0.098	-0.019	-0.028**
			(0.003)	(0.003)		(0.006)	(0.005)		(0.012)	(0.013)
Intermediate Proficiency	0.071	0.121	0.002	0.005	0.144	0.008	-0.002	0.465	0.033	0.035
			(0.009)	(0.008)		(0.022)	(0.022)		(0.028)	(0.027)
Advanced Proficiency	0.049	0.058	0.001	0.004	0.029	-0.009	0.001	0.216	0.010	0.018
			(0.008)	(0.007)		(0.015)	(0.013)		(0.027)	(0.027)
Observations with School/Offer Type	194712	7591	5085	10408	1458	1007	2076	1956	1119	2188
P-value			0.661	0.661		0.592	0.924		0.499	0.995

Notes: This table shows descriptive statistics for Boston Public School (BPS) students and charter lottery applicants. Column (1) shows means for BPS attendees in charter application grades (Pre-K, K, 1, 3, 4, 5, and 8) for 2003-04 through 2013-14. Column (2) shows means for charter lottery applicants who did not receive offers. Columns (3) and (4) report coefficients from regressions of observed characteristics on immediate offers and any offers, controlling for experimental strata dummies. P-values come from tests of whether all non-test score coefficients equal zero. Baseline test scores are only available applicants to the 4th grade or higher. Columns (5) through (10) report analogous results for the subsample with special education classification and ELL classification in the lottery application year.

*significant at 10%; **significant at 5%; ***significant at 1%

Table 2: Post-Application Special Education Classification

	Any Special Education		Substantially Separate Classroom		Partial Inclusion		Full Inclusion		Move to More Inclusive Classroom	
	Trad. Public mean	Charter effect	Trad. Public mean	Charter effect	Trad. Public mean	Charter effect	Trad. Public mean	Charter effect	Trad. Public mean	Charter effect
Baseline Status	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					Panel A: Elementary School					
All Special Education	0.907	-0.190***							0.161	0.294**
		(0.069)								(0.125)
N		254								254
Substantially Separate Classroom	0.903	-0.016	0.629	-0.401**	0.016	0.066	0.177	0.556***	0.226	0.539***
		(0.107)		(0.169)		(0.093)		(0.124)		(0.175)
N		72								72
Partial Inclusion	0.895	-0.445**			0.500	-0.551**	0.289	0.226	0.342	0.464
		(0.226)				(0.222)		(0.254)		(0.287)
N		49								49
Full Inclusion	0.910	-0.144					0.690	0.034	0.060	0.141
		(0.136)						(0.171)		(0.131)
N		126								126
New Students (No Prior Special Ed. Evaluation)	0.014	-0.011*	0.001	-0.002	0.003	0.003	0.008	-0.008*		
		(0.006)		(0.002)		(0.004)		(0.005)		
N		2665								
					Panel B: Middle School					
All Special Education	0.927	-0.161***							0.125	0.301***
		(0.044)								(0.049)
N		1726								1726
Substantially Separate Classroom	0.976	-0.140**	0.897	-0.683***	0.036	0.016	0.028	0.259***	0.071	0.286***
		(0.064)		(0.098)		(0.066)		(0.076)		(0.092)
N		403								403
Partial Inclusion	0.935	-0.143**			0.665	-0.645***	0.156	0.413***	0.193	0.462***
		(0.066)				(0.087)		(0.079)		(0.084)
N		611								611
Full Inclusion	0.886	-0.226***					0.692	-0.100	0.097	0.117**
		(0.077)						(0.090)		(0.059)
N		683								683
					Panel C: High School					
All Special Education	0.841	0.030							0.180	0.112
		(0.103)								(0.092)
N		1173								1173
Substantially Separate Classroom	0.975	-0.442***	0.819	-0.468***	0.071	-0.171*	0.042	0.065	0.130	0.101
		(0.077)		(0.123)		(0.095)		(0.077)		(0.126)
N		333								333
Partial Inclusion	0.884	0.270			0.589	-0.472**	0.179	0.633***	0.254	0.470***
		(0.185)				(0.191)		(0.172)		(0.177)
N		344								344
Full Inclusion	0.726	0.335*					0.511	0.341*	0.156	-0.147
		(0.187)						(0.198)		(0.132)
N		469								469

Notes: This table reports two-stage least squares estimates of the effects of Boston charter enrollment on special education classification and level of classroom inclusion in the fall following the charter lottery. Immediate and waitlist offer dummies instrument for enrollment in charter schools. Estimation is run separately by baseline classroom inclusion type. Effects persist for up to two years following the charter application. All models control for gender, ethnicity, female x minority interaction, baseline special education, baseline ELL, baseline subsidized lunch, experimental strata, year-applied dummies, and grade-applied dummies. Estimates for elementary and middle school sample pool post-lottery outcomes for grades 3-5 and 5-8 respectively and cluster by student identifier and school-grade-year.
*significant at 10%; **significant at 5%; ***significant at 1%

Table 3: Post-Application English Language Learner Classification

	Remain English Language Learner	
	Trad. Public mean	Charter effect
Baseline Status	(1)	(2)
Panel A: Elementary School		
All English Language Learners	0.900	-0.198***
		(0.075)
N		818
Beginning Proficiency	0.989	-0.033
		(0.029)
N		110
Intermediate Proficiency	0.986	-0.126*
		(0.074)
N		349
Advanced Proficiency	0.739	-0.604**
		(0.297)
N		25
New Non-native English Speaking Students	0.637	-0.261***
(No Prior English Lang. Learner Evaluation)		(0.061)
N		856
Panel B: Middle School		
All English Language Learners	0.794	-0.328***
		(0.059)
N		2231
Beginning Proficiency	1.000	0.000
		(0.000)
N		130
Intermediate Proficiency	0.953	-0.420***
		(0.075)
N		1105
Advanced Proficiency	0.570	-0.199**
		(0.085)
N		774
Panel C: High School		
All English Language Learners	0.802	-0.375***
		(0.140)
N		714
Beginning Proficiency	1.000	-0.042
		(0.047)
N		47
Intermediate Proficiency	0.921	-0.384***
		(0.143)
N		356
Advanced Proficiency	0.618	-0.152
		(0.375)
N		209

Notes: This table reports two-stage least squares estimates of the effects of Boston charter enrollment on English Language Learner classification in the fall following the charter lottery. Immediate and waitlist offer dummies instrument for enrollment in charter schools. Estimation is run separately by baseline English proficiency level. Effects persist for up to two years following the charter application. See Table 2 notes for detailed regression specifications. *significant at 10%; **significant at 5%; ***significant at 1%

Table 4: Test Score Effects by Baseline Special Needs Status

	Special Education		English Language Learner		Non-Special Needs	
	Trad. Public mean	Charter effect	Trad. Public mean	Charter effect	Trad. Public mean	Charter effect
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Elementary School			
Math	-0.737	0.309**	-0.326	0.386***	-0.087	0.184***
		(0.123)		(0.101)		(0.046)
N		171		541		591
English	-1.186	0.478***	-0.519	0.360***	-0.128	0.199***
		(0.148)		(0.100)		(0.046)
N		169		539		590
			Panel B: Middle School			
Math	-1.025	0.245***	-0.550	0.306***	-0.129	0.257***
		(0.059)		(0.052)		(0.026)
N		3608		4369		12053
					0.002949852	
English	-1.176	0.177***	-0.763	0.200***	-0.102	0.142***
		(0.062)		(0.050)		(0.024)
N		3595		4373		11986
			Panel C: High School			
Math	-0.920	0.240***	-0.419	0.412***	-0.086	0.333***
		(0.092)		(0.139)		(0.053)
N		1030		493		3926
English	-1.069	0.160	-0.758	0.412**	-0.135	0.214***
		(0.099)		(0.170)		(0.042)
N		1050		503		3974

Notes: This table reports the two-stage least squares estimates of the effects of years spent in charter schools on test scores. Immediate and waitlist offer dummies instrument for years spent in charter schools. Columns (1) and (2) show estimates for applicants with baseline special education status, columns (3) and (4) for applicants with baseline English Language Learner classification, and Columns (5) and (6) for other students. All models control for gender, ethnicity, female x minority interaction, baseline special education, baseline ELL, baseline subsidized lunch, experimental strata, year-applied dummies, and grade-applied dummies. Estimates for elementary and middle school sample pool post-lottery outcomes for grades 3-5 and 5-8 respectively and cluster by student identifier and school-grade-year. Estimates for the high school sample include only scores for tenth grade and cluster by school-grade-year.
*significant at 10%; **significant at 5%; ***significant at 1%

Table 5: Effects on Longer-Term Outcomes by Special Needs Status

	Special Education		English Language Learner		Non-Special Needs	
	Trad. Public mean	Charter effect	Trad. Public mean	Charter effect	Trad. Public mean	Charter effect
	(1)	(2)	(3)	(4)	(5)	(6)
		Panel A: High School Performance				
Meets High School Proficiency Graduation Requirement	0.376	0.244**	0.561	0.367**	0.766	0.154***
		(0.110)		(0.162)		(0.054)
Eligible for State Merit Scholarship	0.042	0.113**	0.128	0.287**	0.257	0.340***
		(0.051)		(0.129)		(0.058)
N		1007		484		3892
		Panel B: AP and SAT Exams				
Took AP	0.102	0.363***	0.299	0.403**	0.336	0.295***
		(0.089)		(0.182)		(0.062)
Number of AP Exams	0.207	0.711***	0.773	0.179	0.003	1.051***
		(0.205)		(0.683)		(0.240)
Took SAT	0.460	0.090	0.617	-0.182	0.640	0.137**
		(0.109)		(0.212)		(0.055)
AP Score 3 or Higher	0.050	0.088	0.182	0.102	0.159	0.108*
		(0.054)		(0.203)		(0.055)
N		961		363		3579
SAT Score (for takers)	1071.2	115.4**	1164.3	76.3	1319.3	77.6**
		(54.0)		(119.1)		(33.0)
N		503		246		2537
		Panel C: High School Graduation				
Four-year Graduation	0.577	-0.365***	0.674	-0.364**	0.687	-0.012
		(0.107)		(0.164)		(0.053)
N		961		363		3579
Five-year Graduation	0.664	-0.154	0.716	-0.457	0.772	0.014
		(0.116)		(0.315)		(0.054)
Dropout	0.184	-0.100	0.135	0.329	0.134	-0.031
		(0.092)		(0.221)		(0.042)
		767		196		2984

Notes: This table reports the two-stage least squares estimates of the effects of charter enrollment on longer-term outcomes. Immediate and waitlist lottery offer dummies instrument for any charter enrollment by the end of 10th grade. The 10th-grade state standardized exam score determines whether students meet the high school proficiency graduation requirement (called Massachusetts Competency Determination) and the State Merit College Scholarship (John and Abigail Adams Scholarship). The latter has higher standards for eligibility. Panel A's sample includes students projected to graduate in Spring 2008 – 2016. Panel B and four-year graduation includes students projected to graduate in Spring 2008 - 2015. Five-year graduation and dropout are restricted to students projected to graduate in 2008 – 2014. All models control for gender, ethnicity, female x minority interaction, baseline special education, baseline ELL, baseline subsidized lunch, experimental strata, year-applied dummies, and grade-applied dummies. Estimates cluster by 10th grade school and year.
*significant at 10%; **significant at 5%; ***significant at 1%

Table 6: Test Score Effects for Special Needs Subgroups

Panel A: Baseline Special Education Level of Classroom Inclusion

		Substantially Separate Classroom		Partial Inclusion		Full Inclusion	
		Trad. Public mean	Charter effect	Trad. Public mean	Charter effect	Trad. Public mean	Charter effect
		(1)	(2)	(3)	(4)	(5)	(6)
Math		-1.392	0.256**	-1.148	0.328***	-0.606	0.269***
			(0.114)		(0.093)		(0.072)
	N		1004		1656		2090
English		-1.614	0.204	-1.243	0.171	-0.791	0.216***
			(0.135)		(0.104)		(0.065)
	N		1004		1658		2092

Panel B: Baseline English Language Learner English Proficiency Level

		Beginning Proficiency		Intermediate Proficiency		Advanced Proficiency	
		Trad. Public mean	Charter effect	Trad. Public mean	Charter effect	Trad. Public mean	Charter effect
		(1)	(2)	(3)	(4)	(5)	(6)
Math		-1.392	0.404***	-0.652	0.370***	0.003	0.296***
			(0.138)		(0.062)		(0.072)
	N		289		2710		1799
English		-1.961	0.498***	-0.904	0.315***	-0.251	0.162**
			(0.145)		(0.057)		(0.063)
	N		292		2719		1801

Notes: This table reports two-stage least squares estimates of the effects of years spent in charter schools for baseline special needs subgroups: by special education level of classroom inclusion and by English proficiency level. The sample includes elementary, middle, and high school lottery applicants. See Table 4 notes for detailed regression specifications.

*significant at 10%; **significant at 5%; ***significant at 1%

Table 7: Test Score Effects by Pre-lottery Test Performance and Special Needs Status

		Special Education		English Language Learner		Non-Special Needs	
Pre-lottery Test Performance within Special Needs Status		Trad. Public mean (1)	Charter effect (2)	Trad. Public mean (3)	Charter effect (4)	Trad. Public mean (5)	Charter effect (6)
				Panel A: Math			
Bottom third		-1.699	0.255***	-1.337	0.248***	-0.905	0.357***
			(0.088)		(0.090)		(0.040)
	N		1360		1491		5077
Middle third		-1.067	0.219***	-0.539	0.334***	-0.100	0.284***
			(0.078)		(0.065)		(0.032)
	N		1540		1613		5285
Top third		-0.302	0.314***	0.254	0.328***	0.592	0.185***
			(0.069)		(0.061)		(0.026)
	N		1597		1706		5123
				Panel B: English			
Bottom third		-1.812	0.189*	-1.474	0.400***	-0.789	0.175***
			(0.110)		(0.073)		(0.040)
	N		1418		1486		5021
Middle third		-1.187	0.114	-0.722	0.305***	-0.080	0.173***
			(0.077)		(0.076)		(0.028)
	N		1487		1580		5224
Top third		-0.443	0.131**	0.009	0.140**	0.451	0.106***
			(0.064)		(0.056)		(0.026)
	N		1592		1617		5213

Notes: This table reports the two-stage least squares estimates of the effects of years spent in charter schools on test scores by baseline test performance and special needs status. Columns (1) and (2) report estimates for the baseline special education students by terciles of their baseline math and English test scores. Columns (3) and (4) report these estimates for baseline English Language Learners and Columns (5) and (6) for baseline non-special needs students. The sample includes elementary, middle, and high school lottery applicants. See Table 4 notes for detailed regression specifications.

*significant at 10%; **significant at 5%; ***significant at 1%

Table 8: Multiple Endogenous Variable Estimates for Test Scores

	Special Education							English Language Learner						
	2SLS	2SLS	2SLS	OLS	2SLS	2SLS	OLS	2SLS	2SLS	2SLS	OLS	2SLS	2SLS	OLS
Endogenous Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
						Panel A: Math								
Charter	0.210***	0.205***	0.204***	0.229***	0.172***	0.164***	0.187***	0.321***	0.282***	0.344***	0.292***	0.239***	0.212***	0.206***
	(0.034)	(0.036)	(0.040)	(0.018)	(0.037)	(0.039)	(0.016)	(0.027)	(0.038)	(0.049)	(0.027)	(0.033)	(0.040)	(0.017)
First-stage F	13.470	12.358	9.213		9.929	8.786		11.071	6.205	4.330		8.523	5.477	
Remove Classification		0.289	0.275	0.231***		0.334	0.214***		0.174	0.537**	0.124***		0.130	0.028
		(0.356)	(0.339)	(0.071)		(0.360)	(0.056)		(0.118)	(0.233)	(0.043)		(0.115)	(0.032)
First-stage F		10.061	8.567			10.178			27.305	1.040			26.639	
Charter X Remove Classification			0.014	-0.031						-0.222*	-0.071**			
			(0.100)	(0.049)						(0.119)	(0.033)			
First-stage F			13.623							3.026				
School Quality Index					0.192***	0.201***	0.203***					0.332***	0.325***	0.337***
					(0.072)	(0.070)	(0.029)					(0.078)	(0.079)	(0.044)
First-stage F					9.849	9.662						17.189	13.826	
Overid. p-value		0.221	0.210		0.472	0.346			0.030	0.046		0.174	0.157	
N				3693							3830			
						Panel B: English								
Charter	0.172***	0.167***	0.167***	0.193***	0.161***	0.154***	0.176***	0.300***	0.243***	0.279***	0.224***	0.242***	0.195***	0.176***
	(0.037)	(0.038)	(0.043)	(0.018)	(0.040)	(0.042)	(0.018)	(0.030)	(0.042)	(0.051)	(0.022)	(0.036)	(0.046)	(0.017)
First-stage F	13.221	12.380	9.472		9.868	8.920		11.095	6.026	4.296		8.471	5.371	
Remove Classification		0.310	0.315	0.319***		0.324	0.270***		0.258**	0.467*	0.159***		0.228*	0.085**
		(0.357)	(0.341)	(0.065)		(0.356)	(0.057)		(0.126)	(0.255)	(0.043)		(0.122)	(0.034)
First-stage F		10.037	8.434			10.152			27.948	1.104			27.272	
Charter X Remove Classification			-0.004	-0.057						-0.128	-0.051*			
			(0.115)	(0.048)						(0.129)	(0.030)			
First-stage F			13.358							3.037				
School Quality Index					0.054	0.062	0.071**					0.233***	0.222***	0.187***
					(0.078)	(0.075)	(0.031)					(0.079)	(0.080)	(0.037)
First-stage F					9.786	9.689						17.586	14.057	
Overid. p-value		0.430	0.398		0.406	0.409			0.025	0.025		0.043	0.036	
N				3705							3844			

Notes: This table displays multiple endogenous variable two-stage least squares (2SLS) and Ordindary Least Squares (OLS) estimates of the effects of time in charter, classification removal, classification removal in charters, and school quality on test scores for students with special needs status at the time of the lottery. School quality is the sum of the non-special needs math and English school 2SLS effects in a model where Boston Public Schools (BPS) is the omitted district. Instruments include individual charter offers and individual charter offers interacted with a predicted reclassification index. See data appendix for details of the predicted reclassification index. The sample includes middle, and high school lottery applicants with baseline test scores. See Table 4 notes for detailed regression specifications.

*significant at 10%; **significant at 5%; ***significant at 1%

Table 9: School Characteristics and Correlation with Charter Effects

			Correlates of School Practices and Charter Effectiveness by Special Needs Group		
School Practices	Boston Public Schools Mean (1)	Charter Sample Mean (2)	Special Education (3)	English Language Learner (4)	Non-Special Needs (5)
		Panel A: General School Characteristics			
"No excuses" index		0.826	0.285	0.505***	0.884***
		(0.120)	(0.446)	(0.104)	(0.304)
Strict behavior code		0.818	0.187**	0.194***	0.247***
		(0.395)	(0.094)	(0.042)	(0.072)
Longer school year		0.591	-0.010	0.130*	-0.036
		(0.503)	(0.065)	(0.078)	(0.061)
Longer school day		0.955	0.335***	0.409***	0.433***
		(0.213)	(0.032)	(0.051)	(0.025)
Emphasize high academic expectations		0.955	0.335***	0.409***	0.433***
		(0.213)	(0.032)	(0.051)	(0.025)
Total per pupil expenditure	$18,766	$17,079	0.000*	0.000	0.000**
		($2,438)	(0.000)	(0.000)	(0.000)
Student to teacher ratio	12.678	12.126	-0.006	-0.015***	-0.008
	(1.790)	(3.092)	(0.015)	(0.004)	(0.012)
% of Teachers licensed in teaching assignment	94.974	52.265	-0.003	-0.005*	-0.003**
	(4.554)	(17.173)	(0.002)	(0.003)	(0.001)
Years of teaching experience in Massachusetts	12.353	2.625	-0.023	-0.085***	-0.061***
	(3.355)	(1.489)	(0.026)	(0.029)	(0.016)
Average teacher salary	$78,237	$65,380	0.000	0.000***	0.000
		(10774.157)	(0.000)	(0.000)	(0.000)
		Panel B: Special Needs School Characteristics			
Special education compliance index	0.685	0.723	-0.323		
		(0.041)	(0.517)		
English Language Learner compliance index	0.511	0.696		0.335	
		(0.066)		(0.629)	
Special education remove classification effect		0.068	-0.069		
		(0.111)	(0.419)		
Special education increased inclusion effect		0.225	0.379*		
		(0.229)	(0.194)		
English Language Learner remove classification effect		0.300		0.347	
		(0.193)		(0.260)	
Special education instructional spending per pupil	$2,299	$988	0.000		
	(2,008)	(519)	(0.000)		
Special needs staff to student ratio	0.030	0.015	-1.445	6.048	
	(0.012)	(0.011)	(4.034)	(4.894)	
N	114	22		22	

Notes: This table reports coefficients from regressions of school-specific treatment effects for each special needs subgroup on 2012-13 school practices in Columns (3) - (5) (one regression for each school practice and student type combination). School-level BPS data is weighted by the proportion of lottery applicants who enrolled in the school. Only district-level data was available for total per pupil expenditure and the compliance indices. All costs are in 2015 CPI-U adjusted dollars. Column (2) displays the mean characteristics for sample charter schools with lottery cohorts with test results (those that reach grade 3 or higher by 2013-2014). Data come from charter school annual reports, Massachusetts Department of Elementary and Secondary Education School District Profiles, Education Personnel Information Management System, School District Expenditures, and Charter School End of Year Financial Reports. Data also come from MA DESE charter inspections including Renew Inspection Reports, site visits, Summary of Reviews, and Coordinated Program Reviews. See the Data Appendix for information on the "no excuses" index.

*significant at 10%; **significant at 5%; ***significant at 1%

1.7 Appendix

1.7.1 Data Appendix

This paper utilizes data from several sources. The charter applicant information was collected from the individual charter schools. This data includes immediate and waitlist offers as well as factors that impact an applicant's ranking in the lottery, including sibling status, disqualifications, late applications, and applying from outside of Boston. Student demographic and school enrollment data comes from the Student Information Management System (SIMS), which includes all of the public school students in Massachusetts. Student standardized test scores come from the state database for the Massachusetts Comprehensive Assessment System (MCAS). The paper also uses English proficiency exam data, SAT and AP records, and the Massachusetts Education Personnel Information Management Systems (EPIMS) data. This Appendix describes each data source and explains the process used to clean and match them.

1.7.1.1 Lottery Data

Massachusetts legally requires charters to admit students via lottery when there are more applicants than seats for a given grade. This paper uses charter lottery records from Spring 2004 to Spring 2014. The sample includes 10 elementary schools, 10 middle schools, five schools serving middle and high schools, and five high schools. For the full list of schools and years, see Appendix Table A1. Because of limited public pre-k enrollment, I exclude Spring 2014 pre-k lotteries from analysis due to relatively low match rates to the administrative data.

The lottery data typically includes applicants' names, dates of birth, and lottery and waitlist offer information. Offers to attend the charter school can occur on the day of the lottery (referred to here as *immediate* $offer$) or after the day of the lottery when students from the randomly sequenced waitlist are contacted as seats become available (referred to as *waitlist* $offer$).

In some years, certain schools gave all applicants offers, so only the immediate offer instrument, not the waitlist offer instrument, can be used for that cohort. For a few lotteries, records did not distinguish the timing of offers, so only one instrument can be used for these cohorts. In other cases, no waitlist offers were given to non-siblings. The lotteries affected by these circumstances are noted in Appendix Table A1.

1.7.1.2 SIMS Data

This research uses SIMS data from the 2003-2004 school year through the 2014-2015 school year. Each year has a file from October and the end of the school year. The observations are at the individual student level. Each student has only one observation in each data file, except when students switch grades or schools within year. The data includes a unique student identifier known as the SASID. This identifier is used to match the SIMS data to the MCAS, English Proficiency Exam, and SAT and AP data described below.

The SIMS dataset contains grade level, year, name, date of birth, gender, race, special education and limited English proficiency status, level of classroom inclusion and type of disability for special education students, free or reduced price lunch status, school attended, suspensions, attendance rates, native language, and immigrant status. Students appear in the state administrative data if they attend a Massachusetts public school. Those who enroll in private or parochial schools or move out of state have missing outcomes data in years they are not in Massachusetts public schools. A student is coded as attending a charter in a school year if there is any record in the SIMS of attending a charter that year. Students who attend more than one charter school within a year are assigned to the charter they attended the longest. If a student attended more than one traditional public school in a year, the analysis uses the school where the student attended for the majority of the year. In the case of attendance ties, the school for the analysis sample was randomly chosen. For baseline characteristics, I designate a student as special education, ELL, or free/reduced lunch if they have this status for either the October or end-of-year file for the application year.

1.7.1.3 State Standardized Exam (MCAS) Data

Massachusetts Comprehensive Assessment System (MCAS) data is used for the 2003-04 through 2013-2014 school years. An observation in the MCAS data refers to an individual student's test score results for a given grade level and year. The MCAS math and English Language Arts (ELA) is administered in grades 3 through 8 and grade 10. Baseline math and ELA scores in the year of charter application are used to check the balance for middle and high school lotteries. The raw test scores are standardized to have a mean of zero within a subject-grade-year in Massachusetts.

1.7.1.4 English Proficiency Exam (MEPA/ACCESS)

English Language Learners in kindergarten through 12th grade in Massachusetts take an annual English proficiency exam. From 2005-2012, the state used the Massachusetts English Proficiency Assessment (MEPA), and starting in 2013, the state switched to the Assessing Comprehension and Communication in English State-to-State for English Language Learners (ACCESS). I standardize the exam scores to center around the state mean for each year. I use state recommendations for interpreting the scores of the exam to categorize students as beginning, intermediate, or advanced English proficiency.

1.7.1.5 SAT and AP Data

I use SAT and AP data files provided to the Massachusetts Department of Elementary and Secondary Education by the College Board. The data include scores on all AP and SAT tests for students projected to graduate in 2008 through 2015. For students who took the SAT more than once, their data includes only the most recent exam score.

1.7.1.6 Staff Data

I develop school level totals of full-time equivalent teachers and staff by various categories using the Massachusetts Education Personnel Information Management Systems (EPIMS) data. I use the state designations for staff type (i.e.. special education therapist, ELL co-teacher/support content) and generate a total number of full-time equivalent teachers in each staff position for that school. This means that if one school has two half-time ELL teachers, they are counted as having one full-time equivalent ELL teacher. The EPIMS data ranges from the 2007-08 through the 2013-14 school years. I use a snapshot of the school staffing from October of these years.

1.7.1.7 Matching Data Sets

Lottery records were matched to the state administrative student-level data using applicants' names, date of birth, grade, and year. The applicants who uniquely and exactly match the grade, year, name, and date of birth (if available) in the state records are assigned the matched SASID. Then the names in the lottery and SIMS data are stripped of spaces, surnames (i.e.. Jr. IV), hyphens, and apostrophes. Students who exactly match after that cleaning process are also assigned the matched SASID. Then reclink, a fuzzy matching STATA program, is used to suggest potential matches for the unmatched students. This matches students with slight spelling differences and those who appear in one grade older or younger than the lottery application grade. These suggested matches are hand checked for accuracy. The remaining unmatched students are searched for by hand in the data. Students in this category were not matched in the earlier methods because their names were misspelled or their first and last names were recorded in the wrong field.

This matching process successfully assigns most applicants a unique student identifier. Appendix Table A15 shows the match rates to the administrative data for each year. Overall, 91.2 percent of applicants to elementary lotteries, 94.9 percent of applicants for middle school, and 96 percent of applicants for high school matched. Any student who enrolls in private, parochial, or out-of-state school does not appear in the state records.

Students with offers are significantly more likely to match to the data by 4.3 percent for elementary school and 3.8 percent for middle school. There is no significant difference for high school. This means that elementary and middle school applicants without offers are slightly more likely to go to private, parochial, or out-of-state schools. As a result, my findings show causal estimates for the set of students who ultimately enroll in Massachusetts Public Schools.

1.7.1.8 Sample Restrictions

Appendix Table A16 shows the sample restrictions imposed upon the raw lottery records. The sample excludes duplicate applicants within an individual school's lottery and applicants who receive higher or lower preference in the lottery. Those with higher or lower preference include late applicants, those who apply to the wrong grade, out-of-area applicants, and siblings. These groups generally have no variation in offer status. If a student applied to multiple charters in different years, I keep only the first application year for that student. Except for estimating the effect of charter attendance on initial special needs designation for new Massachusetts public school students, the sample is further restricted to those with baseline demographics data. With the restrictions imposed, the original raw elementary school sample of 13,281 is narrowed to 6,569. For middle and high school, the raw samples of 24,170 and 18,688 are restricted to 9,501 and 6,555 respectively.

1.7.1.9 Pre-lottery Reclassification Likelihood Estimation

I estimate the pre-lottery reclassification likelihood index in the sample of Boston students who do not apply for charter schools using the following:

$$L_i = \lambda T_i + \alpha_{4t} + \beta_{4g} + \epsilon_{igts} \tag{1.7}$$

where T_i represents a vector of baseline student characteristics including gender, race, free or reduced price lunch, suspensions, days truant, and test scores. The estimation for special education students includes baseline level of classroom inclusion and the estimation for ELLs includes an indicator for native Spanish speakers and the baseline English proficiency exam. Pre-lottery reclassification likelihood index L_i is estimated separately for the different types of reclassification (special education classification removal, special education increased inclusion, and ELL classification removal). I use the coefficients from equation (4) to estimate the pre-lottery reclassification likelihood index on the charter analysis sample. I center the index around the BPS mean within a grade-year.

Figure A6 visualizes the positive relationship between the proportion of students reclassified at different pre-lottery reclassification likelihood values. Charter schools reclassify a higher proportion of students at each pre-lottery reclassification likelihood score compared to traditional public schools.

1.7.2 Threats to Validity

1.7.2.1 Selective Attrition

At the time of the lottery, students with and without random charter offers should be similar. Differential attrition by offer status may lead to selection bias. For example, if not receiving a charter offer makes students less likely to attend Massachusetts public schools, not receiving an offer may alter the likelihood that a student appears in the data.[35] Differential attrition generates selection bias. To test for selection bias, I test the impact of charter offers on the probability that lottery applicants contribute to state math and English exam scores and whether they have a non-missing special needs status post-lottery.[36] Small differences in the follow-up rates by offer status imply that limited selection bias from differential attrition.

Differential attrition for middle and high school lottery applicants with baseline special needs is not statistically significant, as documented in Table A17. Elementary school lotteries have some differential attrition. Special needs students with charter offers are marginally more likely to take a state math or English exam. These differences are fairly small. Elementary ELL students with charter offers are 2.8 percentage points more likely to contribute to exam data than students without charter offers, 83 percent of whom take the exams. These relatively small differences seem unlikely to explain the elementary school exam results. For classification, 21.2 and 8.1 percent respectively of the non-offered special education and ELL elementary applicants attrit from the data, compared to essentially none of those with offers. These differences are significant and substantial, but they are not large enough to explain the ELL classification effect or to fully explain the special education classification effects.

1.7.2.2 School Switching

Charter critics often argue that large achievement gaps between charter and district schools stem in part from charters encouraging lower performing students to leave. This paper's results are not directly affected by whether students enroll or remain in charter schools because the lottery offer status comparisons (the two-stage least squares reduced forms) drive the estimates. The group with lottery offers includes those who enroll and remain in charters as well as those who switch to other schools. Similarly, the group without lottery offers includes some students who manage to eventually enroll in a charter school.

However, excess school switching in charters could potentially inflate my estimates if students who leave would generate negative peer effects (i.e. through disruption). Therefore, Table A18 investigates whether students in charters and traditional publics move schools one year following the lottery at different rates. The lottery applicant population appears very mobile: roughly 50 percent of special needs elementary and middle and 30 percent of high school traditional public school students switch schools.

For elementary and middle school, a large portion of these school moves are mechanical. When I exclude applicants who need to switch schools because they reach the highest grade offered in their school, 30.8 percent of special education and 21.2 percent of ELL elementary applicants in traditional publics switch schools. Similarly, switch rates drop to around 15 percent for middle school special needs applicants in traditional public schools.

The switching rate for elementary and middle school special education students is not statistically

[35] Students who leave the state or enroll in private or parochial schools do not appear in the data.

[36] Post-lottery is defined as the October 1 after the lottery occurs.

significantly different in charter compared to traditional public schools. Elementary ELL students are 13.8 percentage points less likely to switch schools in charter schools. In middle school, ELL switching rates in charter schools are marginally significantly lower by 6.3 percentage points.

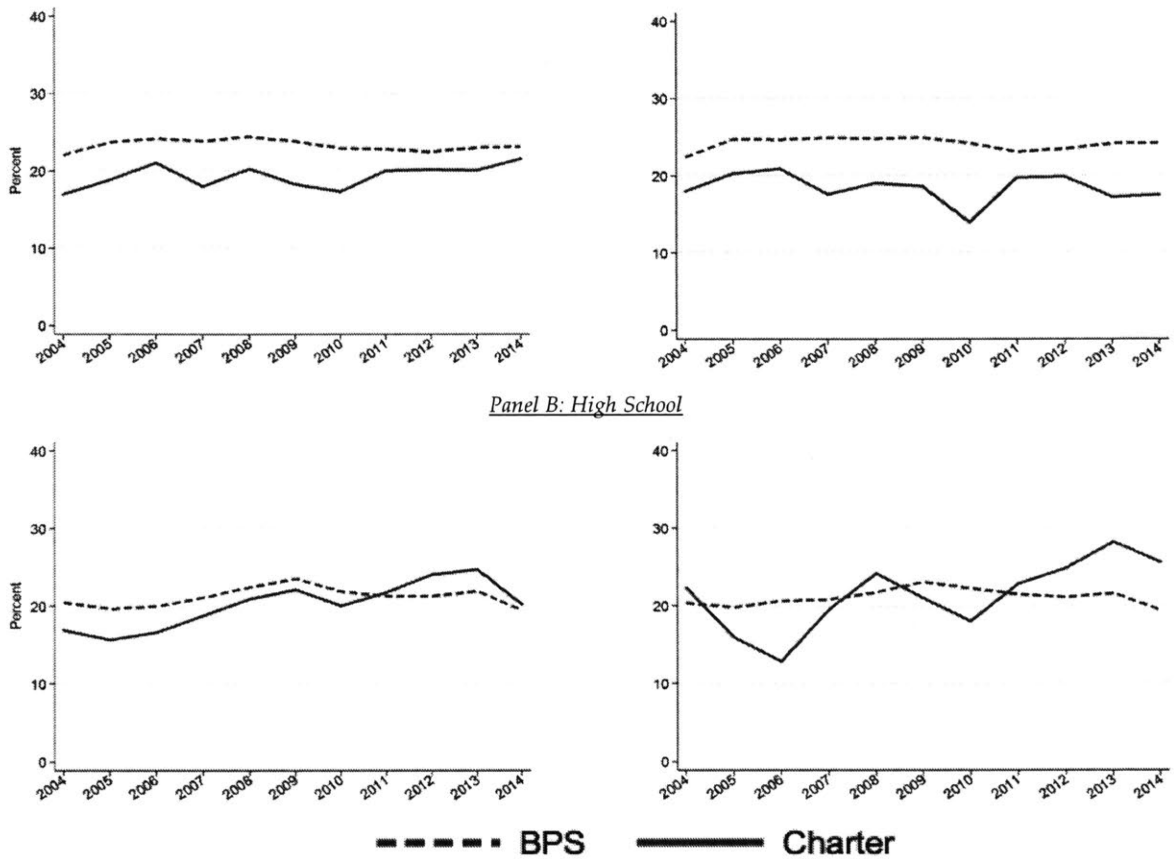
Special education high school applicants are 29.9 percentage points more likely to switch in charters, more than double the school movement rate in traditional public schools. The differential switching comes from two early years. Without these years in the sample, the switching rates of special education students in charters and traditional public schools are not statistically significantly different, and the test score findings are essentially unchanged.

The estimates for ELL high school students are noisy, but not significantly different across school type. Since special needs students are overall similarly or less mobile in charters, it is unlikely that high mobility out of charters drives the main results.

Figure A1: Special Education Prevalence in Charters and Boston Public Schools (BPS)

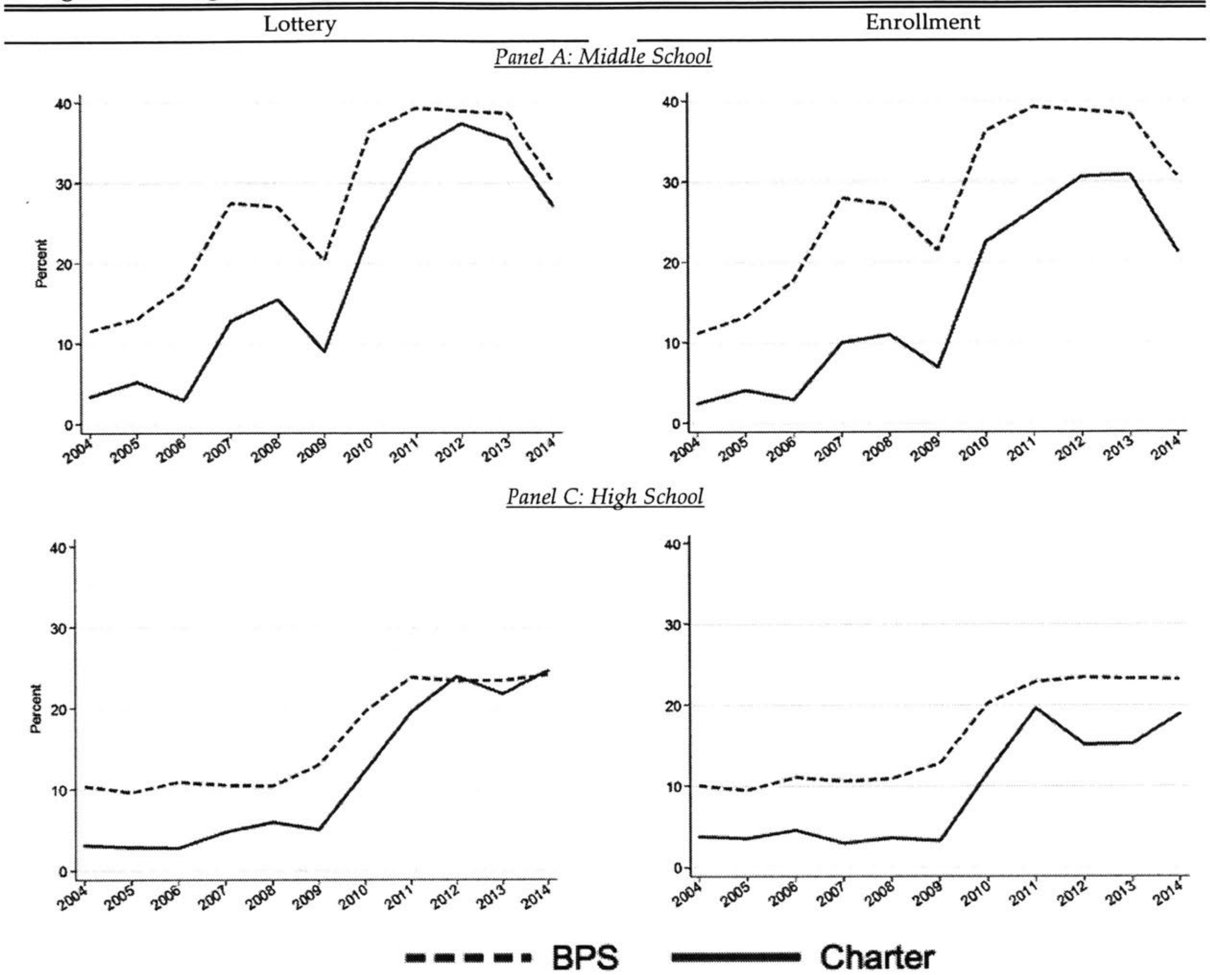
Lottery	Enrollment

Panel A: Middle School



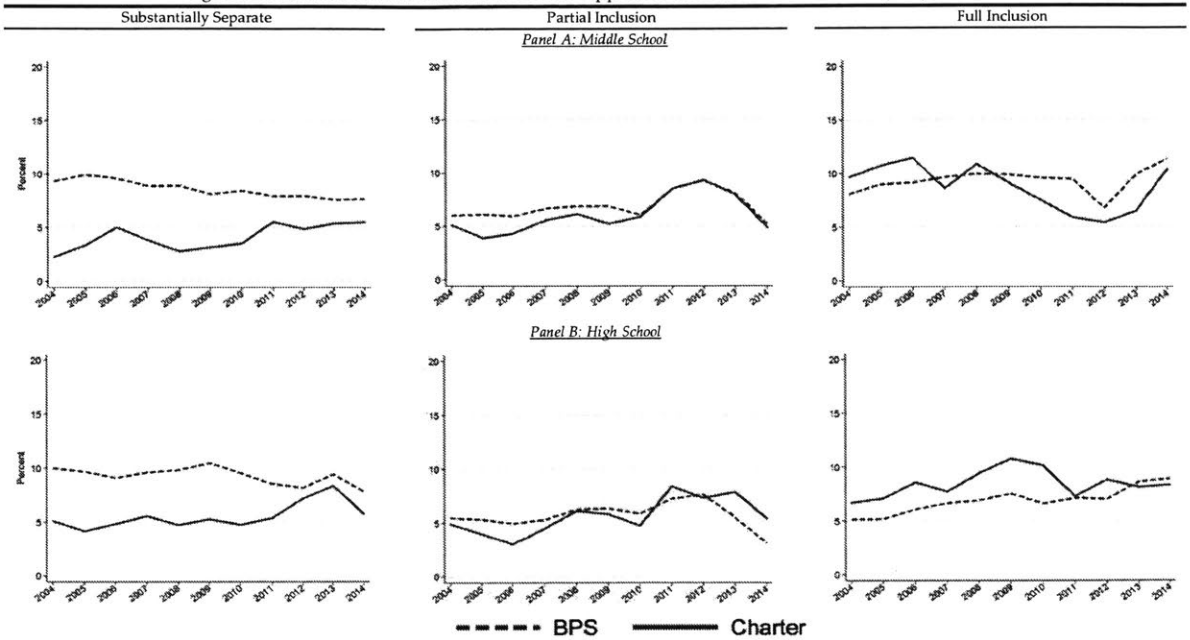
Notes: The graphs on the left plot the percent of students with a special education status at the time of the lottery for charter applicants and Boston Public School (BPS) students in charter application grades (4, 5, and 8). The graphs on the right plot the percent of students with special education status at the time of the lottery for charter enrollees and BPS students in charter entry grades (5, 6, and 9). Using the special education status at the time of the lottery ignores any post-lottery changes to classification.

Figure A2: English Language Learner Prevalence in Charters and Boston Public Schools (BPS)



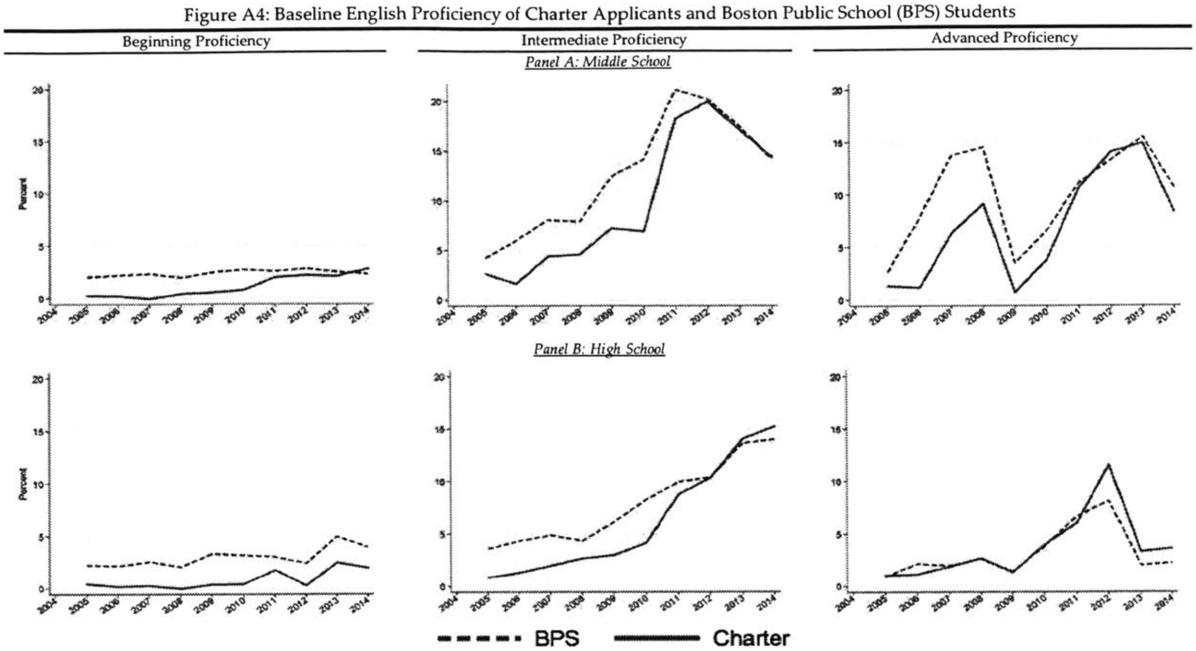
Notes: The graphs on the left plot the percent of students with English Language Learner (ELL) status at the time of the lottery for charter applicants and Boston Public School (BPS) students in charter application grades (4, 5, and 8). The graphs on the right plot the percent of students with ELL status at the time of the lottery for charter enrollees and BPS students in charter entry grades (5, 6, and 9). Using the ELL status at the time of the lottery ignores any post-lottery changes to classification.

Figure A3: Baseline Level of Inclusion of Charter Applicants and Boston Public School (BPS) Students



Notes: This figure plots the percent of students with special education substantially separate, partial, and full classroom inclusion at the time of the lottery for charter applicants and Boston Public School students in charter application grades (4, 5, and 8).

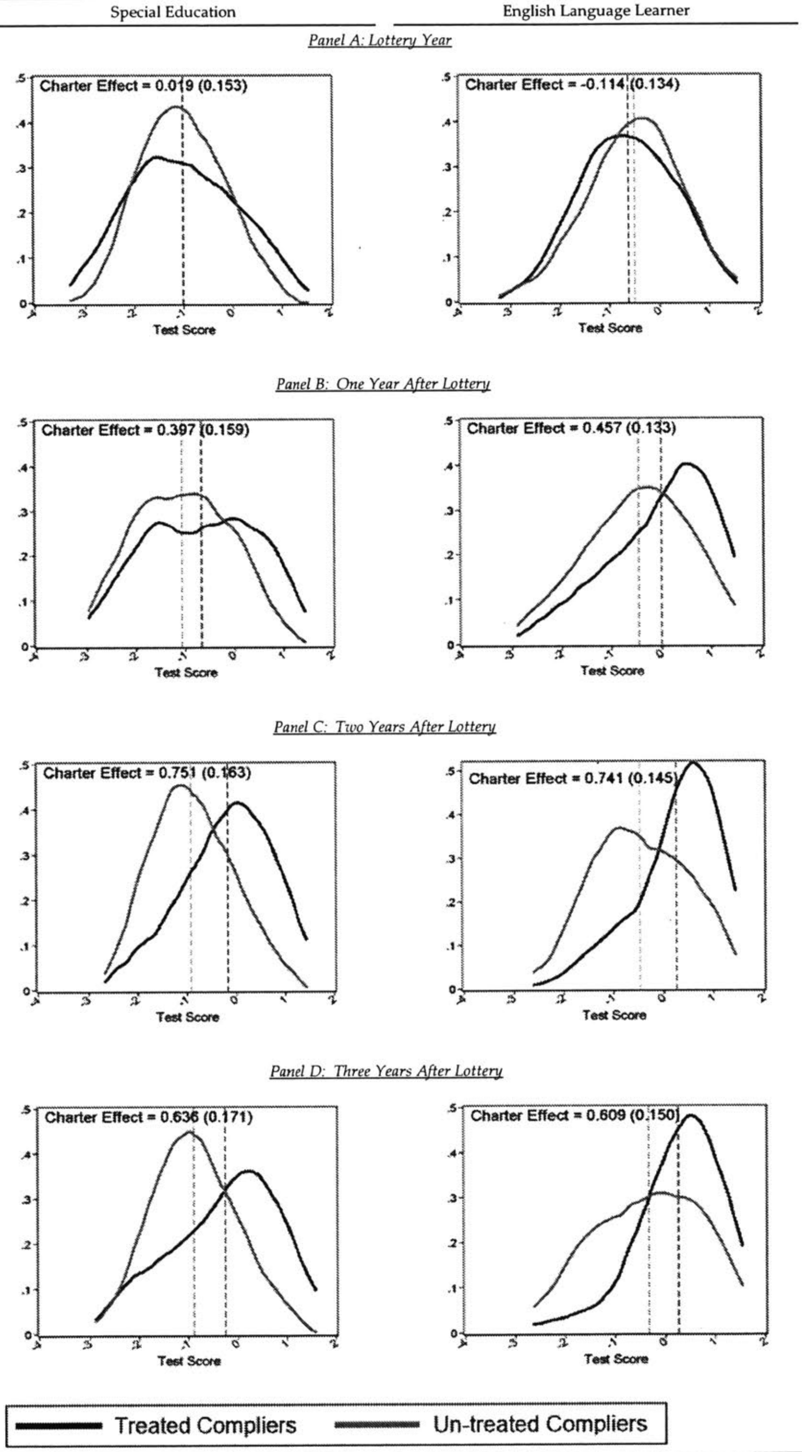
Figure A4: Baseline English Proficiency of Charter Applicants and Boston Public School (BPS) Students



Notes: This figure plots the percent of students with beginning, intermediate, and advanced English proficiency at the time of the lottery for charter applicants and Boston Public School students in charter application grades (4, 5, and 8). English proficiency is measured by the required annual state exam for English Language Learners.

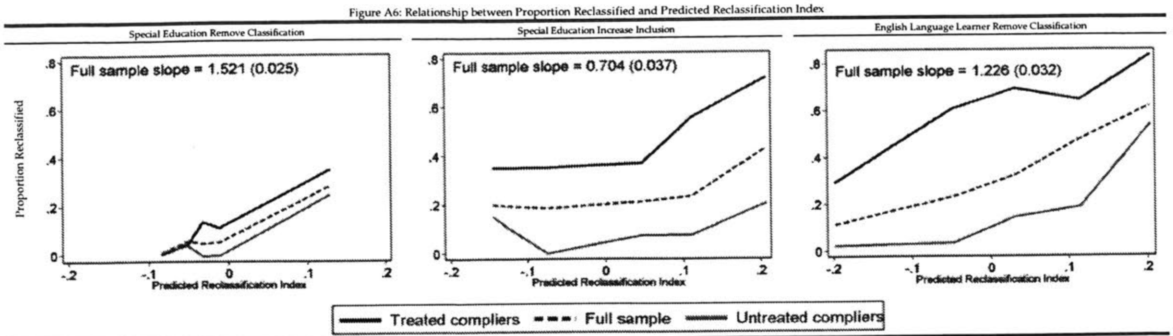
Figure A5: Density of Treated and Non-treated Compliers' Math Test Scores Over Time

Special Education	English Language Learner



Notes: This figure shows the distribution of test scores by pre-lottery special needs status over time for middle school treated and untreated charter compliers. Dashed lines represent the group average. The two-stage least squared estimates for charter effects are displayed in the top left corner with standard errors in parentheses.

Figure A6: Relationship between Proportion Reclassified and Predicted Reclassification Index



Notes: This figure displays the proportion of students reclassified by predicted reclassification index value (grouped into five bins).

A1: Lottery Participation by Schools and Cohorts

Panel A: Elementary School

Application Year/School	Bridge Boston	Brooke East Boston	Brooke Mattapan	Brooke Roslindale	Codman	Conservatory Lab	Dorchester Collegiate Academy	KIPP	Match Community Day	Neighborhood House
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Entry Grade	Pre-K	K	K	K	Pre-K	Pre-K	4	K	Pre-K & 2	Pre-K
2003										Not open
2004				No records						Y
2005						No records	Not open			Y*
2006									Not open	Y*
2007	Not open	Not open	Not open	Y	Not open					Y
2008				Y				Not open		Y
2009				Y**		Y+	No records			Y
2010				Y		Y*	No records			Y
2011	Y+		Y+	Y		Y	No records		Y	Y
2012	Y	Y+	Y	Y*		Y	Y		Y	Y
2013	Y	Y	Y	Y	Y+**	Y	Declined		Y	Y
2014	Y	Y	Y	Y	Y+	Y+		Y	Y	Y
N	561	2300	1296	785	114	739	52	159	1082	1932

Panel B: Middle School

Application Year/School	Dorchester Prep (UCS)	Brooke Roslindale	Brooke Mattapan	Brooke East Boston	Excel East Boston	Excel Orient Heights	Lucy Stone (UCS)	Mission Hill (UCS)	KIPP Boston	UP Academy
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Entry Grade	5	5	5	5	5	5	5	5/6	5	6
2003								Y*		
2004		No records						Y*		
2005					No records			Y*		
2006		Y**	Not open				Not open	Y		
2007	Not open	Y		Not open		Not open		Y	Not open	
2008		Y			Y			Y		
2009		Y			Y			Y		
2010					Y			Y		Not open
2011			Y		Y		Y	Y		Y
2012	Y	Not entry grade	Y	Y**	Y	Y	Y	Y	Y*	Y
2013	Y		Y	Y	Y	Y	Y	Y	Y*	Y
2014	Y**		Y**	Y	Incomplete records		Y**	Y**	Y	Y**
N	1035	254	738	367	519	333	1430	2291	429	1021

Panel C: Combined Middle and High Schools (5th-6th - 12th Grades)

Application Year/School	Academy of the Pacific Rim	Boston Collegiate	Boston Prep	Codman Academy	Match MS
	(1)	(2)	(3)	(4)	(5)
Entry Grade	5/6	5	6	5/6	6
2003		Y	Not open		
	No records		Incomplete records		
2004		Y			Not open
2005	Y	Y	Y**		
2006	Y	Y	Y		
2007	Y	Y	Y	Not entry grade	
2008	Y	Y	Y		Y
2009	Y	Y	Y		Y
2010	Y	Y	Y		Y
2011	Y	Y	Y		Y
2012	Y	Y	Y		Y
2013	Y	Y	Y		Y
2014	No records	Y	Y+	Y	Y
N	1852	3025	1636	69	2137

Panel D: High School

Application Year/School	Boston Green Academy	City on a Hill	City on a Hill II	Codman Academy	Match HS
	(1)	(2)	(3)	(4)	(5)
Entry Grade	9	9	9	9	9
2003		No records		Incomplete records	Y
2004		Y*		Y**	Y
2005		Y		Incomplete records	Y
2006	Not open	Y			Y
2007		Y	Not open	No record	Y
2008		Y*		Y	Y
2009		Y		Y	Y
2010		Y		Y	Y
2011	Y	Y		Y	
2012	Y**	Y		Y	Not entry grade
2013	Y	Y	Y**	Y	
2014	Y**	Y	Y	Y	
N	901	4624	1102	1737	2766

Notes: This table shows study charters and their application cohorts. The counts contain the number of students applying to each school in the study sample, not including siblings, out of area applicants, duplicates, disqualified applicants, and students not matched to the state data. In 2012, Uncommon Schools (Roxbury Prep, Dorchester Prep, and Grove Hall) held a joint lottery. APR had 6th grade lotteries from 2005-2007 and 5th grade lotteries from 2007-2014. Roxbury Prep began using 5th grade lotteries in Spring 2012. This table excludes closed schools and schools that did not provide usable lottery records.

* Only ever offer information is available.

** There is no variation in waitlist offers.

\+ Lotteries for additional entry grades are included in the analysis sample.

A2: Effect of Lottery Offer on Charter Enrollment and Years in Charter

	Special Education		English Language Learner		Non-Special Needs	
	Immediate Offer	Waitlist Offer	Immediate Offer	Waitlist Offer	Immediate Offer	Waitlist Offer
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Elementary School			
Years in Charter	1.626***	1.125***	1.463***	0.831***	2.234***	0.924***
	(0.153)	(0.265)	(0.096)	(0.156)	(0.162)	(0.277)
N	171		542		591	
Enroll in Charter	0.589***	0.364***	0.620***	0.347***	0.709***	0.384***
	(0.060)	(0.086)	(0.030)	(0.042)	(0.031)	(0.049)
N	236		715		682	
			Panel B: Middle School			
Years in Charter	1.035***	0.676***	1.100***	0.661***	1.221***	0.809***
	(0.041)	(0.041)	(0.033)	(0.033)	(0.022)	(0.023)
N	3632		4380		12046	
Enroll in Charter	0.581***	0.387***	0.640***	0.422***	0.629***	0.410***
	(0.030)	(0.030)	(0.025)	(0.026)	(0.017)	(0.017)
N	1607		2052		4696	
			Panel C: High School			
Years in Charter	0.717***	0.490***	0.662***	0.726***	0.714***	0.424***
	(0.084)	(0.079)	(0.116)	(0.105)	(0.038)	(0.037)
N	1055		504		3955	
Enroll in Charter	0.720***	0.470***	0.680***	0.722***	0.717***	0.452***
	(0.082)	(0.079)	(0.109)	(0.105)	(0.039)	(0.038)
N	1160		621		3752	

Notes: This table reports the first stage estimates for the two main two-stage least squares specifications. It displays the effect of lottery offers on years spent in charter schools and an indicator for charter enrollment.

A3: Special Education Classification Two Years After Application

	Any Special Education		Substantially Separate Classroom		Partial Inclusion		Full Inclusion		Move to More Inclusive Classroom	
	Trad. Public mean	Charter effect	Trad. Public mean	Charter effect	Trad. Public mean	Charter effect	Trad. Public mean	Charter effect	Trad. Public mean	Charter effect
Baseline Status	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Elementary School										
All Special Education	0.897	-0.049							0.299	0.359***
		(0.093)								(0.139)
N		137								
Substantially Separate Classroom	0.941	0.058	0.529	-0.620***	0.059	0.144	0.324	0.678***	0.441	0.764***
		(0.071)		(0.167)		(0.120)		(0.127)		(0.168)
N		38								
Partial Inclusion	0.909	0.111			0.182	-0.160	0.364	0.173	0.455	0.062
		(0.093)				(0.120)		(0.208)		(0.182)
N		29								
Full Inclusion	0.848	-0.110					0.565	0.162	0.152	0.110
		(0.157)						(0.235)		(0.157)
N		63								
New Students (No Prior Special Ed. Evaluation)	0.090	-0.027	0.011	-0.014**	0.011	-0.018**	0.067	0.002		
		(0.023)		(0.005)		(0.007)		(0.021)		
N		1138								
Panel B: Middle School										
All Special Education	0.889	-0.124**							0.326	0.234***
		(0.055)								(0.078)
N		1191								
Substantially Separate Classroom	1.000	0.034	0.789	-0.266*	0.037	0.051	0.137	0.393**	0.174	0.410**
		(0.057)		(0.161)		(0.076)		(0.162)		(0.165)
N		271								
Partial Inclusion	0.948	-0.132*			0.354	-0.091	0.441	0.051	0.493	0.183
		(0.078)				(0.113)		(0.129)		(0.119)
N		431								
Full Inclusion	0.743	-0.105					0.466	0.111	0.257	0.105
		(0.102)						(0.110)		(0.102)
N		472								
Panel C: High School										
All Special Education	0.837	0.008							0.306	0.009
		(0.095)								(0.133)
N		848								
Substantially Separate Classroom	0.967	-0.109	0.663	-0.044	0.120	-0.240	0.120	0.076	0.272	-0.056
		(0.088)		(0.189)		(0.148)		(0.141)		(0.203)
N		240								
Partial Inclusion	0.857	-0.295*			0.516	-0.374*	0.273	0.199	0.416	0.494**
		(0.173)				(0.217)		(0.215)		(0.229)
N		241								
Full Inclusion	0.750	0.264					0.465	0.468**	0.250	-0.264
		(0.174)						(0.208)		(0.174)
N		349								

Notes: This table reports two-stage least squares estimates of the effects of Boston charter enrollment on special education classification and level of classroom inclusion two years following the charter lottery. Immediate and waitlist offer dummies instrument for enrollment in charter schools. Estimation is run separately by baseline classroom inclusion type. Effects persist for up to two years following the charter application. See Table 2 notes for detailed regression specifications.
*significant at 10%; **significant at 5%; ***significant at 1%

A4: English Language Learner Classification Two Years After Application

	Remain English Language Learner	
	Trad. Public mean	Charter effect
Baseline Status	(1)	(2)
Panel A: Elementary School		
All English Language Learners	0.781	-0.210
		(0.198)
N		496
Beginning Proficiency	1.000	-0.145
		(0.118)
N		65
Intermediate Proficiency	0.763	-0.152
		(0.220)
N		274
Advanced Proficiency	0.286	-
		-
N		15
New Non-native English Speaking Students	0.565	-0.336***
(No Prior English Lang. Learner Evaluation)		(0.093)
N		308
Panel B: Middle School		
All English Language Learners	0.553	-0.352***
		(0.065)
N		1423
Beginning Proficiency	0.980	-0.309
		(0.231)
N		65
Intermediate Proficiency	0.734	-0.576***
		(0.118)
N		688
Advanced Proficiency	0.283	-0.262***
		(0.069)
N		476
Panel C: High School		
All English Language Learners	0.552	-0.280
		(0.190)
N		392
Beginning Proficiency	0.900	-
		-
N		16
Intermediate Proficiency	0.822	-0.181
		(0.253)
N		166
Advanced Proficiency	0.244	0.188
		(0.461)
N		151

Notes: This table reports two-stage least squares estimates of the effects of Boston charter enrollment on English Language Learner classification two years following the charter lottery. Immediate and waitlist offer dummies instrument for enrollment in charter schools. Estimation is run separately by baseline English proficiency level. Effects persist for up to two years following the charter application. See Table 2 notes for detailed regression specifications. *significant at 10%; **significant at 5%; ***significant at 1%

A5: Staff-to-Student Ratios

	All Staff		Special Education Staff		English Language Learner Staff	
	Trad. Public mean	Charter Effect	Trad. Public mean	Charter Effect	Trad. Public mean	Charter Effect
	(1)	(2)	(3)	(4)	(5)	(6)
Total Staff	0.120	0.045***	0.019	-0.011***	0.015	-0.013***
		(0.011)		(0.001)		(0.001)
Teachers	0.079	0.013***	0.010	-0.010***	0.003	-0.002***
		(0.004)		(0.001)		(0.001)
Specialists	-	-	0.003	-0.001**	0.000	0.000**
				(0.000)		(0.000)
Content Support	-	-	0.004	0.002***	0.001	0.001**
				(0.001)		(0.001)
N (students)			14346			

Notes: This table shows two-stage least squares estimates of the effect of charter enrollment on the staff-to-student ratios. Immediate and waitlist offer dummies instrument for any charter enrollment in the year following the lottery. The sample includes all lottery applicants applying in the 2007-08 through 2013-14 school years. Staffing and student counts data are collected in October of each year. See Table 4 notes for detailed regression specifications.
*significant at 10%; **significant at 5%; ***significant at 1%

A6: School Finances

	Total		Special Education	
	Boston Public Schools	Boston Charter Schools	Boston Public Schools*	Boston Charter Schools
	(1)	(2)	(3)	(4)
Panel A: Per Pupil Expenditures				
Total	$19,214	$16,759		$1,361
		(2,502)		(713)
Total Instructional Spending	$8,913	$9,769	$2,365	$1,325
	(2,395)	(1,470)	$2,365	
Retirement & Insurance	$3,282	$1,345		-
		(410)		
Other Teaching Services	$1,307	$872	$504	$168
	(842)	(652)	(725)	(209)
Professionals	$309	$360	$5	$72
	(183)	(489)	(62)	(146)
Paraprofessionals	$974	$249	$498	$17
	(772)	(398)	(697)	(49)
Contractors	$120	$204	$6	$76
	(373)	(331)	(015)	(144)
Classroom & Specialist Teachers	$6,051	$5,521	$1,567	$808
	(1069)	(844)	(1,231)	(605)
Professional Development	$310	$190	$86	$16
	(134)	(205)	(75)	(52)
Pupil Services	$2,601	$1,994		$36
		(726)		(110)
Operations & Maintenance	$1,249	$1,020		-
		(517)		
Administration	$557	$2,632		-
		(1,471)		
Guidance, Counseling, & Testing	$117	$715	$23	$210
	(346)	(419)	(291)	(196)
Instructional Leadership	$821	$1,627	$159	$100
	(400)	(0,641)	(231)	(117)
Materials, Equipment, & Tech	$308	$843	$27	$22
	(406)	(588)	(035)	(45)
Panel B: Federal and State Grants Per Pupil				
Federal Grants	$1,396	$1,257	$389	$246
		(683)		(115)
State Grants	$89	$6		
		(15)		
Medicaid Reimbursement			$119	$24
			-	(35)

Notes: This table shows the per pupil expenditures and grants per pupil for total spending and special education spending for the 2013-14 school year in 2015 CPI-U adjusted dollars. Districts do not report English Language Learner specific school expenditures. Total enrollment is used to calculate special education spending per pupil (instead of special education enrollment). Items without school-level BPS data do not have standard deviations. If school-level Boston Public Schools (BPS) data is available, BPS statistics are weighted by the proportion of lottery applicants that enroll in individual BPS schools.

A7: Ordinary Least Squares Estimates by Baseline Special Needs Status

		Special Education		English Language Learner		Non-Special Needs	
		Trad. Public mean	Charter effect	Trad. Public mean	Charter effect	Trad. Public mean	Charter effect
		(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Elementary School				
Math		-0.737	0.250***	-0.326	0.200***	-0.087	0.089**
			(0.071)		(0.059)		(0.040)
	N		171		541		591
English		-1.186	0.337***	-0.519	0.194***	-0.128	0.108***
			(0.074)		(0.066)		(0.038)
	N		169		539		590
			Panel B: Middle School				
Math		-1.025	0.231***	-0.550	0.276***	-0.129	0.198***
			(0.019)		(0.021)		(0.012)
	N		3608		4369		12053
English		-1.176	0.187***	-0.763	0.220***	-0.102	0.138***
			(0.019)		(0.018)		(0.010)
	N		3595		4373		11986
			Panel C: High School				
Math		-0.920	0.233***	-0.419	0.102	-0.086	0.171***
			(0.033)		(0.067)		(0.029)
	N		1030		493		3926
English		-1.069	0.197***	-0.758	0.135*	-0.135	0.129***
			(0.028)		(0.070)		(0.021)
	N		1050		503		3974

Notes: This table reports the Ordinary Least Squares estimates of years spent in charter school on state standardized test scores. See Table 4 notes for detailed regression specifications.
*significant at 10%; **significant at 5%; ***significant at 1%

A8: Reduced Form (Intent To Treat) Estimates by Baseline Special Needs Status

		Special Education		English Language Learner		Non-Special Needs	
		No charter offer mean	Charter offer effect	No charter offer mean	Charter offer effect	No charter offer mean	Charter offer effect
		(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Elementary School				
Math		-0.618	0.444**	-0.351	0.587***	-0.100	0.461***
			(0.187)		(0.114)		(0.104)
	N		171		541		591
English		-1.047	0.694***	-0.544	0.528***	-0.154	0.498***
			(0.199)		(0.133)		(0.110)
	N		169		539		590
			Panel B: Middle School				
Math		-0.910	0.204***	-0.449	0.231***	-0.033	0.251***
			(0.055)		(0.055)		(0.032)
	N		3608		4369		12053
English		-1.090	0.162***	-0.687	0.147***	-0.035	0.131***
			(0.058)		(0.049)		(0.028)
	N		3595		4373		11986
			Panel C: High School				
Math		-0.771	0.168***	-0.410	0.255**	-0.073	0.196***
			(0.065)		(0.108)		(0.037)
	N		1030		493		3926
English		-0.963	0.117*	-0.753	0.260**	-0.122	0.128***
			(0.064)		(0.123)		(0.030)
	N		1050		503		3974

Notes: This table reports the Reduced Form estimates of the effect of getting any charter offer on state standardized test scores. See Table 4 notes for detailed regression specifications.
*significant at 10%; **significant at 5%; ***significant at 1%

A9: Charter Effects on English Proficiency Exam for Baseline English Language Learners

	Take English Proficiency Exam		English Proficiency Exam Score	
	Trad. Public mean	Charter effect	Trad. Public mean	Charter effect
School Level	(1)	(2)	(3)	(4)
Elementary School	0.696	-0.103	-0.013	-0.066
		(0.082)		(0.110)
N		536		464
Middle School	0.628	-0.300***	0.593	-0.074
		(0.065)		(0.105)
N		2172		1054
High School	0.490	-0.485***	0.484	0.841*
		(0.163)		(0.468)
N		673		339

Notes: This table reports the two-stage least squares estimates of charter enrollment on whether English Language Learners take the annual Spring English Proficiency exam and their scores. Immediate and waitlist offer dummies instrument for charter enrollment in the year following the lottery. Students who remain classified as English Language Learners take the English Proficiency exam. Models control for gender, ethnicity, female x minority interaction, baseline special education, baseline subsidized lunch, experimental strata, year-applied dummies, grade-applied dummies, and baseline English proficiency exam score. Estimates are clustered by school-grade-year.

*significant at 10%; **significant at 5%; ***significant at 1%

A10: Test Score Effects by Baseline Special Education of Disability

		Intellectual		Communication		Emotional		Learning	
		Trad. Public mean	Charter effect	Trad. Public mean	Charter effect	Trad. Public mean	Charter effect	Trad. Public mean	Charter effect
Exam		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Math		-1.834	0.635	-0.721	0.183	-1.028	-0.329	-1.055	0.337***
			(0.578)		(0.121)		(0.252)		(0.068)
	N		263		1179		361		2783
English		-2.051	0.363	-0.913	0.130	-1.240	-0.584	-1.199	0.236***
			(0.458)		(0.119)		(0.370)		(0.070)
	N		264		1177		365		2785

Notes: This table reports the two-stage least squares estimates of the effects of years spent in charter schools on test scores for students by their baseline disability type for elementary, middle, and high school applicants. Disabilities with fewer than 200 observations are not shown. These include autism, physical disabilities, multiple disabilities, developmental disabilities, and health disabilities. See Table 4 notes for detailed regression specifications.

*significant at 10%; **significant at 5%; ***significant at 1%

A11: Test Score Effects by First Language of Baseline English Language Learners

		Spanish		Hatian Creole		Other	
		Trad. Public mean	Charter effect	Trad. Public mean	Charter effect	Trad. Public mean	Charter effect
Exam		(1)	(2)	(3)	(4)	(5)	(6)
Math		-0.567	0.273***	-0.731	0.587***	-0.236	0.256***
			(0.058)		(0.127)		(0.095)
	N		3120		931		1331
English		-0.786	0.210***	-0.816	0.451***	-0.564	0.083
			(0.056)		(0.124)		(0.107)
	N		3134		931		1329

Notes: This table reports the two-stage least squares estimates of the effects of years spent in charter schools on test scores for students by their first language for elementary, middle, and high school applicants. Languages in the "Other" category had too few students to individually estimate. See Table 4 notes for detailed regression specifications.
*significant at 10%; **significant at 5%; ***significant at 1%

A12: Ordinary Least Squares Post-Application Special Education Classification Estimates

	Any Special Education		Substantially Separate Classroom		Partial Inclusion		Full Inclusion		Move to More Inclusive Classroom	
	Trad. Public mean	Charter effect	Trad. Public mean	Charter effect	Trad. Public mean	Charter effect	Trad. Public mean	Charter effect	Trad. Public mean	Charter effect
Baseline Status	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Elementary School										
All Special Education	0.907	-0.178***							0.161	0.313***
		(0.051)								(0.080)
N		254								254
Substantially Separate Classroom	0.903	0.088	0.629	-0.469***	0.016	0.237***	0.177	0.532***	0.226	0.691***
		(0.072)		(0.124)		(0.080)		(0.099)		(0.112)
N		72								72
Partial Inclusion	0.895	-0.369*			0.500	-0.390***	0.289	0.014	0.342	0.144
		(0.198)				(0.144)		(0.184)		(0.209)
N		49								49
Full Inclusion	0.910	-0.129					0.690	-0.026	0.060	0.180**
		(0.091)						(0.122)		(0.091)
N		126								126
New Students (No Prior Special Ed. Evaluation)	0.014	-0.005	0.001	-0.002	0.003	0.001	0.008	-0.002		
		(0.005)		(0.001)		(0.003)		(0.004)		
N		2665								
Panel B: Middle School										
All Special Education	0.927	-0.109***							0.125	0.226***
		(0.024)								(0.025)
N		1726								1726
Substantially Separate Classroom	0.976	-0.054*	0.897	-0.628***	0.036	0.078**	0.028	0.284***	0.071	0.370***
		(0.029)		(0.054)		(0.033)		(0.046)		(0.053)
N		403								403
Partial Inclusion	0.935	-0.136***			0.665	-0.472***	0.156	0.310***	0.193	0.349***
		(0.036)				(0.045)		(0.041)		(0.041)
N		611								611
Full Inclusion	0.886	-0.128***					0.692	-0.002	0.097	0.081***
		(0.036)						(0.044)		(0.030)
N		683								683
Panel C: High School										
All Special Education	0.841	-0.134***							0.180	0.163***
		(0.038)								(0.034)
N		1173								1173
Substantially Separate Classroom	0.975	-0.272***	0.819	-0.416***	0.071	0.008	0.042	0.089**	0.130	0.186***
		(0.052)		(0.078)		(0.034)		(0.042)		(0.064)
N		333								333
Partial Inclusion	0.884	-0.119**			0.589	-0.335***	0.179	0.214***	0.254	0.285***
		(0.052)				(0.068)		(0.067)		(0.068)
N		344								344
Full Inclusion	0.726	-0.029					0.511	0.053	0.156	0.075*
		(0.053)						(0.054)		(0.041)
N		469								469

Notes: This table reports two-stage least squares estimates of the effects of Boston charter enrollment on special education classification and level of classroom inclusion in the fall following the charter lottery. Immediate and waitlist offer dummies instrument for enrollment in charter schools. Estimation is run separately by baseline classroom inclusion type. Effects persist for up to two years following the charter application. All models control for gender, ethnicity, female x minority interaction, baseline special education, baseline ELL, baseline subsidized lunch, experimental strata, year-applied dummies, and grade-applied dummies. Estimates for elementary and middle school sample pool post-lottery outcomes for grades 3-5 and 5-8 respectively and cluster by student identifier and school-grade-year.
*significant at 10%; **significant at 5%; ***significant at 1%

A13: Ordinary Least Squares Post-Application English Language Learner Classification Estimates

		Remain English Language Learner	
		Trad. Public mean	Charter effect
Baseline Status		(1)	(2)
Panel A: Elementary School			
All English Language Learners		0.900	-0.214***
			(0.064)
	N		818
Beginning Proficiency		0.989	-0.031
			(0.022)
	N		110
Intermediate Proficiency		0.986	-0.134*
			(0.069)
	N		349
Advanced Proficiency		0.739	-0.604**
			(0.297)
	N		25
New Non-native English Speaking Students		0.637	-0.225***
(No Prior English Lang. Learner Evaluation)			(0.047)
	N		856
Panel B: Middle School			
All English Language Learners		0.794	-0.324***
			(0.038)
	N		2231
Beginning Proficiency		1.000	0.000
			(0.000)
	N		130
Intermediate Proficiency		0.953	-0.400***
			(0.045)
	N		1105
Advanced Proficiency		0.570	-0.219***
			(0.052)
	N		774
Panel C: High School			
All English Language Learners		0.802	-0.262***
			(0.048)
	N		714
Beginning Proficiency		1.000	-0.070
			(0.102)
	N		47
Intermediate Proficiency		0.921	-0.253***
			(0.073)
	N		356
Advanced Proficiency		0.618	-0.170**
			(0.085)
	N		209

Notes: This table reports two-stage least squares estimates of the effects of Boston charter enrollment on English Language Learner classification in the fall following the charter lottery. Immediate and waitlist offer dummies instrument for enrollment in charter schools. Estimation is run separately by baseline English proficiency level. Effects persist for up to two years following the charter application. See Table 2 notes for detailed regression specifications. *significant at 10%; **significant at 5%; ***significant at 1%

A14: Test Score Effects for Lotteries with High and Low Proportions of Special Needs

		Special Education		English Language Learner	
		Bottom Quartile	Top Quartile	Bottom Quartile	Top Quartile
		(1)	(2)	(3)	(4)
Math		0.264***	0.321***	0.241***	0.315***
		(0.036)	(0.036)	(0.049)	(0.029)
	N	5711	7148	3656	9703
English		0.196***	0.207***	0.152***	0.199***
		(0.035)	(0.035)	(0.043)	(0.028)
	N	5640	7156	3608	9706
Mean % of Lottery Applicants with Special Needs Status		13.55% (3.99)	23.32% (5.36)	14.08% (10.49)	41.22% (25.11)

Notes: This table reports the two-stage least squares estimates of the effects of years spent in charter schools on test scores for lotteries with the highest and lowest quartile of special needs representation. Immediate and waitlist offer dummies instrument for years spent in charter schools for elementary, middle, and high school lottery applicants. See Table 2 notes for detailed regression specifications.
*significant at 10%; **significant at 5%; ***significant at 1%

A15: Match from Lottery Data to Administrative Data

	Elementary School				Middle School				High School			
			Reg of Match on Offer				Reg of Match on Offer				Reg of Match on Offer	
	Number of Applications	Proportion Matched	Immediate Offer	Any Offer	Number of Applications	Proportion Matched	Immediate Offer	Any Offer	Number of Applications	Proportion Matched	Immediate Offer	Any Offer
Lottery Year	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
2004	150	0.867	0.139***	0.074	268	0.989	-0.006	-0.007	638	0.991	-0.015	-0.010
			(0.029)	(0.071)			(0.026)	(0.013)			(0.013)	(0.015)
2005	141	0.865	-	0.090	616	0.987	0.005	0.002	601	0.990	0.000	-0.003
			-	(0.056)			(0.011)	(0.013)			(0.010)	(0.010)
2006	166	0.910	-	0.098***	742	0.991	0.001	0.004	669	0.991	0.002	-0.005
			-	(0.024)			(0.008)	(0.016)			(0.010)	(0.013)
2007	303	0.901	0.077***	0.043	924	0.984	0.019**	0.034***	997	0.978	0.008	0.013
			(0.026)	(0.031)			(0.008)	(0.013)			(0.009)	(0.009)
2008	322	0.913	0.089***	0.082***	1018	0.957	0.042***	0.061***	837	0.957	0.038***	-0.002
			(0.018)	(0.025)			(0.013)	(0.019)			(0.011)	(0.030)
2009	472	0.960	0.031**	0.051***	1106	0.977	0.004	0.011	898	0.971	-0.017	0.023
			(0.013)	(0.015)			(0.011)	(0.010)			(0.020)	(0.015)
2010	558	0.937	0.013	0.020	1041	0.924	0.065***	0.071***	917	0.954	0.013	0.027**
			(0.028)	(0.024)			(0.016)	(0.017)			(0.012)	(0.013)
2011	1610	0.940	0.032***	0.033***	2614	0.954	0.018***	0.025***	1234	0.930	0.012	0.020
			(0.012)	(0.011)			(0.007)	(0.007)			(0.010)	(0.013)
2012	1864	0.911	0.048***	0.048***	2503	0.939	0.001	0.033***	1499	0.951	0.000	-0.030
			(0.014)	(0.013)			(0.011)	(0.011)			(0.008)	(0.021)
2013	1422	0.884	0.032*	0.052***	2712	0.902	0.045***	0.078***	1537	0.951	-0.003	-0.120
			(0.018)	(0.018)			(0.012)	(0.015)			(0.009)	(0.078)
2014	1085	0.890	0.009	0.020	1938	0.961	0.027***	0.036**	1403	0.952	0.023**	0.111
			(0.022)	(0.021)			(0.007)	(0.014)			(0.010)	(0.106)
All Cohorts	8093	0.912	0.036***	0.043***	15482	0.949	0.023***	0.038***	11230	0.960	0.007**	0.006
			(0.007)	(0.006)			(0.003)	(0.004)			(0.003)	(0.005)

Notes: This table summarizes the match from the state administrative data to the lottery records. The sample excludes late applicants, siblings, disqualified applicants, duplicate names, and out-of-area applicants. Columns (3) and (4) report coefficients from regressions on a dummy for a successful state data match on immediate and any charter offer dummies for the elementary school sample. Year-specific regressions control for charter school dummies. All cohort regressions control for school-by-year dummies.
*significant at 10%; **significant at 5%; ***significant at 1%

A16: Sample Selection

Year of application	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	All
Panel A: Elementary School												
Total number of records	160	166	194	364	396	602	702	2899	2963	2537	2298	13281
Excluding disqualifed applications	160	166	194	360	396	602	702	2889	2956	2479	2280	13184
Excluding late applications	160	166	194	360	396	602	700	2882	2956	2470	2279	13165
Excluding out of area applications	160	160	194	357	395	590	687	2832	2874	2408	2233	12890
Excluding siblings	151	140	166	325	338	525	621	2330	2508	2101	2038	11243
Excluding records not matched to SIMS	131	123	151	296	310	507	585	2225	2336	1942	1858	10464
Keep only first year of charter application	131	123	151	273	294	491	555	1965	2069	1633	1398	9083
Excluding repeat applications	131	121	151	273	294	491	551	1954	2041	1618	1396	9021
Reshaping to one record per student	130	119	138	261	284	409	393	1336	1427	1041	918	6937
Has any demographics	130	119	150	262	285	426	484	1391	1430	1060	832	6569
Has demographics for baseline and/or year 1	29	37	54	205	228	345	392	1156	1131	874	805	5256
Has baseline demographics	1	5	3	26	56	68	62	613	472	249	388	1943
Panel B: Middle School												
Total number of records	341	739	913	1143	1422	1595	1467	4283	4312	4766	3189	24170
Excluding disqualifed applications	341	738	911	1135	1404	1594	1444	4273	4305	4760	3189	24094
Excluding late applications	340	738	909	1135	1363	1566	1397	4163	4196	4583	3187	23577
Excluding out of area applications	340	733	900	1123	1353	1548	1379	4094	4071	4513	3136	23190
Excluding siblings	300	677	836	1021	1223	1408	1249	3758	3760	4320	2865	21417
Excluding records not matched to SIMS	266	634	801	1000	1181	1378	1179	3627	3573	4016	2792	20447
Keep only first year of charter application	266	617	770	962	1093	1282	1038	3308	2962	3469	1975	17742
Excluding repeat applications	266	617	770	962	1093	1282	1038	3308	2962	3458	1960	17716
Reshaping to one record per student	265	523	586	760	868	963	812	2055	1715	1900	1176	11623
Has baseline demographics and in Boston at baseline	176	382	437	571	679	722	623	1790	1499	1594	1028	9501
Panel C: High School												
Total number of records	940	884	942	1330	1211	1300	1500	1835	2049	3280	3417	18688
Excluding disqualifed applications	940	883	942	1327	1210	1289	1500	1818	2040	3278	3417	18644
Excluding late applications	930	880	942	1327	1191	1289	1500	1818	1986	3235	3417	18515
Excluding out of area applications	930	880	939	1327	1191	1276	1465	1787	1979	3136	2762	17672
Excluding siblings	905	864	939	1298	1153	1214	1376	1727	1952	3082	2658	17168
Excluding records not matched to SIMS	858	817	919	1271	1108	1184	1335	1642	1882	2980	2571	16567
Keep only first year of charter application	858	810	910	1161	919	925	984	1208	1369	2192	1416	12752
Excluding repeat applications	858	810	910	1161	919	925	984	1208	1366	2187	1414	12742
Reshaping to one record per student	632	590	656	827	604	629	591	736	786	928	652	7631
Has baseline demographics and in Boston at baseline	508	478	536	751	487	529	503	628	735	848	552	6555

Notes: This table shows the sample restrictions imposed for lottery analysis.

A17: Attrition

	Special Education at Baseline		English Language Learner at Baseline		Non-Special Needs at Baseline	
Outcome	Trad. Public Attrition Rate (1)	Attrition Differential by Offer Status (2)	Trad. Public Attrition Rate (3)	Attrition Differential by Offer Status (4)	Trad. Public Attrition Rate (5)	Attrition Differential by Offer Status (6)
Panel A: Elementary School						
Math Exam	0.266	-0.059*	0.168	-0.027*	0.196	-0.026*
		(0.035)		(0.015)		(0.014)
		217		625		695
English Exam	0.260	-0.071**	0.168	-0.028*	0.198	-0.027*
		(0.035)		(0.015)		(0.015)
		217		625		695
Classification Status	0.212	-0.219**	0.081	-0.114***	0.105	-0.059
		(0.101)		(0.040)		(0.038)
		240		726		716
Panel B: Middle School						
Math Exam	0.201	0.002	0.164	-0.005	0.200	-0.030***
		(0.022)		(0.019)		(0.011)
		4304		4966		13878
English Exam	0.204	0.003	0.164	-0.008	0.203	-0.032***
		(0.021)		(0.018)		(0.011)
		4304		4966		13878
Classification Status	0.114	-0.025	0.120	-0.023	0.148	-0.076***
		(0.031)		(0.027)		(0.018)
		1658		2164		5036
Panel C: High School						
Math Exam	0.287	0.052	0.308	0.125	0.274	-0.022
		(0.041)		(0.104)		(0.021)
		1340		643		4869
English Exam	0.268	0.023	0.291	0.051	0.263	-0.014
		(0.042)		(0.099)		(0.023)
		1340		643		4869
Classification Status	0.080	-0.060	0.027	0.106	0.056	-0.176***
		(0.089)		(0.096)		(0.062)
		1347		819		4596

Notes: This table reports the two-stage least squares estimates of the effect of years spent in charter schools on attriting from the sample for test score and reclassification outcomes. See Table 4 notes for detailed regression specifications.
*significant at 10%; **significant at 5%; ***significant at 1%

A18: Effects on School Switching by Baseline Special Needs Status

	Special Education		English Language		Non-Special Needs	
	Trad. Public mean	Effect	Trad. Public mean	Effect	Trad. Public mean	Effect
	(1)	(2)	(3)	(4)	(5)	(6)
		Panel A: Elementary School				
Any Switch	0.498	0.253*	0.373	-0.002	0.440	-0.120***
		(0.151)		(0.057)		(0.045)
N		296		864		858
Switch excluding transitional grades	0.308	0.095	0.212	-0.138***	0.230	-0.173***
		(0.139)		(0.046)		(0.041)
N		296		864		858
		Panel B: Middle School				
Any Switch	0.549	-0.160***	0.556	-0.176***	0.598	-0.393***
		(0.051)		(0.043)		(0.031)
N		1820		2314		5263
Switch excluding transitional grades	0.160	0.018	0.144	-0.063*	0.205	-0.119***
		(0.039)		(0.032)		(0.023)
N		1820		2314		5263
		Panel C: High School				
Any Switch	0.296	0.257**	0.337	0.068	0.262	0.068
		(0.102)		(0.117)		(0.057)
N		1259		741		4040
Switch excluding transitional grades	0.206	0.299***	0.178	0.178	0.168	0.073
		(0.099)		(0.114)		(0.055)
N		1259		741		4040

Notes: This table reports two-stage least squares estimates of the effects of Boston charter enrollment on switching schools one year following the lottery. Students who do not appear in Massachusetts public schools in October following the charter application are not counted as school switchers. The switch excluding transitional grades equals one for students who switch schools in grades other than the exit grade of their first school. It does not equal to one if the school closed the year the student switched. See Table 4 notes for detailed regression specifications.

Chapter 2

Can Successful Schools Replicate? Scaling Up Boston's Charter School Sector

(Joint work with Sarah Cohodes and Christopher Walters)

2.1 Introduction

The feasibility of scaling up effective programs is a perennial problem in social policy. Successful demonstration projects may fail to reproduce their effects at scale if these impacts are driven by unique inputs or population characteristics. In the education sphere, for example, recent large-scale studies of early childhood programs, class size reductions, and the Success For All curriculum show effects that fall short of the impressive gains seen in smaller-scale evaluations of similar interventions (Heckman et al., 2010; Heckman, Pinto, and Savelyev, 2013; Puma, Bell, and Heid, 2012; Krueger, 1999; Jepsen and Rivkin, 2009; Borman et al., 2007; Quint et al., 2015). This suggests that in some cases the success of education programs may be due to special teachers, school leaders, peer environments, or other factors that cannot be easily replicated.

The potential for sustained success at scale is of particular interest for "No Excuses" charter schools, a recent educational innovation that has demonstrated promise for low-income urban students. These schools share a set of practices that includes high expectations, strict discipline, frequent teacher feedback, high-intensity tutoring, and data-driven instruction. Evidence based on randomized admission lotteries shows that No Excuses charter schools generate test score gains large enough to close racial and socioeconomic achievement gaps in a short time, as well as improvements in longer-run outcomes like teen pregnancy and four-year college attendance (Abdulkadiroğlu et al., 2011, 2015; Angrist, Pathak, and Walters, 2013; Angrist et al., 2012, 2016; Dobbie and Fryer, 2011, 2013, 2015; Tuttle et al., 2013). Other recent studies demonstrate positive effects of No Excuses policies when implemented in traditional public schools or in low-performing schools converted to charter status (Fryer, 2014; Abdulkadiroğlu et al., 2016b). No school district has adopted these policies on a wide scale, however, and No Excuses charters serve small shares of students in the cities where they operate. It therefore remains an open question whether the effects documented in previous research can be replicated at a larger scale.

We address this question using a recent policy change that expanded the charter school sector in Boston, Massachusetts, a city where most charter schools operate according to No Excuses principles. In 2010, Massachusetts passed a comprehensive education reform law that raised the state's cap on the fraction of funding dedicated to charter school tuition payments in low-performing districts. Charter operators that the state deemed "proven providers" with track records of success were permitted to expand existing campuses or open new schools in these districts. As a result, the number of charter schools in Boston increased from 16 to 32 between 2010 and 2014, with most of these new campuses linked to existing No Excuses charter schools. This expansion led to dramatic growth in charter market share in Boston, particularly in middle school: the fraction of sixth grade students attending charter schools increased from 15 to 31 percent between 2010 and 2015.

We use records from randomized charter school admission lotteries to study changes in the effectiveness of Boston's charter middle school sector during this period of rapid expansion. Comparisons of students who randomly receive lottery offers to those who do not receive offers are free of selection bias and therefore generate credible estimates of the causal effects of charter school attendance. The lottery records studied here cover 14 of the 15 charter schools admitting students in fifth or sixth grade, permitting a broadly representative analysis of charter middle schools in Boston.

Lottery-based estimates reveal that Boston's charter sector remained effective while doubling in size. Consistent with previous evidence, our results for cohorts applying before 2010 show that a year of attendance at a Boston charter middle school boosted math achievement by between 0.18 and 0.33 standard deviations (σ) and increased English achievement by about 0.1σ during this period. Results indicate that policymakers selected more effective schools for expansion: proven providers produced larger effects than other charter schools before the reform. Proven providers and other existing charters maintained their effectiveness after the charter expansion.

Estimates for expansion charters show that new campuses generate achievement gains comparable to those of their parent schools. Moreover, expansion charters produce these large impacts while enrolling students that appear more representative of the general Boston population than students at other charters. Together, the estimates for new and existing schools imply an increase in overall charter effectiveness despite the substantial growth in charter market share after the 2010 reform.

The next section provides background on charter schools in Boston and the charter expansion reform. Section 3 describes the data and Section 4 details the empirical framework used to analyze it. Section 5 presents lottery-based estimates of charter school effects and explores variation in these effects across students and schools. Section 6 notes some caveats to our analysis and offers concluding thoughts.

2.2 Background

2.2.1 Charter Schools in Boston

The first charter schools in Boston opened in 1994. Boston charters offer a different educational experience than traditional public schools operating in the Boston Public Schools (BPS) district. Table 1 compares inputs and practices of BPS schools and the 14 charter middle schools in our analysis sample (described in more detail later on). Columns (1) and (5) of Panel A show that charter students spend more days per year and hours per day in school than BPS students. Charter teachers tend to be younger and less experienced than BPS teachers; as a result, they are much less likely to be licensed or designated highly-qualified.[1] Student/teacher ratios are similar in BPS and charter schools, but charters spend somewhat less money per pupil ($18,766 vs. $17,041), a difference driven by lower salaries and retirement costs for their less-experienced teachers (Setren, 2016).

Boston charter schools commonly subscribe to No Excuses pedagogy, an approach that utilizes strict discipline, extended instructional time, selective teacher hiring, frequent testing, high expectations, teacher feedback, data-driven instruction, and tutoring (Carter, 2000; Thernstrom and Thernstrom, 2003). Panel B of Table 1 reports the mean of an index of No Excuses policies, constructed as an equally-weighted average of features typically associated with the No Excuses model.[2] On average, Boston charter schools implement 90 percent of these policies. Charters also commonly offer Saturday and school break programming for homework help, tutoring, and academic enrichment. These practices differ markedly from practices at BPS schools and at non-urban charter schools in Massachusetts (Angrist, Pathak, and Walters, 2013).

Previous research has documented that Boston charters boost math and English standardized test scores (Abdulkadiroğlu et al., 2011; Cohodes et al., 2013). This finding is consistent with studies showing positive test score effects for urban No Excuses charters elsewhere (Dobbie and Fryer, 2011, 2013; Angrist et al., 2012; Abdulkadiroğlu et al., 2015; Chabrier, Cohodes, and Oreopoulos, 2016). Recent evidence shows that Boston charter high schools also increase longer-term outcomes, including SAT scores, Advanced Placement (AP) credit, and enrollment in four-year college (Angrist et al., 2016).

Funding for Massachusetts public school students follows their school enrollment. Specifically, charter schools receive tuition payments from their students' home districts equal to district per-pupil expenditure. The state partially reimburses districts for charter school payments during a transition period, but these reimbursements have not been fully funded in recent years. Prior to 2010, Massachusetts law capped the overall number of charter schools at 120 and limited total charter school

[1] Teachers are designated as highly qualified if they possess a Massachusetts teaching license and a bachelor's degree, and pass a state examination or hold a degree in their subject area. See `http://www.doe.mass.edu/educators/title-iia/hq/hq_faq.html`.

[2] The No Excuses index is an average of indicators equal to one if the following items are mentioned in a school's annual report: high expectations for academics, high expectations for behavior, strict behavior code, college preparatory curriculum, core values in school culture, selective teacher hiring or incentive pay, emphasis on math and reading, uniforms, hires Teach for America teachers, Teaching Fellows, or AmeriCorps members, affiliated with Teach for America alumni, data driven instruction, and regular teacher feedback.

tuition to 9 percent of a district's spending. Charter expenditure in Boston reached this cap in fall 2009 (Boston Municipal Research Bureau, 2008). As a result, the charter cap limited the expansion of charter schools in Boston before 2010.

2.2.2 Charter Expansion

In January 2010, Governor Deval Patrick signed *An Act Relative to the Achievement Gap* into law. This reform relaxed the charter cap to allow the charter sector to double for districts in the lowest decile of performance according to a measure derived from test score levels and growth. The law also included provisions for school turnarounds and the creation of "innovation" schools (Massachusetts State Legislature, 2010).

For Boston and other affected districts, the 2010 reform increased the limit on charter spending from 9 percent to 18 percent of district funds between 2010 and 2017. "Proven providers" – existing schools or school models the Massachusetts Board of Elementary and Secondary Education deemed effective – could apply to open new schools or expand enrollment. The law also allowed school districts to create up to 14 "in-district" charter schools without prior approval from the local teachers' union or proven provider status. Concurrent with the increased supply of charter seats, the law required charters to increase recruitment and retention efforts for high need students and allowed charters to send advertising mailers to all students in the district.[3]

The state received 71 initial applications (some of which were solicited by the state) for new charter schools or expansions from August 2010 to August 2012, and invited 60 percent of applicants to submit final round proposals. To determine whether a school model qualified for proven provider status, the Massachusetts Board of Elementary and Secondary Education compared existing schools using the model to other charters and traditional public schools. Criteria for this evaluation included enrollment of high-need students, attrition, grade retention, dropout, graduation, attendance, suspensions, and performance on state achievement tests (Massachusetts Department of Elementary and Secondary Education, 2015). The state granted proven provider status to four of seven Boston charter middle schools, as well as the KIPP organization, which operated a charter school in Lynn, Massachusetts, but had not yet entered Boston. Together, the provisions of the 2010 reform led to the establishment of 27 new charter campuses between 2011 and 2013, as well as expansions of 17 existing charter schools, typically to new grade levels (Massachusetts Department of Elementary and Secondary Education, 2016).

Charter enrollment in Boston expanded rapidly after 2010. This can be seen in Figure 1, which plots shares of fourth, sixth, and ninth grade students attending charter schools. These statistics are calculated using the administrative enrollment data described below. Sixth grade charter enrollment doubled after the reform, expanding from 15 to 31 percent between 2010 and 2015. Charter enrollment

[3]The state's definition of high need students includes those with special educations status, limited English proficiency, eligibility for subsidized lunch, or low scores on state achievement tests, as well as students deemed to be at risk of dropping out of school.

also grew substantially in elementary and high school, though not as dramatically as in middle school. The share of Boston students in charter schools increased from 7 percent to 11 percent in fourth grade and 9 to 15 percent in ninth grade over the same time period.

Boston's new expansion charter schools have broadly similar characteristics and practices as their proven provider parent schools. This is evident in columns (2) through (4) of Table 1, which describe proven providers, other charters operating before 2010, and new expansions. Like proven providers, expansion schools have longer school days and years than BPS schools, and rate highly on the index of No Excuses practices. Per-pupil expenditure is similar at proven provider and expansion schools, and lower at other charters. New campuses located an average of 3.1 miles from their parent campuses, often expanded into different Boston neighborhoods (see Figure 2).

Expansion charter schools are primarily staffed by young teachers with little teaching experience. As shown in Table 2, 78 percent of teachers at proven providers in the year before expansion were less than 32 years old, while 87 percent of expansion charter teachers were below this threshold in the year after expansion. These and other teacher characteristics come from an administrative database of Massachusetts public school employees (see the Data Appendix). Columns (4) and (7) show that proven providers transferred some teachers from parent campuses to help staff their expansions: 12 percent of former parent teachers moved to expansion campuses, accounting for 25 percent of the teaching workforce at these new schools. Transferred teachers were less experienced than teachers who remained at parent campuses (2.2 years vs. 3.3 years). Most of the remaining expansion teachers had not taught in a Massachusetts school in the previous year (66 percent), though a few transferred from other schools (9 percent). As a result, the average teacher at an expansion charter had only 1.4 years of teaching experience, compared to 2.9 years for teachers at parent campuses and 11.5 years for BPS teachers.

2.3 Data

2.3.1 Data Sources and Sample Construction

We study the effectiveness of Boston charter middle schools using records from randomized admission lotteries conducted between 2004 and 2013. Our sample includes 14 of the 15 Boston charter schools that accept students in 5th or 6th grade, accounting for 94 percent of enrollment for schools in this category during the 2013-2014 school year.[4] Lottery records typically list applicant names along with application grades, dates of birth, towns of residence and sibling statuses. Our analysis excludes sibling applicants, out-of-area applicants, and students who applied to non-entry grades (siblings are guaranteed admission, while out-of-area applicants are typically ineligible). The lottery records also indicate which students received admission offers. We distinguish between immediate offers received on the day of the lottery and later offers received from the waitlist; in some lotteries all students

[4]Two charter middle schools that closed before 2010 are excluded from this calculation. The one missing school declined to provide lottery records.

eventually receive waitlist offers, while in others the records are insufficient to distinguish between immediate and waitlist offers. Further information on school coverage and lottery records appears in Appendix Tables A1 and A2.

We match the lottery records to state administrative data based on name, date of birth, town of residence and application cohort. The administrative data cover all students enrolled in Massachusetts public schools between 2002 and 2014. As shown in Appendix Table A3, we find matches for 95 percent of lottery applicants in this database. Key administrative records include school enrollment, gender, race, special education status, English Language Learner status, subsidized lunch status, and test scores on Massachusetts Comprehensive Assessment System (MCAS) achievement tests. We standardize MCAS scores to mean zero and standard deviation one relative for BPS students by subject, grade and year. In addition to information on charter lottery applicants, we use administrative data on other Boston students to describe changes in charter application and enrollment patterns after the 2010 reform. The Data Appendix provides more details regarding data processing and sample construction.

2.3.2 Descriptive Statistics

Charter application and enrollment patterns in our sample mirror the large increases in charter market share evident in Figure 1. As shown in Table 3, 15 percent of eligible Boston students applied to charter schools with fifth or sixth grade entry before the 2010 reform, 12 percent received offers from these schools, and 10 percent enrolled. This implies roughly 1.5 applicants for each available charter seat. The application rate increased to 35 percent in 2013, and attendance reached 17 percent. The increase in applications therefore outpaced enrollment growth, boosting the number of applicants per seat to 2. This increase in demand was particularly pronounced at other charter schools (neither proven providers or expansions), which saw their applications per seat rise from 1.9 to 4.[5] By 2013, half of charter middle school students attended new expansion campuses.

Table 4 describes the characteristics of BPS students, students enrolled in charter middle schools, and applicants in our randomized lottery sample. Charter applicants and enrolled students are consistently more likely to be black than BPS students. Both before and after 2010, students attending proven providers were less disadvantaged than other Boston students as measured by special education status, limited English proficiency, and fourth grade test scores. Past achievement and other characteristics of students enrolled at proven providers and randomized applicants were similar before the reform, but diverged somewhat afterward. This is due to the fact that some proven providers expanded to serve earlier grades after 2010, resulting in a larger share of middle school students grandfathered in from elementary school.

As shown in columns (11) and (12) of Table 4, the characteristics of students enrolled at expansion charters differ markedly from those of other charter students. Special education and limited English proficiency rates are similar at expansion charters and in the BPS population. Expansion charter

[5]The number of applicants per seat is larger for each individual charter type than for the sector as a whole because some students apply to more than one school.

students also score below the BPS average on 4th grade math and English tests, and are more likely than BPS students to be eligible for subsidized lunches. These facts indicate that expansion charters attract a more disadvantaged, lower-achieving population than their proven provider parent schools. This pattern may reflect the changes in recruitment practices required by the 2010 Achievement Gap Act, which mandated that charter schools take steps to enroll higher-need students.

2.4 Empirical Framework

We use charter lottery offers as instruments for charter school attendance in a causal model with multiple endogenous variables, each representing enrollment in a type of charter school. The structural equation links charter attendance with outcomes as follows:

$$Y_{ig} = \alpha_g + \sum_{k=1}^{K} \beta_k C_{ig}^k + \sum_{j=1}^{J} \delta_j R_{ij} + X_i'\gamma + \epsilon_{ig}, \tag{2.1}$$

where Y_{ig} is a test score for student i in grade g and C_{ig}^k measures years of enrollment in charter school type k through grade g. Charter types include parent campuses, replicates, and other charters; we also distinguish between enrollment before and after the charter expansion law. The parameters of interest, β_k, represent causal effects of an additional year of attendance at each charter type relative to traditional public schools.[6] The key control variables in equation (2.1) are a set of indicators, R_{ij}, for all combinations of charter lottery applications present in the data. Lottery offers are randomly assigned within these "risk sets." A vector of baseline demographic characteristics, X_i, is also included to increase precision.[7]

The first stage equations predicting charter attendance are given by

$$C_{ig}^k = \mu_g^k + \sum_{\ell=1}^{K} \left(\pi_{\ell 1}^k Z_{i1}^\ell + \pi_{\ell 2}^k Z_{i2}^\ell\right) + \sum_{j=1}^{J} \lambda_j^k R_{ij} + X_i'\theta^k + \eta_{ig}^k;\ k = 1...K. \tag{2.2}$$

Here Z_{i1}^k denotes a dummy variable equal to one if applicant i received an offer to attend charter type k on the day of the lottery, and Z_{i2}^k equals one if the applicant later received an offer from the waitlist. Immediate offers are coded to zero in risk sets where we cannot distinguish between immediate and waitlist offers. Like equation (2.1), the first stage also controls for lottery risk set indicators and baseline student characteristics. Two-stage least squares (2SLS) estimates are obtained by ordinary least squares (OLS) estimation of equation (2.1) after substituting predicted values from (2.2) for the charter attendance variables. Standard errors are clustered by student to account for correlation in outcomes across grades.

[6]If charter effects are not linear in years of enrollment, β_k will capture a weighted average of unit causal effects for students shifted across each attendance increment by lottery offers (Angrist and Imbens, 1995).

[7]These characteristics, which are measured in the year prior to a student's lottery application, include gender, race, a female-minority interaction, subsidized lunch status, English language learner status, and special education status.

Our empirical strategy is motivated by the fact that charter lottery offers are randomly assigned within risk sets and therefore independent of family background and all other student attributes. Appendix Table A4 presents a check on this by comparing baseline characteristics for offered and non-offered applicants, controlling for risk sets. These comparisons show that students with and without lottery offers are similar for all charter school types and time periods, indicating that random assignment was successful.[8]

2.5 Effects of Charter School Expansion

2.5.1 Lottery Estimates

Students randomly offered charter seats spend more time in charter schools than students not offered seats. Table 5 reports estimated effects of immediate and waitlist offers on years of charter enrollment for proven providers, expansion charters, and other charters before and after the reform. These estimates correspond to the parameters π_{k1}^{k} and π_{k2}^{k} in equation (2.2). Columns (1) and (3) show that immediate offers boost charter attendance by an average of one year for students applying to proven providers and other charters before 2010. The effects of waitlist offers (reported in columns (2) and (4)) are smaller, likely because some students make arrangements to attend school elsewhere before gaining admission from the waitlist. The first stage coefficients are generally smaller but still positive and significant in the post-expansion period for all charter types. This reflects the fact that less time has elapsed in our data for cohorts applying after 2010, resulting in fewer years of potential charter enrollment between lottery and test dates.

Proven provider charter schools generated larger achievement gains than other charter schools in Boston prior to the 2010 expansion. This can be seen in Table 6, which reports second-stage estimates of equation (2.1). Columns (2) and (3) demonstrate that a year of charter attendance at a proven provider increased math and English scores by 0.33σ and 0.14σ prior to the reform, estimates that are highly statistically significant. Corresponding math and English effects for other Boston charters were 0.18σ and 0.09σ. The difference in effects for proven providers and other charters is statistically significant in math ($p = 0.00$), though not in English. This finding indicates that policymakers selected more effective charter schools for expansion. The large positive impacts for both charter groups are consistent with the results reported by Abdulkadiroğlu et al. (2011) in a subsample of the schools and cohorts studied here.

Columns (5) and (7) of Table 6 reveal that the impacts of proven providers and other charters did not change after the charter expansion reform. For cohorts applying after 2010, proven providers

[8] Even with random assignment, selective attrition may lead to bias in comparisons of those with and without lottery offers. Appendix Tables A3 and A5 show that the attrition rate from our sample is low: we match 95 percent of applicants to the administrative data, and find roughly 85 percent of post-lottery test scores that should be observed in our sample window for matched students. The match rate is 4 percent higher for students offered charter seats, and we are 3 percent more likely to find scores for students with lottery offers at non-proven-provider charters before 2010. This modest differential attrition seems unlikely to meaningfully affect the results reported below.

boosted math and English scores by 0.36σ and 0.19σ per year of attendance, while other charters increased scores by 0.21σ and 0.13σ. These estimates are slightly larger than estimates for earlier cohorts, though the differences between pre- and post-reform effects are not statistically significant for either group. If anything, this pattern suggests that existing Boston charter schools slightly improved their effectiveness after the 2010 reform.

Proven providers also successfully replicated their impacts at expansion campuses. As shown in column (6) of Table 6, a year of attendance at an expansion charter school increases math and English test scores by 0.32σ and 0.23σ. These estimates are comparable to estimates for parent campuses and larger than estimates for other charters during the same time period. Combined with the consistent effects for proven providers and other charters over time, these results imply an increase in overall effectiveness for Boston's charter middle school sector despite the substantial increase in charter market share over this period. The impacts of expansion charters are particularly striking in view of the selection patterns documented in Table 3: new charter campuses generate above-average effects despite serving more typical Boston students.[9] This implies that positive charter effects are not an artifact of a positively-selected peer environment.

2.5.2 Effects for Subgroups

The 2010 charter expansion law encourages charter schools to recruit and retain students with higher needs, as measured by criteria including English proficiency, special education status and past achievement. Table 7 summarizes effect heterogeneity as a function of these characteristics.

The estimates show consistent positive impacts across most subgroups, charter school types, time periods and subjects. Effects are similar for students designated English language learners and students without this designation, though estimates for the former group are often imprecise due to small sample sizes. All estimates are positive for students with and without special education status; effects for special education students appear to be somewhat smaller at proven providers and larger at expansion charters, but these differences may be a chance finding due to the many splits examined. As in previous studies (e.g., Walters, 2014), we find that effects tend to be larger for students with lower previous test scores. The large estimated effects for high-need subgroups at expansion charters are noteworthy: evidently, expansion schools continue to generate substantial gains for these groups despite serving larger shares of such students than other Boston charters.

2.5.3 Variation Across Charter Schools

The results in Table 6 indicate that on average, expansion charter schools are as effective as their proven provider parent schools. It is also of interest to ask whether impacts differ across individual

[9] This is consistent with findings reported by Walters (2014), who argues that charter school effects are likely to be larger for the average Boston student than for the selected set of charter lottery applicants.

charter schools. We explore variation in effects across campuses by estimating a version of equation (2.1) that includes separate endogenous variables for enrollment in each charter school and time period, instrumenting with school- and period-specific lottery offers.

The results of this analysis reveal substantial heterogeneity in impacts across schools. Figure 3 plots school-specific estimates of math effects against corresponding English effects. Schools with larger math effects also generate larger gains in English, and the spread in estimated effects is large for each subject. Some of this variation is due to the considerable sampling error in school-specific estimates, but statistical tests establish that impacts vary across schools. We can reject the hypothesis that effects for all expansion schools equal those of their parent campuses at marginal significance levels in math ($p = 0.07$) but not in English ($p = 0.18$). The hypothesis that effects are equal for all expansion charters is rejected in both subjects ($p = 0.06$ and $p = 0.02$). These results indicate that although effects for parent and replicate campuses are similar on average, some replication efforts are more successful than others. The factors that drive variation in impacts across charter schools are an important subject to be explored in future work.

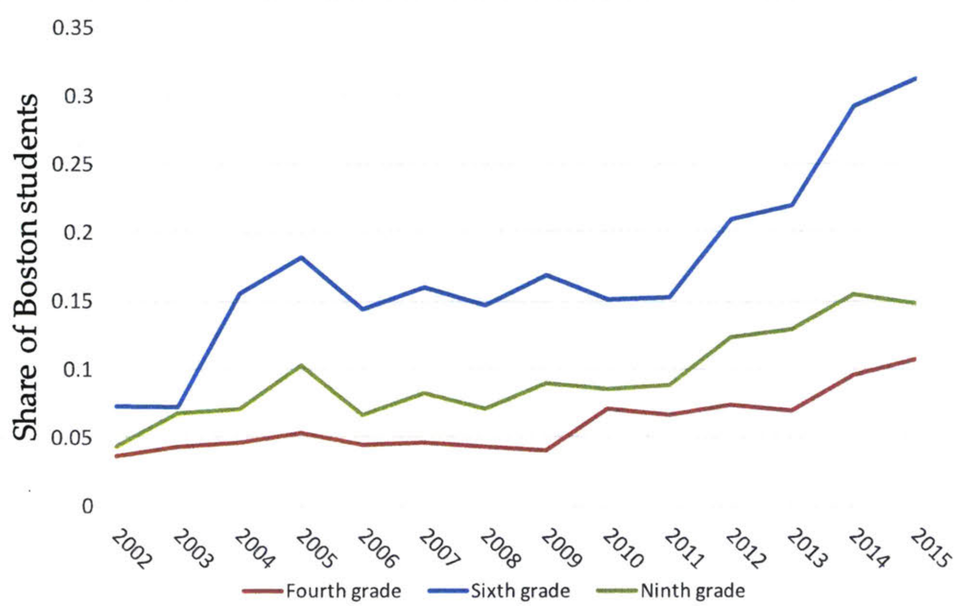
2.6 Conclusion

The replication and expansion of successful schools is one strategy to address persistent achievement gaps in the United States. The efficacy of this strategy requires schools selected for expansion to maintain their success at new locations and with new student populations. Previous research has shown that urban No Excuses charter schools boost test scores markedly for small groups of applicants, suggesting the potential for transformational effects on urban achievement if these gains can be maintained at larger scales. We examine a recent policy change in Massachusetts that doubled Boston's charter sector over a short time period, allowing us to evaluate changes in the effects of No Excuses charters as these schools expanded to serve a larger share of the population.

Our results show that Boston's No Excuses charters reproduced their effectiveness at new campuses. Lottery-based estimates show that schools selected for expansion produce larger gains than other charters, indicating that Massachusetts' accountability regime successfully identified more successful schools. New expansion campuses generate test score gains similar to those of their parent campuses, despite a doubling of charter market share. After expansion, the effects of parent campuses, expansion schools, and other charters are positive for all subgroups.

It is worth noting some caveats to these results. Despite the rapid growth of Boston's charter sector, less than one third of the city's middle school students attend charter schools. Expansion to serve a large majority of students could lead to changes in public school behavior and other general equilibrium effects that are outside the scope of the analysis here. In addition, Boston is a relatively small city that likely faces elastic supply of charter teachers and other inputs. Attempts to implement No Excuses practices more widely could lead to scarcity of quality teachers or other key ingredients necessary for continued success. Nonetheless, our results demonstrate that Boston's charter sector maintained its effectiveness during the substantial expansion considered here.

Figure 1: Charter School Enrollment in Boston



Notes: This figure plots the share of Boston fourth, sixth, and ninth grade students enrolled in charter schools between 2002 and 2015.

Figure 2: Locations of Boston Charter Schools

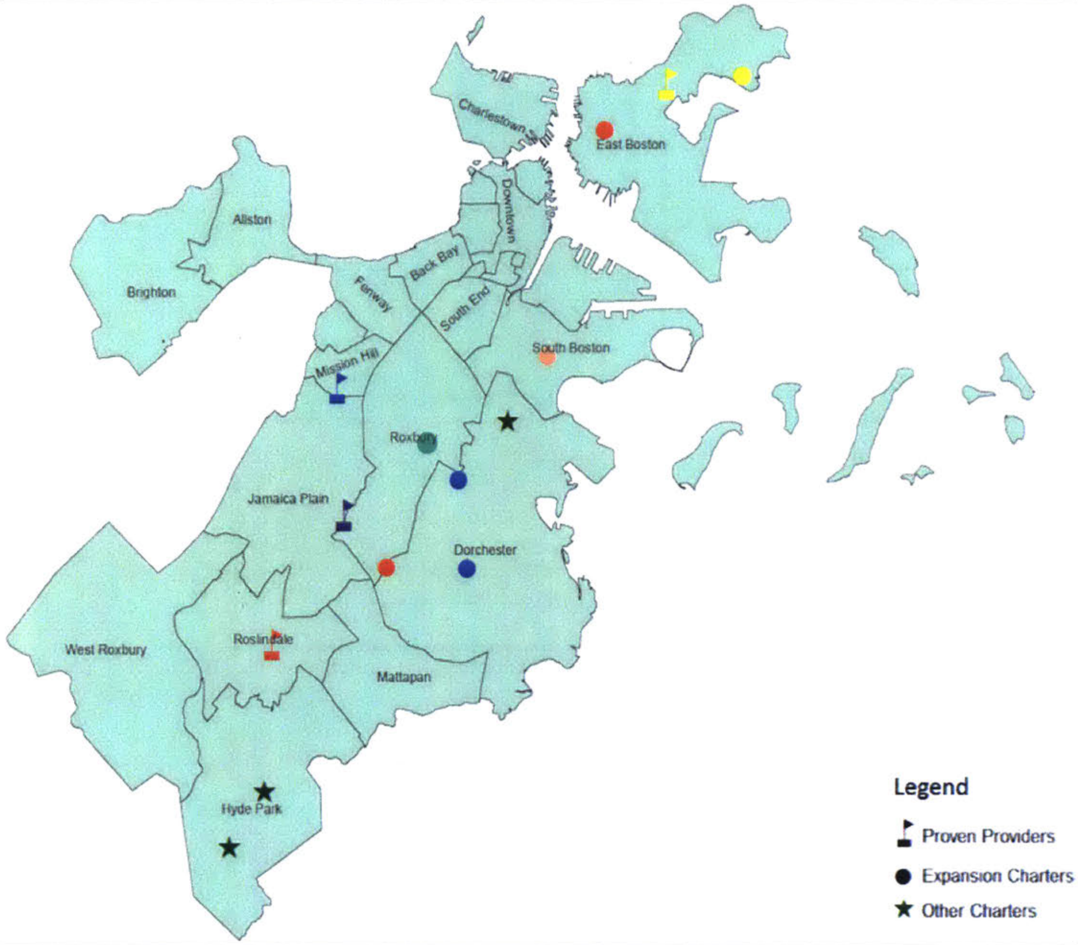
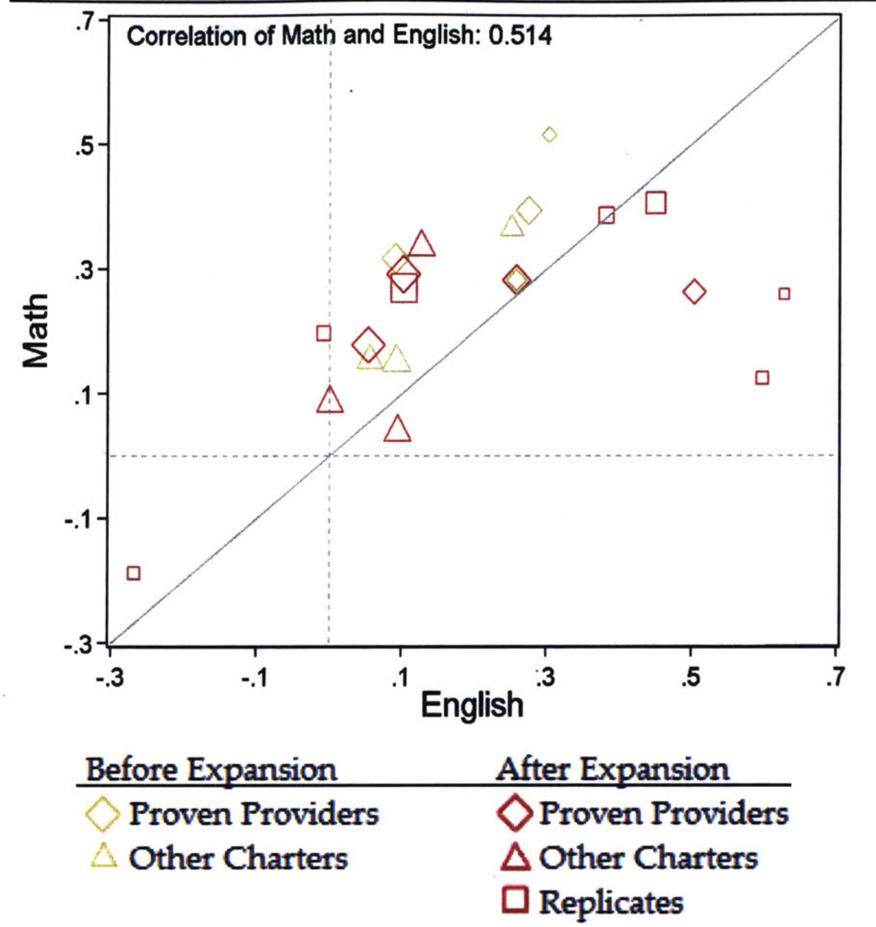


Figure 3: School-specific Estimates



Notes: This figure plots estimates of test score effects for individual charter schools. These estimates come from 2SLS models using school-specific lottery offers as instruments for charter enrollment, treating enrollment in each school and time period as a separate endogenous variable. Models also control for lottery risk sets and baseline covariates. Marker sizes are inversely proportional to the average standard error of estimates for math and English. The 45 degree line is marked in grey.

Table 1: School Characteristics

	All Charters	Proven Providers	Expansion Charters	Other Charters	Boston Public Schools
	(1)	(2)	(3)	(4)	(5)
Panel A: Comparison with traditional public schools					
Days per year	185.9	183.8	186.6	187.3	180.0
Hours per day	8.1	8.1	8.0	8.0	7.3
% of teachers licensed in teaching assignment	47.2	45.7	42.8	59.6	95.1
% of core academic classes taught by highly qualified teachers	78.7	88.9	68.7	88.4	93.2
Average years of teaching experience in MA for teachers	2.6	2.9	1.6	3.3	12.3
Student/teacher ratio	11.2	12.5	10.2	11.7	11.7
Average per-pupil expenditure	$17,041	$17,900	$17,831	$14,052	$18,766
Title 1 eligible	1.0	1.0	1.0	1.0	1.0
Panel B: Charter school characteristics					
Years open through 2012-2013	7.4	11.0	2.4	14.3	
Tutoring	1.0	1.0	1.0	1.0	
Homework help program	0.4	0.3	0.3	1.0	
Saturday programming	0.6	0.5	0.6	0.7	
School break programming	0.5	0.5	0.3	1.0	
No Excuses index	0.9	0.9	0.9	0.8	
Contact parents at least monthly	0.5	0.5	0.4	0.7	
Distance from parent campus (miles)	-	-	3.1	-	
N (schools)	14	4	7	3	5

Notes: This table displays characteristics for charter schools in the analysis sample along with Boston Public Schools (BPS) district schools serving middle school grades. Data sources include charter school annual reports, school websites, Massachusetts Department of Elementary and Secondary Education (MA DESE) School District Profiles, and MA DESE Education Personnel Information Management System (EPIMS) data. Characteristics are measured in the 2012-2013 school year. Per-pupil expenditure is CPI-adjusted to 2015 dollars. The No Excuses index is an equally-weighted average of indicators equal to one if the following items are discussed in a school's annual report: high expectations for academics, high expectations for behavior, strict behavior code, college preparatory curriculum, core values in school culture, selective teacher hiring or incentive pay, emphasis on math and reading, uniforms, hires Teach for America teachers, Teaching Fellows, or AmeriCorps members, affiliated with Teach for America alumni, data driven instruction, and regular teacher feedback.

Table 2: Staffing at Parent and Replicate Charter Schools

		Teachers at Proven Providers in 2010-11				Teachers at Expansion Charters in First Year			
	BPS overall	All	Stay at Parent	Move to Expansion	Leave Network	All	Came from Parent Campus	Came from Other School	New Teacher
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fraction in category	-	1.00	0.62	0.12	0.26	1.00	0.25	0.09	0.66
<32 years old	0.30	0.78	0.73	0.95	0.85	0.87	0.86	0.80	0.89
>49 years old	0.26	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Unlicensed	0.04	0.28	0.24	0.29	0.38	0.53	0.07	0.20	0.76
Years Working in MA Public School:	11.47	2.89	3.26	2.20	2.25	1.44	3.41	3.10	0.45
N (Full Time Equivalent Teachers)	4261	88	54	11	22	55	14	5	36

Notes: This table describes characteristics of teachers at Boston charter schools before and after expansion. Column (1) summarizes Boston Public Schools (BPS) teacher characteristics in 2011-12. Columns (2) - (5) display statistics for teachers working at proven provider charters in the 2010-2011 school year. Columns (6) - (9) show statistics for teachers working at expansion charters during the 2011-2012 school year.

Table 3: Charter Applications and Enrollment

	Before Charter Expansion			After Charter Expansion			
	Any Charter	Proven Providers	Other Charters	Any Charter	Proven Providers	Expansion Charters	Other Charters
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
% of Boston Students Applying	15%	9%	8%	35%	19%	19%	18%
% of Boston Students with Lottery Offers	4%	2%	3%	10%	4%	7%	3%
% of Boston Students with Lottery or Waitlist Offers	12%	7%	6%	23%	10%	15%	6%
% of Boston Students Enrolling in Charters	10%	5%	4%	17%	5%	9%	4%
Applicants per Seat	1.5	1.8	1.9	2.0	3.4	2.2	4.0

Notes: This table summarizes applications and enrollment for Boston charter middle schools in the analysis sample before and after the 2010-11 charter sector expansion. The sample consists of students enrolled in Boston schools in both 4th and 6th grades. Pre-expansion refers to students who applied in spring 2008 or 2009. Post-expansion includes students who applied in spring 2011 through 2013.

Table 4: Characteristics of Boston Middle School Students

	Before Charter Expansion					After Charter Expansion						
	BPS	All Charters		Proven Providers		BPS	All Charters		Proven Providers		Expansion Charters	
	Enrolled	Enrolled	Randomized Applicants	Enrolled	Randomized Applicants	Enrolled	Enrolled	Randomized Applicants	Enrolled	Randomized Applicants	Enrolled	Randomized Applicants
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Female	0.478	0.495	0.486	0.509	0.482	0.476	0.495	0.491	0.483	0.482	0.503	0.485
Black	0.418	0.585	0.561	0.572	0.639	0.313	0.490	0.442	0.459	0.449	0.491	0.453
Latino/a	0.353	0.263	0.238	0.362	0.295	0.435	0.384	0.406	0.456	0.455	0.403	0.431
Asian	0.093	0.008	0.017	0.005	0.012	0.096	0.021	0.033	0.017	0.025	0.025	0.034
White	0.122	0.133	0.170	0.051	0.039	0.130	0.080	0.093	0.048	0.047	0.054	0.054
Subsidized lunch	0.839	0.726	0.684	0.775	0.738	0.792	0.791	0.801	0.832	0.832	0.828	0.830
English Language Learners	0.223	0.114	0.116	0.165	0.159	0.410	0.328	0.363	0.323	0.412	0.388	0.396
Special education	0.248	0.178	0.192	0.174	0.184	0.236	0.188	0.204	0.150	0.200	0.197	0.212
Attended charter in 4th grade	0.002	0.107	0.120	0.081	0.093	0.001	0.120	0.040	0.282	0.028	0.024	0.016
4th grade math score	-	0.108	0.220	0.073	0.046	-	0.066	0.050	0.388	0.051	-0.133	-0.032
4th grade English score	-	0.174	0.309	0.155	0.161	-	0.121	0.075	0.407	0.044	-0.084	-0.038
N	18934	2240	2745	995	1273	8330	2473	4513	666	2264	1233	2437

Notes: This table shows descriptive statistics for Boston middle school students before and after the 2010-11 charter school sector expansion. The sample includes all students who attended Boston schools in 4th grade and 5th or 6th grade between 2004 and 2013. Columns (1) and (6) show statistics for students who did not enroll in a charter school in 5th or 6th grade. Columns (2), (4), (7), (9) and (11) show statistics for students who enrolled in a charter school in 5th or 6th grade. Columns (3), (5), (8), (10) and (12) report statistics for randomized charter school applicants. Randomized applicants exclude siblings, disqualified students, and out of area applicants. Test scores are standardized to have mean zero and standard deviation one in BPS schools by subject, grade and year.

Table 5: First Stage Estimates

	Before Charter Expansion				After Charter Expansion					
	Proven Providers		Other Charters		Proven Providers		Expansion Charters		Other Charters	
	Immediate Offer	Waitlist Offer	Immediate Offer	Waitlist Offer	Immediate Offer	Waitlist Offer	Immediate Offer	Waitlist Offer	Immediate Offer	Waitlist Offer
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Math	1.304***	1.027***	1.554***	0.984***	0.795***	0.400***	0.659***	0.348***	0.930***	0.853***
	(0.067)	(0.050)	(0.047)	(0.061)	(0.054)	(0.048)	(0.046)	(0.041)	(0.052)	(0.071)
N (Applicants)	1279		1909		2303		2416		2405	
English	1.302***	1.027***	1.556***	0.985***	0.792***	0.398***	0.660***	0.345***	0.930***	0.853***
	(0.067)	(0.052)	(0.047)	(0.061)	(0.054)	(0.048)	(0.046)	(0.040)	(0.052)	(0.071)
N (Applicants)	1277		1911		2307		2420		2412	

Notes: This table displays first stage effects of charter lottery offers on years of enrollment in charter schools. Immediate offer equals one for applicants offered seats on the day of the lottery. Waitlist offer equals one for applicants offered seats from the waitlist.
*significant at 10%; **significant at 5%; ***significant at 1%

Table 6: Charter Effects on Test Scores Before and After Charter Expansion

	Before Charter Expansion			After Charter Expansion			
		2SLS			2SLS		
	Non-Charter Mean	Proven Providers	Other Charters	Non-Charter Mean	Proven Providers	Expansion Charters	Other Charters
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Math	0.208	0.332***	0.180***	0.035	0.362***	0.322***	0.209***
		(0.036)	(0.026)		(0.069)	(0.073)	(0.057)
P-value: Equals proven provider			0.000			0.623	0.058
P-value: Equals other charters						0.135	
N (Applicants)	3515	3836	6095	5106	4296	4759	4352
N (Total scores)				17395			
English	0.271	0.140***	0.088***	0.071	0.185**	0.226***	0.134**
		(0.035)	(0.025)		(0.072)	(0.075)	(0.056)
P-value: Equals proven provider			0.164			0.625	0.540
P-value: Equals other charters						0.218	
N (Applicants)	3485	3754	6084	5108	4298	4769	4363
N (Total scores)				17316			

Notes: This table reports 2SLS estimates of the effects of charter school attendance on test scores. The sample stacks post-lottery test scores in grades five through eight. The endogenous variables are counts of years spent in the different charter types (pre-expansion proven providers, pre-expansion other charters, post-expansion proven providers, expansion schools, and post-expansion other charters). The instruments are immediate and any lottery offer dummies for each school type. Controls include lottery risk sets, as well as gender, ethnicity, a female-minority interaction, special education, English language learner, subsidized lunch status, and grade and year indicators. Standard errors are clustered by student.

*significant at 10%; **significant at 5%; ***significant at 1%

Table 7: Charter School Effects for Subgroups

	Math scores					English scores				
	Before expansion		After expansion			Before expansion		After expansion		
	Proven Providers	Other Charters	Proven Providers	Expansion Charters	Other Charters	Proven Providers	Other Charters	Proven Providers	Expansion Charters	Other Charters
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
English Language	0.289***	-0.197	0.499***	0.283*	0.328***	0.164	-0.251*	0.331***	0.219	0.233**
Learner	(0.088)	(0.157)	(0.099)	(0.146)	(0.116)	(0.100)	(0.136)	(0.106)	(0.144)	(0.118)
N (applicants)	468	455	1729	1804	1275	468	454	1733	1807	1279
Not English	0.332***	0.193***	0.248***	0.330***	0.144**	0.126***	0.096***	0.090	0.239***	0.090
Language Learner	(0.040)	(0.027)	(0.092)	(0.081)	(0.066)	(0.037)	(0.025)	(0.096)	(0.083)	(0.063)
N (applicants)	3368	5640	2567	2955	3077	3286	5630	2565	2962	3084
Special Education	0.219**	0.157**	0.239	0.622***	0.183	0.041	0.119*	0.129	0.299	0.163
	(0.104)	(0.064)	(0.187)	(0.175)	(0.209)	(0.116)	(0.062)	(0.201)	(0.200)	(0.224)
N (applicants)	693	1178	823	930	758	683	1171	818	936	763
Not Special	0.347***	0.185***	0.402***	0.268***	0.189***	0.157***	0.091***	0.230***	0.220***	0.109*
Education	(0.039)	(0.029)	(0.072)	(0.081)	(0.059)	(0.036)	(0.026)	(0.074)	(0.079)	(0.057)
	3143	4917	3473	3829	3594	3071	4913	3480	3833	3600
Below-mean	0.359***	0.237***	0.465***	0.486***	0.183**	0.124*	0.108**	0.313***	0.289***	0.185**
baseline score	(0.058)	(0.043)	(0.099)	(0.112)	(0.075)	(0.070)	(0.048)	(0.108)	(0.099)	(0.086)
N (applicants)	1460	2050	2078	2224	1874	1282	1817	1858	2150	1684
Above-mean	0.345***	0.155***	0.230***	0.287***	0.240***	0.177***	0.076***	0.031	0.184**	0.132**
baseline score	(0.035)	(0.026)	(0.075)	(0.068)	(0.055)	(0.031)	(0.023)	(0.080)	(0.074)	(0.059)
N (applicants)	2376	4045	2218	2535	2478	2472	4267	2440	2619	2679

Notes: This table reports 2SLS estimates of the effects of charter school attendance on test scores for subgroups of students. The sample stacks post-lottery test scores in grades five through eight. The endogenous variables are counts of years spent in the different charter types. The instruments are immediate and any lottery offer dummies for each school type. Controls include lottery risk sets, as well as gender, ethnicity, a female-minority interaction, special education, English language learner, subsidized lunch status, and grade and year indicators.

*significant at 10%; **significant at 5%; ***significant at 1%

2.7 Appendix

2.7.1 Data Appendix

We use lottery records, student demographic and enrollment data, state standardized test scores, and school personnel files in this article. Lottery records collected from individual schools contain the list of applicants, offer status, and factors that affect an applicant's lottery odds, including sibling status, disqualifications, late applications, and applying from outside of Boston. The Student Information Management Systems (SIMS) dataset contains enrollment and demographic data for all public school students in Massachusetts. Student standardized test scores come from the state database for the Massachusetts Comprehensive Assessment System (MCAS). The Massachusetts Education Personnel Information Management Systems (EPIMS) database provides school staff information. Next we describe these datasets, the matching process, and sample construction.

2.7.1.1 Lottery Records

Massachusetts legally requires charters to admit students via lottery when more students apply to a charter school than the number of available seats for a given grade. Our paper uses records from charter lotteries conducted between spring 2004 to spring 2013 for 14 charter schools accepting students in 5th or 6th grade. Each of the 14 schools contributes oversubscribed lottery data.[10] Schools vary in the grades they serve and in years of operation. Table A1 lists this information and the years each school contributes to the analysis. We exclude one school that did not provide lottery records (Smith Leadership Academy) and two schools that closed before the charter expansion (Uphams Corner Charter School in 2009 and Fredrick Douglas Charter School in 2005).

Lottery data typically includes applicants' names, dates of birth, and lottery and waitlist offer status. Offers to attend charter schools either occur on the day of the lottery (referred to as *immediate* $offer$) or after the day of the lottery when students receive offers from the randomly sequenced waitlist as seats become available. In three out of the 65 lotteries in the study, the schools gave all applicants offers or did not give waitlist offers to non-siblings. Four lotteries did not distinguish the timing of the offers so we code the immediate offer variable to equal zero for these cohorts.

The Uncommon Schools/Roxbury Preparatory charter network held a single lottery for its three campuses in the Spring 2012 and Spring 2013 lotteries. When the school called a students lottery number, the student could pick from the campuses that still had open seats. Our lottery records show which campus they picked at the time of the lottery. We find the last lottery number for each campus and code all students with better lottery numbers as having offers from that campus.

Uncommon Schools offered seats from the waitlist as they became available for individual campuses.

[10]We do not have Spring 2004 lottery records for Brooke Roslindale, Boston Prep, and Academy of the Pacific Rim or Spring 2005 records for Brooke Roslindale. Brooke Roslindale does not have lotteries in after charter expansion because their elementary school students filled the middle school seat. All other schools and years have oversubscribed lottery data.

Parents chose to accept or decline waitlist offers for single schools. If they declined, they were taken off the waitlist and would not be considered for seats at the other campuses.

2.7.1.2 Enrollment and Demographics

The SIMS data contains individual level data for students enrolled in public schools in Massachusetts from 2003-2004 through 2013-2014. The data contains snapshots from October and the end of the school year. Each student has only one observation in each time period, except when students switch grades or schools within year. Fields include a unique student identifier, grade level, year, name, date of birth, gender, ethnicity, special education status, limited English proficiency status, free or reduced price lunch status, school attended, suspensions, attendance rates, and days truant.

We code students as charter attendees in a school year if they attended a charter at any point during a year. Students who attend more than one charter school in a year are assigned to the charter they attended the longest. Students who attend more than one traditional public school and no charter schools in a year are assigned to the school they attended the longest. We randomly choose between schools if students have attendance ties between the most attended schools.

2.7.1.3 Test Scores

This paper uses individual student math and English Language Arts (ELA) Massachusetts Comprehensive Assessment System (MCAS) test scores from 2003-2004 through 2013-2014. Massachusetts public school students take the exam each year in grades grades 5 through 8. Data includes the unique student identifier. We standardize the raw scores to to have a mean of zero within subject-grade-year in Massachusetts.

2.7.1.4 Staff Records

The Education Personnel Information Management Systems (EPIMS) contains yearly staff level data for all employees in Massachusetts public schools. We use data collected in October of the 2007-08 through the 2013-14 school years. Data includes job position, school, full time equivalency, date of birth, date of hire for first public school job in Massachusetts, license status, and highly qualified status. We use the full time equivalency of all staff and teachers. If one school has two half time teachers, they are counted as one full time equivalent teacher. A teacher who teaches at multiple schools counts towards the staff statistics at each school.

2.7.1.5 Matching Data

We use applicants' names, date of birth, grade, and year to match their lottery records to the state enrollment data. The applicants who uniquely and exactly match the grade, year, name, and date of birth (if available) in the state records are assigned to the matched unique student id. After this initial match, we strip names in the lottery and enrollment data of spaces, surnames, hyphens, and apostrophes. Unique matches after this cleaning are assigned to the matched unique student id. Then, we use reclink, a fuzzy matching STATA program, to suggest potential matches for the remaining students. This matches students with slight spelling differences and those who appear in one grade older or younger than the charter application grade. We hand check these suggested matches for accuracy. We search for the remaining unmatched students by hand in the data. Typically this last group contains name truncations, name misspellings, or first and last names in the wrong field.

The matching process assigns 95 percent of applicants to the state administrative records (see Table A3). Students who do not match either enroll in private, parochial, or out-of-state schools, have names and birthdates too common to match, or have spelling errors too extreme to match with confidence. Receiving a charter offer makes students 3.8 more likely to match to the data, as shown in Table A3. As a result, our findings show causal estimates for the set of students who enroll in Massachusetts Public Schools.

We match the enrollment and demographic data to the student test scores using the unique student identifier. Students who attend out of state, private, or parochial schools do not have test score outcomes for their years outside of Massachusetts public schools.

2.7.1.6 Sample Restrictions

We exclude applicants who receive higher or lower preference in the lottery. Late applicants, those who apply to the wrong grade, out-of-area applicants, and siblings fall into these categories and typically have no variation in offer status. When students have duplicate applications within an individual school's lottery, we keep only one application. If students apply to charter schools in different years, we use only the first application year. We restrict the sample to students with baseline demographics data, excluding students applying from outside of Massachusetts public schools. With these restrictions imposed, the original raw sample of applications narrows from 20,981 to 8,473.

Table A1: Charter Middle Schools in Boston

	Year Opened (1)	Grades (2)	Outcome Years In Analysis (3)
Parent campuses			
Roxbury Preparatory: Mission Hill Campus	1999 - 2000	5 - 8 (12)	2004-05 - 2013-14
Brooke Roslindale	2002 - 03	5 - 8	2006-07 - 2009-10
Excel East Boston	2003 - 04	5 - 9 (12)	2008-09 - 2013-14
MATCH Middle School	2008 - 09	6 - 8	2008-09 - 2013-14
Expansion Charters			
Roxbury Preparatory: Lucy Stone Campus	2011 - 12	5 - 8	2011-12 - 2013-14
Roxbury Preparatory: Dorchester Campus	2012 - 13	5 - 7 (8)	2012-13 - 2013-14
Brooke Mattapan	2011 - 12	5 - 8	2011-12 - 2013-14
Brooke East Boston	2012 - 13	5 - 7 (8)	2012-13 - 2013-14
Excel Orient Heights	2012 - 13	5 - 7 (8)	2012-13 - 2013-14
KIPP	2012 - 13	5 - 7 (8)	2012-13 - 2013-14
UP Academy Boston	2011 - 12	6 - 8	2011-12 - 2013-14
Other Charters			
Academy of the Pacific Rim	1997 - 98	5 - 12	2005-06 - 2013-14
Boston Collegiate	1998 - 99	5 - 12	2004-05 - 2013-14
Boston Prep	2004 - 05	6 - 12	2005-06 - 2013-14
Not Included in Study			
Helen Davis Leadership Academy	2003 - 04	6 - 8	declined to participate
Frederick Douglas Charter	2000 - 01	6 - 10	closed in 2004-05
Uphams Corner Charter	2002 - 03	5 - 8	closed in 2008-09

A2: Lottery Records

Year of application	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	All
Total number of records	341	739	913	1143	1422	1595	1467	4283	4312	4766	20981
Excluding disqualifed applications	341	738	911	1135	1404	1594	1444	4273	4305	4760	20905
Excluding late applications	340	738	909	1135	1363	1566	1397	4163	4196	4583	20390
Excluding out of area applications	340	733	900	1123	1353	1548	1379	4094	4071	4513	20054
Excluding siblings	300	677	836	1021	1223	1408	1249	3758	3760	4320	18552
Excluding records not matched to SIMS	266	634	801	1000	1181	1378	1179	3627	3573	4016	17655
Keep only first year of charter application	266	617	770	962	1093	1282	1038	3308	2962	3469	15767
Excluding repeat applications	266	617	770	962	1093	1282	1038	3308	2962	3458	15756
Reshaping to one record per student	265	523	586	760	868	963	812	2055	1715	1900	10447
Has baseline demographics and in Boston at baseline	176	382	437	571	679	722	623	1790	1499	1594	8473

Notes: This table describes the processing of charter lottery records.

Table A3: Match from Lottery Data to Administrative Data

			Reg of Match on Offer	
	Number of Applications	Proportion Matched	Immediate Offer	Any Offer
Lottery Year	(1)	(2)	(3)	(4)
2004	268	0.989	-0.006	-0.007
			(0.026)	(0.013)
2005	616	0.987	-	0.002
			-	(0.013)
2006	742	0.991	-	0.004
			-	(0.016)
2007	924	0.984	0.019**	0.034***
			(0.008)	(0.013)
2008	1018	0.957	0.042***	0.061***
			(0.013)	(0.019)
2009	1106	0.977	0.004	0.011
			(0.011)	(0.010)
2010	1041	0.924	0.065***	0.071***
			(0.016)	(0.017)
2011	2614	0.954	0.018***	0.025***
			(0.007)	(0.007)
2012	2503	0.939	0.001	0.033***
			(0.011)	(0.011)
2013	2712	0.902	0.045***	0.078***
			(0.012)	(0.015)
All Cohorts	15482	0.949	0.023***	0.038***
			(0.003)	(0.004)

Notes: This table summarizes the match from the lottery records to administrative student data. The sample excludes late applicants, siblings, disqualified applicants, duplicate names, and out-of-area applicants. Columns (3) and (4) report coefficients from regressions on a dummy for a successful match on immediate and any charter offer dummies. All regressions control for school-by-year dummies.

*significant at 10%; **significant at 5%; ***significant at 1%

Table A4: Covariate Balance

	Before Charter Expansion		After Charter Expansion		
	Proven Providers	Other Charters	Proven Providers	Expansion Schools	Other Charters
	(1)	(2)	(3)	(4)	(5)
Female	0.000	-0.004	-0.005	0.011	0.020
	(0.034)	(0.028)	(0.027)	(0.027)	(0.028)
Black	-0.026	0.007	-0.027	-0.025	-0.015
	(0.032)	(0.027)	(0.027)	(0.026)	(0.028)
Latino/a	0.027	0.000	-0.001	0.005	-0.010
	(0.031)	(0.022)	(0.027)	(0.026)	(0.027)
Asian	-0.014	0.007	0.008	0.010	0.000
	(0.009)	(0.008)	(0.010)	(0.011)	(0.009)
White	0.016	-0.003	0.007	0.001	0.018
	(0.011)	(0.024)	(0.010)	(0.012)	(0.017)
Subsidized Lunch	0.015	0.010	-0.011	-0.016	-0.016
	(0.029)	(0.027)	(0.020)	(0.019)	(0.023)
English Language Learners	-0.005	-0.001	-0.004	-0.039	-0.027
	(0.023)	(0.014)	(0.027)	(0.026)	(0.025)
Special Education	-0.005	0.005	0.002	0.013	0.018
	(0.027)	(0.022)	(0.021)	(0.022)	(0.022)
Attended charter before applying	0.010	-0.008	-0.015	-0.015*	-0.003
	(0.019)	(0.020)	(0.010)	(0.008)	(0.014)
Baseline math score	-0.024	-0.022	0.058	-0.032	-0.003
	(0.071)	(0.052)	(0.050)	(0.051)	(0.055)
Baseline English score	-0.036	0.000	0.048	0.038	0.012
	(0.070)	(0.052)	(0.052)	(0.051)	(0.055)
N (offered)	1009	1309	1466	1825	1142
P-value	0.594	0.891	0.526	0.134	0.978

Notes: This table reports coefficients from regressions of baseline characteristics on charter offers, controlling for lottery risk set indicators. P-values are from tests of the hypothesis that all coefficients are zero.
*significant at 10%; **significant at 5%; ***significant at 1%

Table A5: Attrition

	Before Charter Expansion			After Charter Expansion			
		Offer Differential			Offer Differential		
	Non-offered Followup Rate	Proven Providers	Other Charters	Non-offered Followup Rate	Proven Providers	Expansion Charters	Other Charters
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Math	0.834	0.018	0.032**	0.869	0.000	0.013	-0.023
		(0.018)	(0.015)		(0.015)	(0.016)	(0.018)
N				20102			
English	0.825	0.018	0.034**	0.869	0.001	0.011	-0.025
		(0.017)	(0.015)		(0.015)	(0.016)	(0.018)
N				20102			

Notes: This table investigates attrition for randomized charter school lottery applicants. Columns (1) and (4) report fractions of follow-up test scores in grades five through eight that are observed for students not offered seats. Columns (2)-(3) and (5)-(7) report coefficients from regressions of a follow-up indicator on a lottery offer indicator (immediate or waitlist) and students not offered seats. Regressions control for lottery risk sets, as well as gender, ethnicity, a female-minority interaction, special education, English language learner, subsidized lunch status, and grade and year indicators. Standard errors are clustered by student.
*significant at 10%; **significant at 5%; ***significant at 1%

Chapter 3

Race to the Tablet? The Impact of Personalized Table Educational Programs

3.1 Introduction

Tablets, laptops, and other devices have a large and growing presence in U.S. classrooms. Primary and secondary schools spend an estimated 8.38 billion dollars on educational software and digital content and 4.9 billion on devices annually (Education Technology Industry Network, 2015; Huang, 2016). Educational technology companies claim that their programs target students' gaps in skills and improve student outcomes. Despite the increasing adoption of technology in the classroom, limited work on its effectiveness exists.

This paper analyzes the impact of a popular educational technology program on middle school students' academic outcomes using a randomized controlled trial (RCT). Two Boston charter schools participated in the study and randomly assigned their middle school students to a technological intervention or control group classrooms. The treatment group worked with a personalized learning tablet software that targeted skills the student lagged behind in most for 28 minutes a day, four days a week for three-fourths of the school year. The control groups met in a separate classroom during this time. In one school the control group read independently and the other school sorted the control group students into teacher-led tracked classrooms based on ability.

One school fully implemented the study while the other partially implemented the program. In the school with full implementation, the personalized technology program increased students' scores on the English quarterly exam and on the end of year math exam. Other test results, the quarterly math and annual English results, were imprecise. The technology intervention had no observable effect in the school that partially implemented the program, suggesting that the students need to use the program for a substantial amount of time for it to be effective. Subgroup and distributional analysis show similar effects across different student backgrounds and baseline abilities. This supports the hypothesis that the program's personalization is an important mechanism in explaining the findings.

This study contributes to a growing literature on the effectiveness of technology in education. The limited research evaluating the impact of computers and internet in classrooms has shown mixed results. Researchers find no effect of computers in classrooms on student test scores when little is known about how the computers are utilized in the classroom (Angrist and Lavy, 2002; Machin, McNally, and Silva, 2006; Goolsbee and Guryan, 2006). Banerjee et al. (2007) and Barrow, Markman, and Rouse (2009) find evidence that math computer programs have positive effects on test scores. Rouse and Krueger (2004) find no positive evidence of an English computer program on English language skill growth. Muralidharan, Abhijeet, and Ganimian (2016) finds positive effects of a personalized learning technology in India on student's math test scores. This study is one of the first to analyze modern technology, such as tablets and app-based learning tools, in a U.S. context.

The next section provides details on the technology intervention, data, and sample. Section 3 outlines the empirical framework and Section 4 reports the results and discusses mechanisms. The final section concludes.

3.2 Background and Data

3.2.1 Intervention Details

The eSpark program curates educational apps to create a personalized curriculum for each student based on their performance on a Common Core aligned math and English Language Arts (ELA) pre-test. Using the test results, eSpark creates a roadmap of skills for the student to study and practice, starting with the most basic. Students learn and practice the skill they lag most behind in through interactive apps on the iPad. Once students masters their first concept, they move onto the next skill. Depending on their ability at the start of the program, students can work on below grade level skills to catch up or continue to more advanced concepts. The program has a substantial market share: districts in over 25 states and over 80,000 students currently use eSpark.

The study consists of separate randomized controlled trials (RCTs) with two charter schools in Boston: UP Academy Boston and UP Academy Dorchester. In the 2013-14 school year, 438 middle school students at UP Academy Boston participated in the study. Student-level random assignment chose 60 students to participate in eSpark. Randomization was stratified by grade and subject the student scored lowest on the pre-test with 15 students each selected from sixth and seventh grades and 30 students selected from eight grade. This left between 118 and 122 students in the control group in each grade. Due to the small sample size, prior to randomization we agreed to re-sample until the treatment and control groups' baseline test scores were equal at the 90 percent confidence level.

The school assigned the treatment group to work with the eSpark program in a separate classroom during the school day for 28 minutes a day, four days a week, for three-fourths of the school year. While the treatment group used eSpark, the control group received supplemental teacher led instruction. Students in the control group were assigned to math, reading, or writing classes based on which subject they scored lowest on and they were grouped by ability within the subject. Therefore, the RCT compares the individual-level personalization of lessons from app-based technology to a coarser classroom-level ability tracking led by a teacher.

Additionally, UP Academy Dorchester conducted an RCT in the 2015-16 school year with 210 fifth through seventh graders. I randomly assigned 99 students to the treatment group with one third assigned to each grade. I stratified the randomization by grade and class so that results could not be confounded by the treatment group randomly having higher or lower quality teachers. The randomization plan required that all of the demographic characteristics and baseline test scores be balanced at 90 percent confidence level or higher and that a joint F-test for joint balance had a p-value of 0.30 or higher. The randomization was re-run if the sample failed the joint balance or individual variable balance requirements. The school intended for the treatment to be similar to UP Academy Boston: 28 minutes during the school day, four days a week, for three-fourths of the school year. The control read independently in a separate classroom while the treatment group worked with eSpark.

3.2.2 Data and Descriptive Statistics

UP Academy provided student-level demographics, class and teacher assignment, test score, behavior, attendance, and grades data. Both schools administered an end of year exam (MCAS or PARCC) and four quarterly exams (ANETs). I standardize the baseline test scores to the state mean by grade and the end of year and quarterly exams to the school mean by grade. I only have quarterly exam data for the study schools, so I cannot standardize to a broader population. For the end of year exam, results are robust to standardizing to the state mean.

UP Academy Dorchester provided detailed eSpark login data that documents each day the student logged in, and whether they focused on the orientation, math, or English lessons. UP Academy Boston did not have this usage data available, so I use attendance in eSpark classrooms to measure usage.

UP Academy Boston and UP Academy Dorchester, both located in the city of Boston, serve mostly minority students and students from low-income families. Table 1 shows the demographic characteristics of the two charter schools, Boston charters overall, Boston Public Schools, and Massachusetts public schools. Over 50 percent of students in the study identify as black and 33 percent identify as Latino. Representation of black and Latino students is similar to Boston charter schools' and larger than Massachusetts overall. Black students are more represented in the study than Boston Public Schools and Latino students are slightly underrepresented in the study relative to Latino representation in Boston Public Schools.

Special education students make up over a fifth of the students in the study, Boston Public Schools, and Massachusetts. English Language Learners comprise 16 - 23 percent of the study sample. Boston Public Schools has more representation of English Language Learners (28 percent) and Boston charter schools have less (10 percent).

Over 82 percent of students in the study come from economically disadvantaged families that qualify for free or reduced price lunch. This proportion exceeds the prevalence of free or reduced price lunch in Boston charter schools (57 percent), Boston Public Schools (65 percent) and Massachusetts overall (32 percent).

Despite the higher prevalence of economic disadvantage, a larger proportion of students in the study meet proficiency on their pre-study standardized math and English Language Arts exam than Boston Public Schools students. Other work documents that students who apply to UP Academy Boston and Dorchester had low baseline test scores at the time of application and that attendance at these schools has a strong positive effect on lottery applicants' test scores (Abdulkadiroğlu et al., 2016a; Setren, 2016).

3.3 Empirical Framework

I use the random assignment to the treatment group as an instrument to estimate the causal effect of the eSpark program in a two-stage least squares setup. The second-stage equation links exposure to the treatment with outcomes as follows:

$$y_i = \alpha + \beta X_i' + \gamma T_i + \epsilon_i \tag{3.1}$$

where y_i is the outcome of interest for student i, including test scores, attendance, grades, and behavior. The vector X_i' captures student-level characteristics including grade dummies, ethnicity, subsidized price lunch status, gender, special education status, English Language Learner status, and baseline test scores. T_i represents the proportion of the school year the student attended the eSpark classroom.

The first stage equation is:

$$T_i = \kappa + \mu X_i' + \pi Z_i + \eta_i \tag{3.2}$$

where Z_i indicates whether student i was randomly selected for the treatment group and π captures the effects of assignment to the treatment group on exposure to eSpark. Like the second-stage equation, the first stage includes controls for grade, demographic characteristics, and baseline test scores.

The random assignment makes it likely that students in the treatment and control groups have similar characteristics and baseline abilities. Table 2 shows that the observable characteristics, pre-randomization test scores and demographics, are similar in both schools' treatment and control groups. Differences in baseline characteristics are insignificant and mostly small. The p-values from the joint tests are high suggesting that the observable characteristics in the treatment and control groups are similar.

Random assignment to the eSpark treatment significantly increases time spent with the eSpark program. Both schools began the eSpark program in the second quarter of the school year. UP

Academy Boston switched five students from the treatment to the control group mid-year and a few study participants repeated a grade or withdrew from the school before or during the study. The two-stage least squares methodology accounts for these non-random changes. Table 3 shows that students randomly assigned to eSpark have 97.9 percentage points higher attendance in an eSpark classroom than students in the control group in the second quarter of the school year. The fourth quarter's first stage (see Column 3 of Table 3) reflects the few incidents of non-random changes to eSpark assignment: by the fourth quarter, treatment group students spent 87.2 percentage points more time in eSpark during quarters 2 through 4 than the control group.

UP Academy Dorchester did not fully implement the eSpark program and as a result has a much smaller first stage. The school started the eSpark program later, with students only doing the pre-testing and orientation in the second quarter of the school year. Fifth graders spent far fewer days in the eSpark program than the school intended: few assigned fifth graders participated in eSpark beyond the orientation. By the end of the year, students assigned to the treatment group spent 60.1 percentage points more days assigned to the eSpark classroom than the control group. While the students were in an eSpark classroom, they logged into eSpark only 34.3 percentage points more often than the control group. The fourth quarter had particularly low usage with treatment students spending only 5.3 percentage points more time in eSpark than the control group. I instrument for time in eSpark for the UP Academy Dorchester analysis because it contains finer detail of actual eSpark usage.

The eSpark usage data for UP Academy Dorchester reports time spent on math and English Language Arts lessons. Students spent slightly more time in on math lessons in eSpark than they did on English lessons (shown in Table 3). The first stage also shows that students did not work on math or English lessons until the third quarter; eSpark usage in the second quarter focused on orientation.

3.4 Results

3.4.1 Quarterly Exam Results

The eSpark intervention had positive effects on UP Academy Boston students' academic outcomes. Table 4 shows the the stacked estimates of the quarterly exams students took during the study period (the second through fourth quarter). The eSpark program appears to have a positive effect for math scores and growth. Students who spend time in eSpark score 0.141 standard deviations higher than the control group according to the OLS estimates. The reduced form and two-stage least squares math estimates are too noisy to be conclusive, but have similar point estimates. The eSpark treatment also appears to have a positive effect on students math score growth, both from the first quarter and annually, but the estimates are noisy.

Spending the year in eSpark leads students to score 0.172 standard deviations higher on their English exams and promotes 0.275 standard deviations in English score growth from the first quarter score. Since test scores are standardized to the school mean score by grade, these estimates mean the treatment causes students to score on average about two standard deviations higher than their peers on the English exam. The results are significant at the 90 percent level. The OLS and two-stage least squares estimates are similar, suggesting that OLS is unbiased.

The OLS, reduced form, and two-stage least squares results for UP Academy Dorchester are too noisy to be conclusive. The OLS and reduced form estimates are close to zero for both math and English, suggesting the program had a null effect. Perhaps this is due to the partial implementation in UP Academy Dorchester, since students spent a relatively small amount of time with the eSpark program.

I present the quarterly exam results stacked to increase precision. This means that each student has an observation for each of the quarters and I cluster the standard errors by student. Appendix Table 1 shows the quarterly, unstacked results. The English score estimates increase each quarter, suggesting a cumulative effect. The math estimates and the English score growth estimates do not display a clear pattern.

3.4.2 End of Year Exam Results

Spending a year in eSpark led UP Academy Boston students to perform significantly better on their end of year math exam than students in the control group. The two-stage least squares estimate shows students scored 0.202 standard deviations higher with a year in eSpark. To compare the math effects to other effect sizes in the literature, I standardize the math exam scores to the state mean in a given grade and year. Student test scores rise by 0.154 standard deviations from a year using the personalized learning technology. This effect is substantial and almost as large as the lottery estimates of attending a Boston charter school which range from 0.2 to 0.4 standard deviations (Cohodes et al., 2013; Angrist, Pathak, and Walters, 2013; Abdulkadiroğlu et al., 2011, 2016a; Setren, 2016). In other words, use of personalized learning technology less than two hours a week boosted students' math scores nearly as much an intensive intervention that changed the school model, school culture, educational services, and amount of instructional time students experienced. The personalized technology math effects amount to 22 percent of the black-white achievement gap in Massachusetts.

The English Language Arts effects are too imprecise to conclude whether time in eSpark led to higher, lower, or similar test scores. In other research, ELA results are commonly less precise than math results. A larger study would be able to yield more precise results.

Results for UP Academy Dorchester are too noisy to be conclusive.

3.4.3 Academic Grades and Behavioral Outcomes

I did not find any significant effects for quarterly or end of year grades and exam scores in either subject. School staff explained that class grades often reflect student effort and behavior instead of skill mastery.

Analysis did not reveal a substantial effect of eSpark on student behavioral outcomes. Estimates were inconclusive for eSpark's affect on merits, demerits, detention, and late or incomplete homework. Results suggest that participating in eSpark led to lower tardiness, lower in school suspensions, and more absences, but the results are noisy and subject to multiple testing issues considering several behavioral outcomes were analyzed (see Table 6).

3.4.4 Effects by Subgroup and Distributional Effects

The personalized learning technology program has similar impact across different demographics and baseline abilities in UP Academy Boston. Evidence that the program effects all students similarly supports the hypothesis that the technology generates gains by personalizing the lessons to individual students' needs. Given the noisy and insignificant effects for UP Academy Dorchester, I will not display subgroup and distributional effects for those students.

The program has similar effects across gender, race, free lunch status, special education status, and English Language Learner status as shown in Table 7. Effects are strongest for seventh and eighth graders for both the quarterly and annual exams and effects, suggesting perhaps better implementation in these grades.

Effects are also generally similar across baseline ability. Table 8 shows the two-stage least squares estimates of eSpark by baseline test scores. Most of the estimates are noisy and imprecise, but point estimates across the different quartiles are largely similar. This suggests that eSpark has a similar effect across baseline ability and supports the personalization hypothesis. The bottom quartile point estimates are an exception to this pattern. The estimates are negative, but too imprecise to determine a positive, negative, or null effect.

Figure 1 displays the distributional effects graphically for the end of year exam. Before the intervention, the treated and un-treated compliers performed slightly below the state mean for their grade. The distributions are similar: a Kolmogorov-Smirnov test fails to reject that the treated and un-treated complier distributions are different. However, visually, the un-treated complier distribution appears slightly skewed to the lower end of the test score distribution. The bottom tail and top third of the distribution have similar densities in the treated and control group, but more un-treated compliers score between -2 and -0.5 standard deviations on the baseline exam and slightly fewer un-treated compliers score around the state mean compared to the treated compliers.

After the intervention, both the treatment and control groups' math test scores surpass the state mean. This shows that the eSpark gains arise from actual student gains and not from the control group performing worse. The overall gains reflect the quality of UP Academy Boston which Abdulkadiroğlu et al. (2016a) shows has a positive effect on student outcomes. While a Kolmogorov-Smirnov test fails to reject that the two distributions are different, the treated complier distribution lies to the right of the un-treated complier distribution. This suggests a similar effect of the eSpark intervention across student ability and supports the personalization hypothesis.

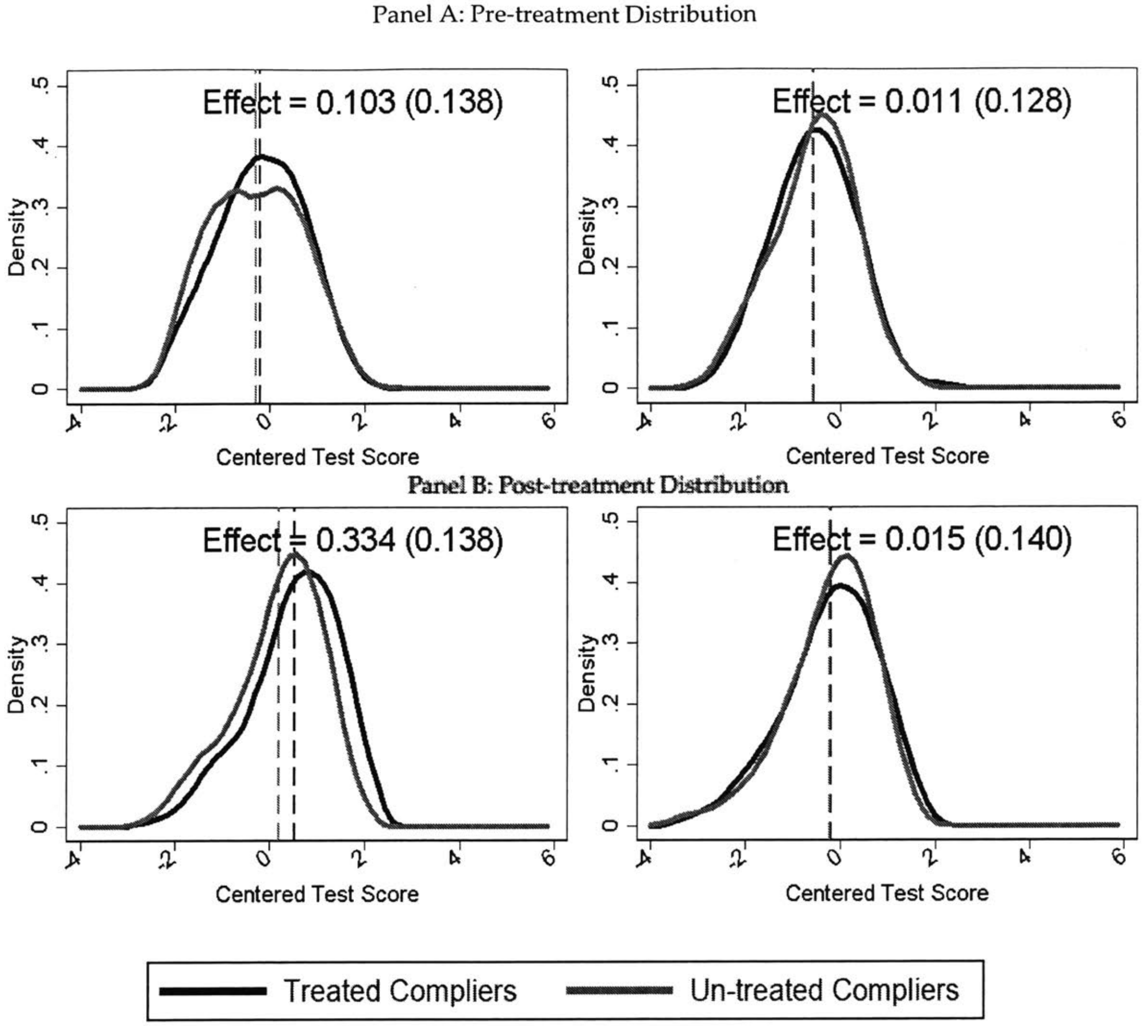
3.5 Conclusion

This paper estimates the impact of a personalized tablet learning technology using two randomized controlled trials in Boston middle schools. The results are mixed: the school that fully implemented the program with 28 minutes a day, four days a week for three-fourths of the school year saw positive effects for math and English test scores. Students in the treatment group of the other school spent fifty percent less time with the technology on average. This school had noisy and imprecise results. The mixed results suggest that amount of time students spend with the technology plays a key role in its effectiveness. More work is needed to understand how impacts vary with time intensity.

As schools spend an increasing amount of time and financial resources on educational technology, it's important to understand the impact on student learning. This project estimates the impact of one popular technology program in two schools and the results suggests that personalization of lessons and substantial time use plays an important role generating positive results. More work is needed to test the effectiveness of different technology programs across different types of students and schools and to isolate the mechanisms that lead to successful education technology interventions. Potential mechanisms include personalization, soft skill improvement (such as grit and learning strategies), and increased attentiveness by generating interest in the subject or boosting engagement.

Figure 1: Density of Treated and Un-treated Compliers' Test Scores

Math English



Notes: This figure shows the distribution of test scores for treated and untreated compliers in UP Academy Boston for before and after the technology intervention. Dashed lines represent the group average. The two-stage least squared estimates are displayed with standard errors in parentheses. Kolmogorov-Smirnov statistics and p-values are from bootstrap tests of distributional equality for treated and untreated compliers.

Table 1: Descriptive Statistics

	Study Participants				
	UP Academy Boston	UP Academy Dorchester	Boston Charter Schools	Boston Public Schools	Massachusetts Public Schools
Baseline Characteristics	(1)	(2)	(3)	(4)	(5)
Female	0.50	0.56	0.51	0.48	0.49
African American	0.50	0.62	0.51	0.34	0.08
Latino/a	0.33	0.33	0.35	0.41	0.17
White	0.09	0.00	0.10	0.13	0.66
Asian	0.06	0.01	0.02	0.09	0.06
Other Race	0.03	0.04	0.02	0.03	0.03
Subsidized Lunch	0.82	0.84	0.57	0.65	0.32
Special Education	0.24	0.21	0.17	0.22	0.19
English Language Learner	0.23	0.16	0.10	0.28	0.07
Proficient or Higher in Math	0.46	0.44	0.43	0.28	0.50
Proficient or Higher in English	0.46	0.49	0.48	0.34	0.61
N	438	210	8211	28480	578043

Notes: This table shows student characteristics for the study participants, Boston charter schools, Boston Public Schools, and Massachusetts public schools. Study participant data comes from UP Academy records in the year of the intervention (2013-14 and 2015-16 respectively). The remaining charter and public school data comes from the Massachusetts School District Profiles in 2013-14 and 2015-16.

Table 2: Covariate Balance

	UP Academy Boston			UP Academy Dorchester		
	Treatment Mean	Control Mean	Difference	Treatment Mean	Control Mean	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
Baseline Math Score	-0.250	-0.340	0.090	-0.483	-0.299	-0.185
			(.11)			(.126)
Baseline English Score	-0.568	-0.578	0.010	-0.498	-0.392	-0.106
			(.105)			(.11)
Female	0.467	0.505	-0.039	0.596	0.523	0.073
			(.07)			(.069)
Black, Latino, or Other	0.800	0.854	-0.054	0.990	0.991	-0.001
			(.055)			(.014)
White	0.100	0.093	0.007	0.000	0.000	.
			(.042)			.
Asian	0.100	0.053	0.047	0.010	0.009	0.001
			(.04)			(.014)
Subsidized Lunch	0.833	0.823	0.011	0.838	0.847	-0.008
			(.052)			(.051)
Special Education	0.250	0.241	0.009	0.242	0.180	0.062
			(.06)			(.057)
English Language Learner	0.183	0.235	-0.052	0.172	0.144	0.028
			(.055)			(.051)
N	60	378	438	99	111	210
			0.838			0.686

Notes: This table shows descriptive statistics for treatment and control groups in both study schools. Columns (3) and (6) report coefficients from regressions of observed characterstics on random assignment to the treatment group. Test scores are centered at the state mean by grade. P-values come from tests of whether all the coefficients equal zero.
*significant at 10%; **significant at 5%; ***significant at 1%

Table 3: Effect of Assignment to Treatment on Fraction of School Days Spent in eSpark

		UP Academy Boston			UP Academy Dorchester			
		Quarter 2	Quarter 3	Quarter 4	Quarter 2	Quarter 3	Quarter 4	Final Exam
		(1)	(2)	(3)	(4)	(5)	(6)	(4)
Time in eSpark Class		0.979***	0.909***	0.872***				0.601***
		(.01)	(.013)	(.016)				(.037)
	N	438	438	438				207
Time in eSpark App					0.066***	0.250***	0.053***	0.343***
					(.008)	(.024)	(.006)	(.032)
	N				207	207	207	207
					0.001	0.117***	0.034***	0.160***
Time in eSpark App: Math					(.)	(.018)	(.005)	(.023)
					207	207	207	207
	N							
					0.000	0.086***	0.019***	0.112***
Time in eSpark App: English					(.)	(.015)	(.004)	(.018)
					207	207	207	207
	N							

Notes: This table shows the first stage estimates for the effect of random selection for the treatment group on time exposure to the eSpark program. Time in eSpark class measures attendance in the eSpark classroom. UP Academy Dorchester provided login data for actual usage of the eSpark application by subject. All models control for baseline test scores, English Language Learner status, special education status, free and reduced price lunch, gender, ethnicity, and grade.
*significant at 10%; **significant at 5%; ***significant at 1%

Table 4: Quarterly Test Score Effects

	UP Academy Boston				UP Academy Dorchester			
	Control Mean	OLS	Reduced Form	2SLS	Control Mean	OLS	Reduced Form	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Math Score	-0.047	0.141**	0.112	0.119	0.076	0.030	-0.017	-0.172
	(1.003)	(0.070)	(0.071)	(0.075)	(1.055)	(0.248)	(0.079)	(0.790)
N				1109				751
Math Growth from First Quarter	-0.065	0.139	0.105	0.113				
	(0.693)	(0.089)	(0.088)	(0.093)				
N				1058				
Math Annual Growth	-0.027	0.094	0.091	0.098				
	(0.814)	(0.086)	(0.081)	(0.086)				
				585				
English Score	-0.045	0.165*	0.161*	0.172*	0.056	-0.032	0.006	0.057
	(0.985)	(0.095)	(0.093)	(0.098)	(0.998)	(0.258)	(0.075)	(0.741)
N				921				785
English Growth from First Quarter	-0.078	0.255*	0.257*	0.275*				
	(1.015)	(0.151)	(0.148)	(0.156)				
N				847				
ELA Annual Growth	-0.106	0.043	0.053	0.057				
	(0.981)	(0.121)	(0.121)	(0.129)				
				456				

Notes: This table reports the OLS, reduced form, and two-stage least squares estimates of the effects of the eSpark intervention on student quarterly test scores called ANETs. Random assignment to eSpark instruments for time in eSpark. Data is stacked at the student by quarter level, with data from the second through fourth quarters. All models control for baseline test scores, English Language Learner status, special education status, free and reduced price lunch, gender, ethnicity, and grade. Standard errors are clustered at the individual student level.
*significant at 10%; **significant at 5%; ***significant at 1%

Table 5: End of Year Test Score Effects

	UP Academy Boston				UP Academy Dorchester			
	Control Mean	OLS	Reduced Form	2SLS	Control Mean	OLS	Reduced Form	2SLS
Scores centered at	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: Math				
School Level	-0.017	0.178*	0.181*	0.202**	0.033	4.823	0.061	5.065
	(1.010)	(0.098)	(0.094)	(0.103)	(1.099)	(3.071)	(0.095)	(7.563)
N				394				201
State Level	0.145	0.136*	0.138*	0.154*				
	(0.866)	(0.081)	(0.077)	(0.085)				
N				394				
				Panel B: English				
School Level	0.005	-0.037	-0.025	-0.028	0.027	2.871	0.079	6.525
	(0.993)	(0.103)	(0.098)	(0.107)	(1.062)	(3.332)	(0.103)	(8.232)
N				397				201
State Level	-0.251	-0.027	-0.014	-0.016				
	(0.885)	(0.091)	(0.087)	(0.095)				
N				397				

Notes: This table reports the OLS, reduced form, and two-stage least squares estimates of the effects of the eSpark intervention on the end of year exam. UP Academy Boston students took the MCAS and UP Academy Dorchester students took the PARCC exam. Random assignment to eSpark instruments for time in eSpark. Test scores are standardized and centered at the state of school level by the average score in that grade and year. All models control for baseline test scores, English Language Learner status, special education status, free and reduced price lunch, gender, ethnicity, and grade.
*significant at 10%; **significant at 5%; ***significant at 1%

Table 6: Behavioral Outcome Effects for UP Academy of Boston

		Control Mean	OLS	Reduced Form	2SLS
		(1)	(2)	(3)	(4)
Tardy		2.847	-0.725*	-0.998*	-1.067*
		(5.180)	(0.428)	(0.517)	(0.554)
	N				1202
Suspension		0.206	-0.111**	-0.108**	-0.115**
		(0.638)	(0.051)	(0.043)	(0.046)
	N				1188

Notes: This table reports the OLS, reduced form, and two-stage least squares estimates of the effects of the eSpark intervention on behavioral outcomes. Random assignment to eSpark instruments for time in eSpark. Data is stacked at the student by quarter level, with data from the second through fourth quarters. All models control for baseline test scores, English Language Learner status, special education status, free and reduced price lunch, gender, ethnicity, and grade. Standard errors are clustered at the individual student level.

*significant at 10%; **significant at 5%; ***significant at 1%

Table 7: Exam Effects by Demographic Subgroups for UP Academy Boston

	End of Year Exam		Quarterly Exam					
			Math			English		
				Growth from	Annual		Growth from	Annual
	Math	English	Score	1st Quarter	Growth	Score	1st Quarter	Growth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Male	0.247	-0.112	0.119	0.146	0.012	0.152	0.162	0.207
	(0.159)	(0.162)	(0.101)	(0.096)	(0.112)	(0.160)	(0.151)	(0.233)
N	203	204	552	552	528	451	451	411
Female	0.134	0.015	0.125	0.127	0.200	0.162	0.154	0.387*
	(0.129)	(0.138)	(0.105)	(0.099)	(0.135)	(0.117)	(0.119)	(0.202)
N	191	193	557	557	530	470	470	436
Black	0.059	-0.180	0.007	0.062	-0.010	0.033	0.075	0.406*
	(0.158)	(0.144)	(0.109)	(0.102)	(0.166)	(0.124)	(0.122)	(0.235)
N	195	197	546	546	531	446	446	423
Hispanic	0.212	0.071	0.170	0.230*	0.004	0.186	0.208	0.268
	(0.185)	(0.191)	(0.131)	(0.121)	(0.134)	(0.185)	(0.189)	(0.211)
N	128	128	356	356	322	305	305	256
Free Lunch	0.207*	-0.032	0.166*	0.183**	0.209**	0.220**	0.206**	0.277
	(0.111)	(0.115)	(0.088)	(0.082)	(0.091)	(0.110)	(0.105)	(0.176)
N	321	323	903	903	860	741	741	677
Special Education	0.305	0.190	0.142	0.155	-0.183	0.231	0.224	0.550*
	(0.243)	(0.258)	(0.185)	(0.182)	(0.189)	(0.259)	(0.269)	(0.286)
N	91	91	244	244	219	201	201	183
English Language Learner	0.173	0.128	0.058	0.108	0.847***	0.087	0.068	0.023
	(0.258)	(0.270)	(0.167)	(0.148)	(0.185)	(0.160)	(0.177)	(0.278)
N	87	87	251	251	243	206	206	192
Grade 6	-0.164	-0.219	-0.136	-0.114	0.137	0.106	0.079	-0.058
	(0.222)	(0.216)	(0.147)	(0.142)	(0.220)	(0.176)	(0.179)	(0.256)
N	127	127	358	358	326	341	341	312
Grade 7	0.397**	0.081	0.311*	0.371**	0.258	0.473***	0.536***	0.485**
	(0.195)	(0.214)	(0.161)	(0.168)	(0.193)	(0.165)	(0.157)	(0.230)
N	127	128	343	343	332	334	334	307
Grade 8	0.317**	-0.051	0.195**	0.197**	0.018	0.017	-0.002	0.445*
	(0.134)	(0.146)	(0.096)	(0.087)	(0.091)	(0.119)	(0.119)	(0.244)
N	140	142	408	408	400	246	246	228

Notes: This table reports the two-stage least squares estimates of the effects of the eSpark intervention on student quarterly and end of year test scores. Random assignment to eSpark instruments for time in eSpark. For the quarterly exam, data is stacked at the student by quarter level, with data from the second through fourth quarters. Test scores are centered at the school level by the average score in that grade and year. All models control for baseline test scores, English Language Learner status, special education status, free and reduced price lunch, gender, ethnicity, and grade. Standard errors are clustered at the individual student level.
*significant at 10%; **significant at 5%; ***significant at 1%

Table 8: Exam Effects by Baseline Academic Scores for UP Academy Boston

	End of Year Exam		Quarterly Exam					
			Math			English		
	Math	English	Score	Growth from 1st Quarter	Annual Growth	Score	Growth from 1st Quarter	Annual Growth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bottom Quartile	-0.108	-0.211	-0.225	-0.101	0.062	-0.203	-0.223	0.531**
	(0.244)	(0.227)	(0.210)	(0.192)	(0.267)	(0.163)	(0.171)	(0.242)
N	95	96	257	257	235	210	210	194
Second Quartile	0.191	-0.242	0.372**	0.364*	0.395	0.569**	0.600***	0.293
	(0.241)	(0.284)	(0.180)	(0.191)	(0.276)	(0.231)	(0.228)	(0.473)
N	95	95	259	259	246	219	219	193
Third Quartile	0.141	0.061	-0.011	0.041	0.073	0.237	0.194	0.206
	(0.165)	(0.207)	(0.121)	(0.131)	(0.147)	(0.166)	(0.148)	(0.342)
N	100	102	287	287	277	239	239	221
Top Quartile	0.139	-0.035	0.081	0.098	0.053	0.218	0.266*	0.257
	(0.134)	(0.132)	(0.118)	(0.116)	(0.093)	(0.158)	(0.157)	(0.237)
N	104	104	306	306	300	253	253	239

Notes: This table reports the two-stage least squares estimates of the effects of the eSpark intervention on student quarterly and end of year test scores by quartile of baseline math and English end of year exam performance. Random assignment to eSpark instruments for time in eSpark. For the quarterly exam, data is stacked at the student by quarter level, with data from the second through fourth quarters. Test scores are centered at the school level by the average score in that grade and year. All models control for baseline test scores, English Language Learner status, special education status, free and reduced price lunch, gender, ethnicity, and grade. Standard errors are clustered at the individual student level.
*significant at 10%; **significant at 5%; ***significant at 1%

Appendix Table 1: Attrition

	UP Academy Boston		UP Academy Dorchester	
	Control Mean	Attrition Differential by Treatment Status	Control Mean	Attrition Differential by Treatment
	(1)	(2)	(3)	(4)
Quarterly Math Score	0.160	-0.016	0.104	0.057
		(.041)		(.3)
N		1314		828
Math Growth from First Quarter	0.201	-0.031		
		(.047)		
N		1314		
Math Annual Growth	0.573	-0.073		
		(.059)		
N		1314		
End of Year Math Score	0.101	0.006	0.036	1.964
		(.048)		(2.099)
N		438		207
Quarterly English Score	0.289	0.039	0.059	0.247
		(.043)		(.258)
N		1314		828
English Growth from First Quarter	0.349	0.014		
		(.049)		
N		1314		
ELA Annual Growth	0.660	-0.028		
		(.053)		
N		1314		
End of Year English Score	0.098	-0.032	0.036	1.964
		(.047)		(2.099)
N		438		207

Notes: This table reports the two-stage least squares estimates of the effects of the eSpark intervention on attriting from the sample. Random assignment to eSpark instruments for time in eSpark. All models control for baseline test scores, English Language Learner status, special education status, free and reduced price lunch, gender, ethnicity, and grade. Standard errors are clustered at the individual student level.

*significant at 10%; **significant at 5%; ***significant at 1%

Appendix Table 2: UP Academy Boston Quarterly Exam Results

		First Quarter		Second Quarter		Third Quarter		Fourth Quarter	
		Control Mean	2SLS	Control Mean	2SLS	Control Mean	2SLS	Control Mean	2SLS
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Math Levels		-0.008	0.043	-0.024	0.103	-0.062	0.147	-0.055	0.109
		(1.019)	(0.096)	(1.011)	(0.081)	(0.994)	(0.126)	(1.005)	(0.113)
	N		395		381		365		363
Math Growth from Quarter 1				-0.050	0.074	-0.069	0.175	-0.076	0.094
				(0.651)	(0.101)	(0.735)	(0.135)	(0.696)	(0.123)
	N				363		348		347
Math Annual Growth		0.002	0.100	0.006	0.077	-0.031	0.015	-0.058	0.207
		(0.796)	(0.143)	(0.832)	(0.141)	(0.717)	(0.175)	(0.890)	(0.157)
			203		202		196		187
English Levels		0.032	-0.180	-0.016	0.060	-0.059	0.223	-0.074	0.340
		(0.979)	(0.126)	(1.003)	(0.123)	(0.980)	(0.137)	(0.964)	(0.240)
	N		378		366		356		199
English Growth from Quarter 1				-0.042	0.242	-0.130	0.369*	-0.053	0.134
				(0.955)	(0.162)	(1.057)	(0.199)	(1.050)	(0.313)
	N				336		328		183
ELA Annual Growth		0.037	0.081	-0.031	-0.100	-0.176	0.093	-0.130	0.519
		(1.020)	(0.197)	(0.929)	(0.161)	(0.972)	(0.228)	(1.113)	(0.533)
	N		194		192		184		80

Notes: This table reports the two-stage least squares estimates of the effects of the eSpark intervention on student quarterly test scores. Random assignment to eSpark instruments for time in eSpark. Test scores are centered at the school level by the average score in that grade and year. All models control for baseline test scores, English Language Learner status, special education status, free and reduced price lunch, gender, ethnicity, and grade. Standard errors are clustered at the individual student level.

*significant at 10%; **significant at 5%; ***significant at 1%

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