



Blueprint Labs

Discussion Paper #2026.09

Two Decades of Massachusetts Charter School Effects

Geoffrey Kocks

July 2026

The views expressed in this paper are those of the authors and do not necessarily reflect the views of MIT Blueprint Labs, the Massachusetts Institute of Technology, or any affiliated organizations. Blueprint Labs working papers are circulated to stimulate discussion and invite feedback. They have not been peer-reviewed or subject to formal review processes that accompany official Blueprint Labs publications.



MIT Department of Economics
77 Massachusetts Avenue, Bldg. E53-390
Cambridge, MA 02139

Two Decades of Massachusetts Charter School Effects*

Geoffrey Kocks[†]

July 6, 2026

Abstract

This paper estimates effects of Massachusetts charter school attendance for students applying to charters from 2002 to 2022, focusing on changes over time. Admissions lotteries provide random variation to estimate causal charter attendance effects on standardized test scores, SAT outcomes, and college enrollment. Consistent with earlier analyses of Massachusetts charters, estimates for the 2002–14 applicant cohorts indicate that the state’s charters markedly improved student outcomes. Estimates for 2015–19 applicants, however, are much smaller. Estimated test score and college effects for this period are not statistically significantly different from zero. Boston-area charter schools saw the largest decline in impact, a change that coincided with high rates of leadership turnover and increased staffing by teachers without subject-area expertise. Changes in charter effects appear to be unrelated to charter school expansions, shifts in the composition of students, or (for test scores) the redesign of assessments. For cohorts entering in 2020 and later, charter effects rebounded, with Boston-area charter effects reaching the level seen prior to 2015. An analysis of post-pandemic charter effectiveness suggests that school-specific value-added is positively correlated with an emphasis on formative and diagnostic assessments.

*I thank Elizabeth Link and Abigail Orbe for excellent research assistance. I thank Joshua Angrist and Parag Pathak for their guidance throughout this project and Massachusetts DESE for providing data. I thank Sarah Cohodes, Sharada Dharmasankar, and Tim Nicolette for valuable discussions. I am grateful to Eryn Heying, Jennifer Jackson, and Niamh McLoughlin for invaluable administrative support. Thanks also to participants at the 2026 AEFPP Annual Conference for helpful comments. This paper reports on research conducted under data-use agreements between MIT, the project’s principal investigator, and MA DESE. This paper reflects the views of the author alone. I acknowledge generous funding from the NSF GRFP under grant 2141064, the Blueprint Charter School Research Collaborative, and the Center on Reinventing Public Education Post-Pandemic Recovery and Renewal Grant.

[†]MIT Department of Economics. Email: gkocks@mit.edu

1 Introduction

A substantial body of lottery-based studies has shown that Massachusetts charter schools markedly boost student achievement. The state’s charter schools, especially those in Boston, have been especially effective at boosting students’ state standardized test scores, SAT scores, and college enrollment (Cohodes and Roy, 2025), mirroring findings from other urban areas nationally (CREDO, 2023; Clark et al., 2015). This research treats the charter sector’s advantage as a stable “charter effect,” without considering how effects may change over time. However, schools evolve due to changes in leadership and educational practices. Such developments may be particularly pronounced in charter schools, which were designed as “laboratories of innovation” with enhanced flexibility to experiment with new learning approaches (Budde, 1988). Large average charter school effects may therefore mask important differences over time, especially during major shocks like the COVID-19 pandemic and periods of changes in school inputs.

The most recent lottery-based evaluations of the state’s charter effects extend only through cohorts applying in 2014 or earlier, leading to a paucity of evidence on more recent years (Cohodes and Roy, 2025). Since then, the charter landscape experienced many changes, creating both challenges and opportunities for charter schools to employ their autonomy, even prior to the COVID-19 pandemic. I classify these changes into four categories: reforms to state standardized exams (in both 2015 and 2017), expansions of the charter sector changing the composition of schools (Cohodes et al., 2021), changes in the population of charter applicants, and changes in school practices or characteristics. The final category includes a wide range of organizational and instructional changes, such as retention of charter school leaders, changes in the subject-area expertise of charter school teachers, and efforts to reduce suspensions. It also includes changes in the practices and performance of traditional public schools.

In 2020, the COVID-19 pandemic created an unprecedented public health and educational crisis, providing a test of the ability of charter schools to adapt their learning practices (CREDO, 2022). During the initial years of the pandemic, student achievement fell nationally, with the National Assessment of Educational Progress (NAEP) showing significant declines in fourth and eighth grade reading scores and the largest drop in math scores since its initial assessments in 1990 (NAEP, 2022a,b). Recovery from these losses was both slow and uneven, with the percentage of Massachusetts students meeting expectations in math and reading increasing by 2 and 1 percentage points, respectively, between 2022 and 2023 (MA DESE, 2023a). This uneven recovery widened achievement gaps (Fahle et al., 2023), with the largest learning losses occurring for low-income and minority students, who

disproportionately enroll in charter schools.

In this paper, I ask three research questions. First, I ask how the effects of Massachusetts charter schools on student outcomes have evolved throughout the two decades between 2002 and 2022. This analysis encompasses two distinct periods that have not yet been studied: the period immediately prior to the COVID-19 pandemic (2015–2019) and the COVID-19 era (2020–2022). Second, I isolate a set of plausible hypotheses that are consistent with the trends in MA charter performance during the pre-pandemic period. Finally, I use a novel survey of charter school administrators to describe how charter schools responded to the COVID-19 pandemic. I then correlate reported practices with school-specific value-added measures to identify the practices adopted among the most effective schools.

To answer the first research question, I identify causal charter school effects by using charter admissions lotteries as a source of random variation for charter enrollment. The main outcomes are effects of charter schools on math and English language arts (ELA) scores on the Massachusetts Comprehensive Assessment System (MCAS) exam, SAT scores, and post-secondary enrollment. Lottery methods eliminate selection bias that comes from the decision of families to seek out charter schools. Overall from 2002–2022, I find that charter schools boosted math test scores by 0.15 standard deviations per year of enrollment and ELA test scores by 0.08 standard deviations per year of enrollment, with particularly large effects among Hispanic, Black, limited English proficiency (LEP), and free- and reduced-price lunch (FRPL) students. I then estimate effects separately by the year in which students enter charter lotteries, tracing the evolution of charter effects throughout two decades. These estimates reveal that causal effects of MA charters declined in the second half of the 2010s (for example, boosting math scores by 0.26 standard deviations per year of charter enrollment from 2010–2014 compared to traditional public schools, while being statistically indistinguishable from the traditional public schools from 2015–2019), before partially recovering in the COVID era (boosting math scores by 0.14 standard deviations per year of enrollment from 2020–2022). I observe similar trends for scores in other subject areas and SAT scores; there is no detectable shift in charter effects on post-secondary enrollment. Boston-area charter schools exhibited the largest fluctuations in effectiveness, with larger declines in the second half of the 2010s, as well as larger post-COVID rebounds, with their ELA effects in 2020–2022 outpacing the 2010–2014 performance.

I then explore candidate hypotheses that may explain the reduced charter effects from 2015–2019. I first rule out several plausible hypotheses, including that new charter schools may be less effective, that new charter applicants may benefit less, and that the redesign of state standardized tests may explain the decline. I therefore focus on a set of explanations in which changes in school characteristics – either among charter schools or non-charter options

– explain trends in charter effects. The declines in charter effects during the five-year period are concentrated in Boston-area charter schools. I then identify school characteristics that disproportionately changed in Boston-area charter schools, relative to Boston-area traditional public schools, during the same period in which effects declined. The time series patterns suggest that leadership turnover and changes in teacher subject-area expertise are consistent with the decline in charter effects.

Finally, I explore the post-COVID rebound in charter effectiveness by examining how MA charter schools responded to the COVID-19 pandemic and assessing which practices were correlated with pandemic-era effectiveness. To this end, I conduct a survey of charter school administrators from 29 charter middle and high schools. Schools reported a large and significant increase in the use of virtual tools and activities in response to the pandemic (+33.3 percentage points for the use of virtual tools), as well as hiring additional educators (+23.3 percentage points), family engagement (+13.3 percentage points), attendance coaches (+13.3 percentage points), and identifying students at risk of chronic absenteeism (+13.3 percentage points). They reported little change in the use of assessments or tutoring. The use of virtual tools and activities exhibits a strong negative correlation with school-specific post-COVID value-added while the use of assessments displays a strong positive correlation.

This paper relates to a large literature on the pre-pandemic effects of charter schools and the practices that contribute to charter effectiveness. This literature has generally found that while there is large national heterogeneity in charter school performance (CREDO, 2023; Clark et al., 2015), MA charter schools strongly improved student achievement for those entering charter schools between 2002 and 2014 (Abdulkadiroğlu et al., 2011; Angrist et al., 2013, 2016; Cohodes et al., 2021; Cohodes and Pineda, 2024). Researchers have argued that practices commonly referred to as “No Excuses” were particularly effective in producing test score gains both within MA and nationally, with an emphasis on features such as high expectations, frequent teacher feedback, high-dosage tutoring, increased instructional time, and data-driven instruction as correlates of effective charter schools (Angrist et al., 2013; Chabrier et al., 2016; Dobbie and Fryer Jr, 2013; Epple et al., 2016; Fryer Jr, 2014). I build on this literature by extending the time period covered by charter lotteries, demonstrating dynamics of charter effects within a single setting, and by connecting trends during this period to observable school characteristics and practices. My emphasis on the dynamics of charter effects over time illustrates that effects depend on the school inputs, rather than reflecting a constant “charter effect.”

This paper also relates to a recent literature on the relative effects of charter schools in the aftermath of the COVID-19 pandemic. Researchers have evaluated charter schools in Tennessee using propensity score methods (Kho et al., 2025) and Ohio using value-added

methods (Lavertu, 2024). These studies have generally found that charter schools experienced learning loss comparable to traditional public schools, but in some cases have recovered more quickly afterwards, depending on the grade level and geography. Yet, these studies have not used randomization from admissions lotteries. This paper fills that gap by utilizing credible lottery randomization, and applying it to a setting where comparison to an extended pre-pandemic period is readily available.

Finally, this paper relates to a literature on effective practices to promote learning recovery in the aftermath of the COVID pandemic. Within the charter sector, existing work focuses on immediate responses during the first year of the pandemic (Center for Research on Education Outcomes, 2022; Boast et al., 2020) or case studies within New York SUNY-authorized schools (Allen et al., 2022). These studies found that charter schools initially prioritized technology access, communication with families, and student supports. Compared with traditional public schools, charters were more likely to provide real-time instruction and monitor attendance. In New York, strategies for learning recovery included social-emotional learning programs, flexible curricula, and adaptive learning technologies; however, the existing studies do not attempt to evaluate the effectiveness of these approaches. Within other education sectors, researchers have evaluated individual COVID-era policies such as online tutoring (Kraft et al., 2022). In addition, this paper speaks to the effectiveness of policies that have been evaluated prior to the COVID-19 pandemic and have subsequently been implemented by many schools, such as increased instructional time (Kraft and Novicoff, 2024), high-dosage tutoring (Fryer Jr and Howard-Noveck, 2020; Guryan et al., 2023; Nickow et al., 2024; Robinson et al., 2021), summer programs (Lynch et al., 2023), and computer-assisted learning (Bettinger et al., 2023). I contribute to this literature by conducting a standardized survey within Massachusetts, comparing practices to a baseline prior to the pandemic, and correlating these practices with measures of school effectiveness.

2 Setting and Data

2.1 Massachusetts Charter Sector

Massachusetts first authorized charter schools in 1993 under the Massachusetts Education Reform Act. Charter schools are public, but have more autonomy than traditional public schools in staffing, budgeting, and school design. There are two primary types of charter schools under state law: Commonwealth charter schools, which operate independently from local school committees, and Horace Mann charter schools, which operate with oversight from local school committees and the local teachers’ union. Cohodes et al. (2021) find that

compared to traditional public schools, charter schools in the state have more instructional time and less experienced teachers.

In the 2024-25 school year, MA had 73 charter schools in operation, consisting of 68 Commonwealth charters and 5 Horace Mann charters (MA DESE, 2024b); between 2002 and 2022, there were 94 distinct charter schools operating. Approximately 5 percent of the state’s students enroll in charter schools (MA DESE, 2024a). 29 percent of the schools are in Boston, 50 percent are in other urban areas in the state, and 21 percent are in rural or suburban areas (Massachusetts Charter Public School Association, 2022). Many of the charter schools are oversubscribed, generating random variation in offers; in fall 2022, 87 percent of the charters had waitlists (MA DESE, 2022).

Previous research finds that MA charters positively affected ELA and math scores on the MCAS exam, as well as SAT scores and college enrollment, for students entering between 2002 and 2014 (Cohodes et al., 2021; Cohodes and Pineda, 2024). Researchers have attributed the success of urban charter schools in particular to a philosophy often called “No Excuses” (Angrist et al., 2013), which emphasizes structure, high expectations, behavioral norms, and teacher feedback (Dobbie and Fryer Jr, 2013; Carter, 2000). However, since the most recent lottery evaluations of MA charter schools, many schools nationally have moved away from some “No Excuses” practices (Torres, 2022). In MA, policy changes such as Chapter 222, which took effect in the 2015 school year, may have restricted the ability of schools to implement such practices by making it more difficult to suspend students (Felix, 2020). In addition, throughout the 2010s, Massachusetts modified its state standardized exam multiple times.¹ If previously measured charter success was specific to either “No Excuses” practices or training for skills on particular vintages of the MCAS exam, these changes could shift measurements of charter effects.

In spring 2020, MA charters, like the rest of the educational system, had to confront the novel challenges of the COVID pandemic. MA charter schools exhibited substantial variation in their initial responses, with 18 percent of the state’s charters spending more than three-quarters of the 2020-21 school year in a fully remote format and another 28 percent spending less than a quarter of the year in a fully remote format (COVID-19 School Data Hub, 2023). Learning loss from the pandemic is well-documented; in Massachusetts overall, the proportion of students in grades 3–8 “meeting or exceeding expectations” in math and reading fell 11 percentage points and 10 percentage points, respectively, between

¹Between 2013 and 2015, the state piloted the use of the Partnership for Assessment of Readiness for College and Careers (PARCC) exam, with schools having the option to administer either the MCAS or PARCC exam for grades 3–8 ELA and math in spring 2015. Beginning in spring 2017, MA adopted a computer-based Next-Generation MCAS exam for grades 3–8 math and ELA, which expanded to include science and high school level exams beginning in spring 2019.

2019 and 2022 (MA DESE, 2023b); this is equivalent to four months of lost learning in reading and almost seven months of lost learning in math (Center for Education Policy Research, 2022). Figure 1 illustrates time-series evidence of learning loss patterns, based on student performance on the MCAS in grade 8. Panel A shows large declines in math proficiency for both traditional public and charter students between 2019 and 2021; larger drops for charter students created a performance gap. Panel B shows smaller drops for ELA, although the state did not administer the MCAS exam in spring 2020 due to the COVID pandemic. However, Panels C and D show that among free and reduced-price lunch (FRPL) students, drops in achievement levels between charter schools and traditional public schools were similar between 2019 and 2021, allowing a charter advantage to persist among this group.

2.2 Lottery and Administrative Data

The starting point of the sample is lotteries for Massachusetts middle schools (Grade 5 and Grade 6 entry) and high schools (Grade 9 entry).² See Appendix Table C1 for a full list of the lotteries used in each year between 2002 and 2022. The lottery sample includes 243 school-by-year files of lottery data, including 32 of the 94 charter middle and high schools operating during this time period. Of these schools, 19 are in the Boston area and 13 are outside of the Boston area.³ Lottery data generally include an indicator for whether an applicant received an immediate or waitlist offer for the school on the lottery date. In addition, lottery records contain indicators for priority groups, such as sibling status.

To construct the sample of eligible lottery students, I follow the procedure from Cohodes et al. (2021), which excludes students missing an administrative ID number, students with sibling priority, students who are ineligible (by being out-of-area, applying late, or disqualified), and students who apply to non-entry grades or multiple grades in the same school year. The resulting sample consists of 34,569 total applicants, of which 27,679 apply to Boston-area charters and 6,890 apply to non-Boston charters; no students in the data apply to both types of charters.

I link these lottery files to administrative records from MA DESE.⁴ The administrative data include student enrollment and outcomes from school years 2002-03 through 2024-25.

²By law, Massachusetts charter schools are required to admit students by lottery if they are oversubscribed.

³I define “Boston-area schools” as those located in Boston and any adjacent town, as these are the areas that draw a substantial number of students from Boston. Specifically, this includes Boston as well as Cambridge, Somerville, Watertown, Newton, Brookline, Milton, Winthrop, Chelsea, Revere, and Everett.

⁴Lottery files are merged to administrative records using a fuzzy match procedure. Students from the lottery sample are matched using combinations of their name, date of birth, application grade, and location.

Within these data, the Student Information Management System (SIMS) contains student-level enrollment for all Massachusetts public school students, including their school, grade level, and demographics within each school year. Each student is assigned a unique statewide identifier (SASID) by DESE, which allows for students to be tracked over time and for administrative data sources to be merged together.

The primary student outcomes from the administrative data are state standardized test scores, SAT outcomes, and college enrollment. The state standardized test is based on the MCAS. MCAS math and ELA exams are given in grades 3–8 and grade 10, while science is given in grades 5, 8, and 10. The state did not administer the MCAS exam in spring 2020 due to the COVID pandemic. Throughout, MCAS scores are normalized to have mean 0 and standard deviation of 1 within each grade-subject-year. The MCAS exam has changed over time, including an option for schools to administer an alternative exam during two years; Appendix A.2 provides details on how these scores are harmonized over time. Data on college enrollment outcomes come from the National Student Clearinghouse (NSC) data linked by DESE.

In addition to these student outcomes, I use the administrative data from DESE to construct school-level measures of characteristics and practices, among all students at the schools, rather than just the sample of students in the analysis sample. These measures include AP test-taking for high school students, out-of-school suspension rates, teacher subject-area expertise, and attrition from teachers and school leaders.

2.3 Survey Data

I complement the administrative and lottery data with a survey of MA charter school administrators which documents their school practices and philosophies in recent years. This survey updates one previously administered by Angrist et al. (2013), and additionally includes questions about pandemic-specific policies to address learning loss. The survey was given between March 2024 and January 2026 to principals or senior administrators at MA charter schools that serve middle or high school grades. 29 out of the 70 charter middle and high schools in the state responded to the survey.⁵

The survey addresses school practices across four broad areas: learning recovery strategies, school day policies, classroom practices and curricular emphasis, and school organizational structure. For COVID-specific questions, respondents were asked about practices between March 2020 and June 2024. See Appendix B for the complete set of questions asked

⁵This is based on 18 distinct responses, as some responses covered middle and high schools within the same system. A small number of respondents opted to complete the survey over the phone, which included a smaller number of questions.

in the survey instrument, as well as additional details about survey implementation. The survey responses provide a rich set of measures of school practices to understand how charter schools changed since 2012 and specifically in response to the COVID pandemic.

2.4 Descriptive Statistics

Table 1 describes the characteristics of charter schools in the sample, and compares them to traditional public schools in the state. Column 1 reports averages for the 32 charter schools ever in the lottery data, while Columns 2 and 3 split the sample into Boston-area charters (19 schools) and non-Boston charters (13 schools). For comparison, Column 4 shows statistics for traditional public schools. Patterns are generally consistent with those previously documented in earlier years by Cohodes et al. (2021). Compared to traditional public schools, charter schools have teachers with fewer years of experience (5.7 years in charters compared to 10.6 years in non-charters) and charter schools serve a more socioeconomically disadvantaged student population, as measured by Title I eligibility (0.78 eligible in charters compared to 0.37 in non-charters). Comparing Columns 2 and 3 shows that these patterns are particularly pronounced for Boston-area charters, in which teachers have an average of 4.8 years of experience and all schools are Title I eligible.

Table 2 shows characteristics of students in the sample, along with a comparison to non-charter enrollees. Consistent with previous research, charter applicants are more likely than non-charter students to be Black or Hispanic and are more likely to be on free or reduced-price lunch.⁶ Approximately 13 percent of charter applicants are already attending a charter school when entering a charter lottery. Randomized applicants to Boston-area charters are more likely than those from other regions to be Black or Hispanic, FRPL, or have limited English proficiency. Boston-area applicants generally have low baseline ELA and math scores (0.43 and 0.39 standard deviations below the state-wide mean, respectively), while applicants to charter schools in other regions have baseline performance similar to other students.

3 Empirical Framework

3.1 Charter Sector Effects

My empirical approach follows other lottery-based charter studies by using random assignment from admissions lotteries to estimate causal effects of charter enrollment on student outcomes. In this framework, lottery offers are instruments for years of charter enrollment.

⁶Relative to earlier papers (e.g., Cohodes et al. (2021)), there has been an increase during this period in the share of applicants that are Hispanic and a decrease in the share that are Black.

Let Y_{ig} denote an outcome for applicant i measured in grade g . These outcomes include MCAS exam scores, SAT scores, and post-secondary outcomes. The structural equation is:

$$Y_{ig} = \alpha_g + \beta C_{ig} + \sum_{j=1}^J \delta_j R_{ij} + X_i' \gamma + \epsilon_{ig}, \quad (1)$$

where C_{ig} is the number of years of enrollment in any charter school between the lottery year and the year in which Y_{ig} is measured. R_{ij} is an indicator variable for whether i belongs to risk set j , based on the unique combinations of charter schools to which an applicant applies within each year and grade level, out of application possibilities $j \in J$. X_i contains characteristics measured prior to the lottery: gender, race, female-minority interaction, FRPL status, ELL status, and special education status. X_i also includes year fixed effects. For MCAS outcomes, it also includes fixed effects for the grade level in which the student took the exam. MCAS outcomes may also have multiple observations per student, so standard errors are clustered at the student level. The parameter of interest, β , gives the causal effect of each additional year of charter enrollment relative to enrollment in other schools.

Charter enrollment is not random, so I instrument years of charter enrollment using admissions lottery offers. The first-stage equation is:

$$C_{ig} = \mu_g + \pi_1 Z_{1i} + \pi_2 Z_{2i} + \sum_{j=1}^J \lambda_j R_{ij} + X_i' \theta + \xi_{ig}, \quad (2)$$

where Z_{1i} denotes an immediate offer to any charter school in the lottery data and Z_{2i} denotes a waitlist offer to any charter school in the lottery data.

Equations 1 and 2 are estimated using two-stage least squares (2SLS). To obtain precise estimates of charter effects during a long time horizon, I first estimate effects on each outcome among all observed lottery applicants (applications fall 2002 through fall 2022). I then separately estimate effects using lotteries across four separate periods: 2002–2009, 2010–2014, 2015–2019, and 2020–2022. Estimates for 2010–2014 and 2015–2019 correspond to the first and second half of the 2010s, respectively. Estimates for 2020–2022 correspond to applicants who potentially entered charter schools during the COVID-19 pandemic. As previous studies have limited estimates to applicants through 2014, estimates during the periods 2015–2019 and 2020–2022 are new to this study. Finally, I generate year-specific effects by estimating the system separately by lottery year. While year-specific estimates are less precise than pooled estimates, this approach traces out the dynamics of charter effects.

Appendix Table C2 reports first-stage estimates over time, separately for the sample

corresponding to the 2SLS estimation for each subject area and time period. Overall, within the math and ELA sample, an initial charter offer increases charter enrollment by about 1.05 years by the time the MCAS score is recorded in the data, while a waitlist charter offer increases enrollment by about 0.85 years. Notably, first-stage estimates have generally declined over time; in the math sample, initial offers increased charter enrollment by 1.33 years among 2002–2009 lottery cohorts, by 0.92 years among 2010–2014 lottery cohorts, and by 0.62 years among 2020–2022 lottery cohorts. The smaller first stage in more recent years partially reflects the fact that for the more recent cohorts, the only observed MCAS exams occurred relatively close to the lottery date; since the maximum number of post-lottery years for these cohorts is smaller, the data is right-censored in recent years.

Appendix Table C3 reports results of balance tests, indicating that across the sample of lottery years, most student characteristics are unrelated to whether students receive charter offers. Any remaining imbalances (such as LEP students being slightly more likely to receive a waitlist offer) are small and are unlikely to affect the estimation of charter effects. However, including student characteristics as controls in the estimation helps address any imbalances remaining after randomization, and also improves precision.

3.2 School-Specific Value-Added

To examine correlates of charter effectiveness during the pandemic period, I supplement the lottery-based estimates with well-controlled OLS estimates of individual school value-added. These are estimated with MCAS outcomes during the post-COVID period, using the 2020-21 through 2023-24 school years. This allows for a larger sample of schools when correlating charter effects and practices from the survey, as lottery records are not available from all schools completing the survey. For the value-added model, rather than just using lottery applicants, I use a sample of all middle and high school enrollees in both charter school and traditional public schools during this period.

The estimating equation for student i taking the MCAS in grade g in year t at school j is:

$$Y_{igt} = \alpha_{gt} + X_i'\theta + \sum_j \beta_j D_{ij} + \eta_{igt}, \quad (3)$$

where Y_{igt} is a normalized MCAS score and α_{gt} is a vector of grade-by-year fixed effects. The covariate vector X_i includes a cubic in the MCAS score from two years prior and indicators for gender, LEP, special education, prior charter enrollment (again from two years earlier), race/ethnicity groups, and an interaction between gender and minority status. D_{ij} is an indicator for student i enrolling in school j , with separate indicators for each charter school

and a single indicator for all non-charter options.⁷ Under the assumption that conditional on controls, there are no unobserved factors that affect both student achievement and the enrollment decision, the vector β_j identifies the causal effect of enrolling in each charter school on MCAS scores (Angrist et al., 2024).

4 Lottery Estimates

4.1 Evolution of Charter Effects

I begin by estimating the overall effects of charter school attendance on student outcomes across the full set of lottery cohorts. Column 1 of Table 3 reports the effects of each year of charter enrollment on MCAS scores for applicants entering lotteries between 2002 and 2022. The pooled estimates indicate that on average, charter enrollment markedly increases MCAS scores, with each year of charter enrollment boosting math scores by 0.15 standard deviations, ELA scores by 0.08 standard deviations, and science scores by 0.22 standard deviations. Column 1 of Table 4 reports corresponding estimates for longer-run outcomes, based on SAT scores and attending any college.⁸ Charter enrollment increases SAT composite scores by approximately 11.5 points per year of enrollment and increases the probability of post-secondary enrollment by approximately 1.3 percentage points.

However, the average effect of attending charter schools differs based on when students applied. To see how charter effects have varied over time, I estimate the lottery model separately by charter lottery year. Figure 2 plots cohort-specific estimates of the effects of years of charter enrollment on MCAS scores, where each point shows an estimated effect for a given lottery cohort. For math, ELA, and science, these plots reveal that charter schools consistently had positive effects for all cohorts through the early 2010s. Between 2013 and 2017, however, the positive charter effects decline steadily, with effects approaching zero and even becoming negative for some cohorts, although these negative estimates are mostly imprecise. Following this period of declining effects, estimates among more recent cohorts show evidence of a recovery in charter effects, especially since the COVID-19 pandemic. For several cohorts, estimates for students entering lotteries since 2020 become positive again, although confidence intervals are wider due to a weaker first stage and fewer years of post-lottery MCAS measures. This suggests that, as measured by MCAS scores, the effects

⁷Two-year lags are used for achievement and charter enrollment because the MCAS exam is administered in grade 10 but not grade 9. Therefore, for students entering a charter high school lottery, they do not take an MCAS exam until two years later.

⁸Because these outcomes are measured several years after the charter lotteries in many cases, when splitting results across years, results are not shown for the 2020–2022 time period.

of the state’s charter schools relative to traditional public schools dropped throughout the mid-2010s but appear to be rebounding in more recent years.⁹

To summarize the patterns more precisely, Columns 2 through 5 of Table 3 report estimates of MCAS score effects that group cohorts into multi-year periods. This reveals large positive effects of charter enrollment on test scores in all subject areas from 2002–2014. In the latter half of the 2010s, however, effects are much lower than in the 2010–2014 period; for ELA, effects are negative and marginally significant, suggesting a decrease of 0.05 standard deviations per year of enrollment. Estimates from 2020–2022 are less precisely estimated, but suggest a rebound in charter effects, with significant and positive effects in math and science. Appendix Table C4 and Appendix Table C5 show that for both math and ELA, the declining effect of charter enrollment on MCAS scores occurred in both middle schools and high schools, although high school estimates are much noisier due to fewer post-lottery exam observations. Results for longer-run outcomes in Table 4 suggest a similar change throughout the 2010s. Comparing Columns 3 and 4, while charter enrollment boosted SAT composite scores by 21 points per year of enrollment in the first half of the decade, it decreased scores by 39 points per year in the second half. Results for any post-secondary enrollment are less precise but exhibit a similar decline in point estimates.¹⁰ Taken together, these results suggest a decline in charter school effects between 2015 and 2019, as well as a partial recovery in effects for the post-COVID cohorts.

4.2 Geographic Variation in Charter Effects

Previous research on Massachusetts charter schools shows the largest test score gains among urban charters (Angrist et al., 2013; Cohodes and Pineda, 2024), especially those within Boston (Angrist et al., 2016; Cohodes et al., 2021).¹¹ Motivated by these findings from earlier lottery years, I contrast charter effects across two dimensions: whether the charter school is in the Boston area and whether the charter school is in an urban area.

Table 5 shows charter effects separately by period for Boston-area charters and charters in other regions.¹² In the first half of the 2010s, Boston charters had large positive impacts on MCAS scores in all subject areas (0.27σ per year for math, 0.18σ per year for ELA,

⁹Appendix Figure C1 shows analogous cohort-specific results for effects on SAT scores and any post-secondary enrollment. These show similar patterns, although effects for later cohorts are much noisier.

¹⁰There is not enough data to estimate the effect of attending a charter school on SAT scores or college-going for students who applied after 2019.

¹¹Cohodes and Pineda (2024) note that when looking at longer-run outcomes, such as college completion, non-urban charter schools may boost outcomes beyond what may be reflected by short-run test scores.

¹²Following Cohodes and Pineda (2024), this is estimated in a single 2SLS framework, where the first-stage outcome is years of attendance in a charter school of type k , which consists of either Boston-area or non-Boston charters. Instruments consist of immediate offers and waitlist offers in each type of charter.

and 0.32σ per year for science). In contrast, by the second half of the decade, effects were much smaller, with negative but statistically insignificant point estimates in some cases (-0.05σ for math, -0.06σ for ELA, and 0.11σ for science). Across all three subject areas, the estimates for 2015–2019 are statistically different from those for 2010–2014. Notably, for math and ELA scores, there is evidence that Boston-area charters recovered their 2010–2014 levels of effectiveness during 2020–2022. Estimates for math effects are similar to those from 2010–2014, while estimates for ELA effects are larger than those from 2010–2014.

In contrast, charter schools from other regions in the state experienced much smaller declines in effectiveness throughout the 2010s. While effects on MCAS scores in other regions were smaller than those from Boston-area charters and generally insignificant in 2010–2014, there is little change between the first and second half of the decade, with effects on math scores reduced by only 0.06σ and effects on ELA scores reduced by only 0.12σ . Taken together, this evidence suggests that both the decline in charter effects on MCAS scores and subsequent rebound were driven primarily by the Boston-area charters.

Patterns by region for charter effects on SAT scores are similar in Table 6, with larger declines in effects between the first and second half of the 2010s in Boston-area charters than those in other regions. Panel B shows that while Boston-area charter schools boosted SAT composite scores by 25.7 points per year of enrollment from 2010–2014, they lowered scores by 43.1 points per year of enrollment from 2015–2019; both estimates are statistically significant.¹³ In contrast, charter schools in other regions have no effect on SAT scores in either period. This evidence suggests that the decline in charter effects on SAT scores in 2015–2019 was also concentrated in Boston-area schools. Charter effects on post-secondary attendance do not show as clear of a pattern; point estimates from 2015–2019 are slightly smaller than from 2010–2014, but I cannot rule out that the effects are the same.¹⁴

There are fewer differences in trends based on whether charter schools are in urban areas, as shown in Appendix Table C6. I follow Cohodes and Pineda (2024) in defining urban charter schools as those where the school district participated in the Massachusetts Urban Superintendents Network. Throughout the 2010s, there is a similar trend in effectiveness overall among urban and non-urban charters, implying that whether or not a charter school is in the Boston area is the more important factor in predicting the dynamics.

¹³Panel A shows that charter attendance also modestly increases the probability that students attempt the SAT, and that this effect grows throughout the 2010s. In principle, this could introduce negative selection, but this is unlikely to explain the effects on scores. Effects on taking the exam grow only modestly during the period (by 1.5 percentage points), so negative selection would need to be implausibly large to explain the substantial decline in effects on the SAT composite score.

¹⁴Column 4 only shows results through fall 2019 lotteries, ensuring that it is possible to observe the first year of post-secondary enrollment for all students if they enroll immediately after completing high school. Nevertheless, if students enroll later, observations for eventual post-secondary enrollment may be censored.

4.3 Explaining Pre-COVID Declining Charter Impacts

Why did the effectiveness of Massachusetts charter schools compared to traditional public schools decrease from 2015–2019? This section assesses the plausibility of several possible explanations. In particular, I consider four possible explanations: (i) reforms to the MCAS exam; (ii) changes in the set of charter schools in the state; (iii) changes in the population of students applying to charter schools; or (iv) changes in school practices or characteristics. The changes in school practices could include either changes in the charter schools or the traditional public schools. I discuss each of these hypotheses in turn.

4.3.1 Reforms to Standardized Tests

One potential explanation for the decline in charter effects is that it reflects reforms to the MCAS exam that took place throughout the 2010s, rather than changes in underlying school effectiveness; this could be important if charter schools emphasize standardized test preparation and base their curricula on specific versions of tests (Merseeth, 2009).¹⁵ During the study period, the state transitioned from the Legacy MCAS exam to partial adoption of the PARCC exam in 2015 to the Next-Generation MCAS beginning in 2017 for math and ELA.

There are several pieces of evidence that make this explanation unlikely. First, the magnitudes and timing of the changes for science outcomes are similar to those for math or ELA outcomes, despite reforms to the science exam not taking place until later. Second, Appendix Figure C2 shows charter effects on MCAS scores based on the year of the MCAS exam, rather than lottery years. This shows a gradual decline in charter effects, rather than discrete jumps during years of the exam redesigns. This downward trend in charter effects also begins prior to any of the exam redesigns. Finally, Table 4 shows similar declines of charter effects on SAT scores during this period, which would be unrelated to changes in the MCAS exam.

4.3.2 Changes in the Set of Charter Schools

A second possible explanation is that as the composition of charter schools in the state changed, the new schools were less effective.¹⁶ Cohodes et al. (2021) study earlier expansions

¹⁵Within Massachusetts, evidence that charters focus on test preparation is limited. While many charter schools reported in 2012 that they emphasize measurable achievement gains (Angrist et al., 2013), other work has found that charter students do not perform disproportionately better on commonly-tested items than uncommonly-tested items in the state (Cohodes, 2016).

¹⁶MA DESE (2025) indicate that while there was only a slight increase in the number of charter schools in the state between 2012 and 2020, this obscures that some new schools opened while others closed. Beyond differences in the charter schools operating, a more subtle explanation could be that schools for which lottery

resulting from the 2010 change in the state charter cap, finding that high-performing charter schools were successfully able to scale, but it is possible that this pattern of success did not continue.

To assess this explanation, I re-estimate the year-specific charter effects restricting to the sample of the 22 charter schools that are observed early in the decade, by having available lottery records for any year between fall 2010 and fall 2014. In this setup, the endogenous variable is years enrolled in any charter school, but the instrument consists of offers at any of the early charter schools. Risk sets remain defined based on the full set of charter schools where students apply. These results are shown in Appendix Figure C3 and Appendix Table C7. They indicate that even within this sample of early schools, there is a similar decline in charter effects on MCAS scores in all subject areas in the second half of the 2010s. For example, within this set of schools, the effect of each year of charter enrollment declines from 0.26σ from 2010–2014 to -0.03σ from 2015–2019 for math, and from 0.18σ from 2010–2014 to -0.05σ from 2015–2019 for ELA. This pattern suggests that effects are also not driven by a change in charter school composition.

4.3.3 Changes in Composition of Charter Student Applicants

A third potential explanation is that the characteristics of lottery applicants in the sample changed over time, if there was a shift toward applicants who benefit less from charter school attendance. If this were the case, then the average gains from charter enrollment could decline even if charter schools maintained their earlier levels of effectiveness for each group of students. Applicant characteristics could change, for example, through changes in demographics of the school-age population over time or changes in the applicant population due to factors like targeted outreach or changes induced by shifts in the application system (Avery et al., 2025).

I investigate this hypothesis by first assessing heterogeneity in average charter effectiveness over time by student characteristics, and then examining trends in the characteristics of applicants over time, separately by lottery cohort. Table 7 reveals that among the 2002–2022 cohorts, charter effects are particularly large for Hispanic, Black, LEP, and FRPL applicants, markedly increasing their MCAS math, ELA, and science scores. Appendix Figure C4 plots how charter applicant characteristics changed over time, based on race/ethnicity and FRPL status. This indicates that throughout the 2010s, the only clear trend in the composition of charter applicants is a slight increase in Hispanic applicants.¹⁷ Since Hispanic students were

data were available changed over time.

¹⁷Otherwise, the only noticeable changes are discrete changes as schools entered or left the sample, which does not align with the continuous decline in charter effects.

among those who benefited the most from charter enrollment across all years, the increase in their application shares would predict an increase in charter effects. I therefore rule out changes in applicant composition as a driver of declining charter effects during the 2010s.

4.3.4 Changes in School Characteristics and Practices

Having ruled out changes in student applicant composition, school composition, and the standardized tests as drivers of changes in charter effects, I then focus on changes in school practices. This encompasses the broad range of characteristics, philosophies, and strategies of both charter schools and traditional public schools, which influence the relative effectiveness of charter schools by changing counterfactual school quality.

I do not identify a single explanation that fully accounts for the decline in charter effects. Instead, I pursue the following approach to determine several school characteristics which plausibly line up with the decline. Section 4.2 showed that Boston-area charter schools experienced the largest declines in effects throughout the 2010s. I then examine a range of school characteristics and practices that are measurable in state administrative data. For a characteristic to be a plausible candidate for trends in effects, it must change contemporaneously with the period when effectiveness began to decline (approximately 2012 through 2017) within Boston-area charters. The trends in the candidate characteristic or practice should demonstrate a divergence between Boston-area charters and Boston-area traditional public schools, with no such divergence taking place in other regions.

I consider five different school characteristics and practices that are observable in DESE administrative or public data: AP test-taking among high school students (as a proxy for advanced curricular offerings), out-of-school suspensions (as a proxy for disciplinary stringency), teacher subject-area expertise, teacher turnover, and school leader (i.e., principal, headmaster, headmistress, or head of school) turnover. More details on the data sets and definitions used for these measures are discussed in Appendix A. While this is not an exhaustive list of potential school practices and characteristics that could change charter school effects, it represents a starting point for features that could plausibly affect charter performance. For AP test-taking, Cohodes and Feigenbaum (2021) note that during the 2010s, Boston Public Schools (BPS) increased their offerings of AP courses. If there are other similar improvements in BPS and other traditional public school course options, this could explain the decline of charter effects relative to traditional public schools. For out-of-school suspensions, changes could reflect a combination of discipline laws enacted in Massachusetts as well as a broader shift away from “No Excuses” models.¹⁸ For teacher subject-area exper-

¹⁸Since previous charter research has generally associated these practices with the most effective charter schools (Dobbie and Fryer Jr, 2013; Angrist et al., 2013), it is possible that any declines in disciplinary

tise, changes could reflect either differences in who becomes a teacher or differences in where charter schools hire teachers, such as changes in the popularity of programs like Teach for America (TFA).¹⁹ My definition of subject-area expertise is whether teachers either majored in the subject area that they teach or are licensed in that field. Finally, changes in teacher and leader turnover may create instability or result in less effective leaders if the original leaders were particularly high-performing.²⁰ If initial charter leaders had strong management skills, a literature on the variation and importance of leadership in school performance suggests that their departure could be detrimental for student outcomes (Bloom et al., 2015; Di Liberto et al., 2015; Branch et al., 2012; Fryer et al., 2017; Bartanen et al., 2024).

First, Figure 3 compares the patterns over time of these practices and characteristics among charter schools and non-charters in Massachusetts overall. Panels A through D show the averages of various characteristics during each school year. Panel E shows leadership turnover by year, based on the share of schools that still have the same leader as they did in the first observed year. Of particular interest is the period from 2012–2017 when the charter schools experienced declines in effectiveness. Overall, there is little visual evidence of divergent trends between charters and non-charters with respect to AP test-taking or out-of-school suspensions.²¹ There is some evidence of differences in school leadership turnover in Panel E; although differences are modest, they are significant at the 5 percent level in 2016 and 2017. There is more evidence of divergent trends in teacher subject-area expertise and turnover (panels C and D). Panel C shows a decline in the share of teachers with a degree in their subject area or licensed in their subject area between 2013 and 2017 only within charter schools, coinciding with the timing of a decline in charter effectiveness; meanwhile the share of teachers with subject-area expertise in non-charters steadily increased during this same period. Panel D shows similar patterns in teacher attrition in the state’s charter schools, steadily increasing from approximately 25 percent annually in 2012 to about 33 percent by 2016, while non-charters displayed constant rates of attrition.

To be consistent with the reduced charter effects from 2015–2019, however, these same

stringency could be related to declines in relative charter effectiveness.

¹⁹Angrist et al. (2013) found that urban Massachusetts charters previously drew a large share of teachers from programs like TFA, which have declined in size during this period. Clotfelter et al. (2007) finds that subject-area expertise, as measured by certification, positively affects student achievement.

²⁰Importantly, it is also possible that high turnover rates are a consequence, rather than a cause of declining charter effects. I am not able to disentangle a direction of causality when patterns occur simultaneously. Nevertheless, any correlation would suggest whether this is a plausible candidate hypothesis.

²¹During this period, charter schools also continued to have a causal effect on suspension. Appendix Table C8 shows estimates of the causal effect of each year of charter enrollment on both out-of-school suspensions and in-school suspensions. This analysis omits the 2010–2014 period because of changes in the reporting requirements for suspensions during the middle of that period. Nevertheless, this suggests that during both the pre-COVID and post-COVID eras, charters remained more likely than traditional public schools to suspend students.

patterns should be particularly strong in Boston-area charter schools, with fewer changes in other regions. Figure 4 shows the time series of the same characteristics only among Boston-area charters while Figure 5 shows the time series within other regions. These figures continue to suggest that changes in AP test-taking and suspensions are likely unrelated to trends in charter effects, with patterns in charters mirroring the patterns of non-charters in both regions. They also continue to suggest that declines in teacher subject-area background are consistent with declines in effectiveness; within Boston-area charter schools, the share of teachers with subject-area expertise decreased from over 55 percent to about 40 percent between 2012 and 2017, while patterns were generally flat among non-Boston charters. Based on the Boston and non-Boston differences, teacher attrition seems less important; the largest increases in teacher attrition generally occurred outside of the Boston area. In addition, the geographic split highlights that school leadership changes are also a plausible hypothesis, with a large departure of Boston-area charter leaders between 2013 and 2017 (relative to non-charters in the same region); in contrast, outside of Boston, charter leader attrition rates were lower and were almost identical to attrition rates among non-charters. Within the Boston area, differences in leadership turnover between charters and non-charters are significant at the 5 percent level for each year 2015–2018. There are similar patterns when comparing CEO attrition rates between Boston-area charters and other charters in Figure 6; by 2017, only about 20 percent of Boston-area charters have their original CEO observed in the data, while this share is about 60 percent for charters in other areas.

Taken together, these exploratory analyses suggest that declines in teacher subject-area expertise and the departure of school leaders are both plausible hypotheses for the decline of MA charter effects in 2015–2019. Importantly, this does not establish a causal relationship between these factors, and there are many other potential factors that I am not able to consider in these analyses. Nevertheless, the case for these factors playing a role in charter trends is much stronger than for any of the other hypotheses considered.

5 Explaining the Pandemic-Era Charter Advantage

The results from Section 4.1 suggest that MA charter school performance increased since the COVID pandemic, particularly among the Boston-area charters. How did charter schools use their flexibility and autonomy during this period of increased effectiveness? To investigate possible drivers of this rebound, I use results from the survey of charter practices. First, I provide novel survey evidence of contemporary charter school practices in MA. On its own, this does not indicate which specific practices are effective, but it describes the characteristics of the sector as a whole, during a period of improved effectiveness. Second, I correlate

these responses with individual school-level value-added estimates, which suggests specific practices that may have been the most effective.

5.1 Pandemic-Era Practices

First, Table 8 summarizes reported charter school characteristics and practices, based on the survey conducted between 2024 and 2026. All questions in this table were also included in the survey conducted in 2012 by Angrist et al. (2013), providing for a comparison between charter practices during these periods. This suggests meaningful changes in charter schools during that 14-year period, although on its own, the survey cannot distinguish when the changes took place. Notably, among the schools that responded to both surveys, there is a large decline in Saturday school (37.5 percentage point decrease), the presence of college icons in the classroom (57.1 percentage point decrease), a reported emphasis on a strict adherence to school-wide standards (57.1 percentage point decrease), and an emphasis on discipline and comportment (42.9 percentage point decrease). There are also modest reported decreases in average math and ELA instructional time, although these differences are not statistically significant within the overlap sample. Overall, this suggests that the rebound in charter effects since the pandemic occurred without schools re-adopting educational models that heavily emphasize strict standards or discipline.

Next, Table 9 reports survey results for the set of questions related to practices specifically used to combat pandemic-driven learning loss. Respondents were asked whether their schools “often or always” used a range of practices, both prior to the pandemic and since the pandemic. Among all 29 schools in the survey sample, this suggests a large and statistically significant increase in the use of technology-driven practices, such as a higher use of virtual tools (an increase of 33.3 percentage points) and virtual activities (an increase of 20.0 percentage points). Schools additionally reported hiring additional educators (an increase of 23.3 percentage points) and taking measures to reduce absenteeism, such as engaging families, using attendance coaches, and identifying students at risk for chronic absenteeism. In contrast, there is little evidence that charter schools expanded their use of interventions such as tutoring that were highlighted as effective in pre-pandemic literature. There was only a slight reported increase in the share of charters using after-school tutoring (from 33.3 percent to 40.0 percent), while during-school tutoring remained unchanged at 36.7 percent.

Taken together, the results from these tables suggest that since the pandemic, MA charters continued to de-emphasize philosophies such as discipline and rigid standards, while adapting to the pandemic by utilizing tools like virtual learning, efforts to increase attendance, and additional hiring. While it seems that the state’s charters boosted student

achievement post-pandemic, the survey evidence alone is not sufficient to establish that these particular changes led to the rebounds in effectiveness. One key limitation is that this evidence is averaged across all charter schools in the sample, without distinguishing those that are the most effective. Another limitation is that the survey does not reveal whether traditional public schools adopted some of the same practices. Therefore, in the next section, value-added estimates for individual schools are used to provide evidence on specific practices correlated with effectiveness.

5.2 Characteristics of Effective Pandemic-Era Charters

Table 10 reports the relationship between COVID-era value-added estimates from Equation 3 and pandemic-era practices from the survey. Specifically, value-added math and ELA estimates are regressed on each pandemic-era charter practice individually, with observations weighted by the inverse of the standard error on the school-specific value-added estimate. In each regression, indicators are included for middle school, urban schools, and Boston-area schools. While this analysis is not causal, it suggests the practices that the most effective charter schools have adopted during the pandemic. In addition, using value-added measures as the outcome ensures that practices are correlated with actual school effects, rather than just baseline student achievement levels.

There is a negative relationship between value-added and some of the most commonly adopted pandemic practices during the post-COVID period (Columns 2 and 4). For both math and ELA, there is a negative and significant relationship between value-added and the use of virtual tools, virtual activities, attendance coaches, and remedial instruction. In the cases of attendance coaches and remedial instruction, the relationship between post-COVID value-added and the use of pre-COVID practices is also negative, suggesting that this relationship may reflect unobserved differences across schools or reverse causality; for example, schools that already struggle with student attendance may have both low value-added and need to hire attendance coaches. Nevertheless, in the cases of virtual tools and virtual activities, the relationship between post-COVID performance and pre-COVID adoption is much weaker, suggesting that the correlation does not just reflect persistent differences in school effectiveness.

The null estimates on the relationship between effectiveness and tutoring contrast with existing literature on the benefits of tutoring interventions (Nickow et al., 2024). However, as Kraft and Goldstein (2020) note, tutoring on its own is not a guaranteed panacea for promoting student learning, as tutoring generally needs to be high-dosage, personalized, and consistent in order to be effective.

In contrast, the post-COVID use of diagnostic and formative assessments has a strong and positive correlation with school effectiveness. Notably, these practices were not more common among the better-performing post-COVID schools prior to the pandemic, suggesting that the post-COVID correlation does not simply reflect widespread usage in schools that were already effective. The apparent effectiveness of assessments in promoting student achievement is consistent with correlations previously found by Angrist et al. (2013), where practices such as math drills and cold calling had a strong association with achievement.

6 Conclusion

This paper uses variation from admissions lotteries to provide the first causal evidence on how the effects of charter schools on student achievement evolved over two decades in Massachusetts. I find novel patterns in which charter effects first declined in the second half of the 2010s and then partially rebounded since the COVID-19 pandemic. This suggests that charter effectiveness is not a fixed characteristic of the sector, but instead reflects underlying school practices and organizational choices. Future work can continue tracking the evolving trends in school effectiveness to determine if the current positive charter effects persist and if they also extend to longer-run outcomes such as college completion.

Exploratory analysis isolates potential school characteristics and practices that are consistent with the observed patterns in school effectiveness. The timing of pre-pandemic declines in effectiveness – combined with the concentration of this trend within Boston-area charters – mirrors the departure of Boston-area charter leaders and a decline in subject-area expertise among Boston-area charter teachers. These factors are therefore plausible hypotheses for the decline in charter effectiveness, but this paper does not establish a causal relationship between the factors. Since the pandemic, when charter effectiveness once again increased, the sector reported widespread adoption of practices such as increased staff hiring and virtual tools. Of the adopted practices, the use of diagnostic and formative assessments is most strongly correlated with school-specific value-added. Future research can use these correlations as a starting point to identify promising interventions for experimental analyses.

References

- ABDULKADIROĞLU, A., J. D. ANGRIST, S. M. DYNARSKI, T. J. KANE, AND P. A. PATHAK (2011): “Accountability and flexibility in public schools: Evidence from Boston’s charters and pilots,” *The Quarterly Journal of Economics*, 126, 699–748.
- ALLEN, E., V. MASSÉUS, K. CLAYTON, AND A. KILE (2022): “Accelerated Learning in Practice: Promising Practices from the SUNY Charter Schools’ 2021–22 School Visit Season,” Tech. rep., SUNY Charter Schools Institute.
- ANGRIST, J., S. COHODES, S. DYNARSKI, P. PATHAK, AND C. WALTERS (2016): “Stand and deliver: Effects of Boston’s charter high schools on college preparation, entry, and choice,” *Journal of Labor Economics*, 34, 275–318.
- ANGRIST, J., P. HULL, P. A. PATHAK, AND C. WALTERS (2024): “Credible school value-added with undersubscribed school lotteries,” *Review of Economics and Statistics*, 106, 1–19.
- ANGRIST, J., P. PATHAK, AND C. WALTERS (2013): “Explaining charter school effectiveness,” *American Economic Journal: Applied Economics*, 5, 1–27.
- AVERY, C., G. KOCKS, AND P. A. PATHAK (2025): “The Algorithm Advantage: Ranked Application Systems Outperform Decentralized and Common Applications in Boston and Beyond,” Tech. rep., National Bureau of Economic Research.
- BARTANEN, B., A. N. HUSAIN, AND D. D. LIEBOWITZ (2024): “Rethinking principal effects on student outcomes,” *Journal of Public Economics*, 234, 105115.
- BETTINGER, E., R. FAIRLIE, A. KAPUZA, E. KARDANOVA, P. LOYALKA, AND A. ZAKHAROV (2023): “Diminishing Marginal Returns to Computer-Assisted Learning,” *Journal of Policy Analysis and Management*, 42, 552–570.
- BLOOM, N., R. LEMOS, R. SADUN, AND J. VAN REENEN (2015): “Does management matter in schools?” *The Economic Journal*, 125, 647–674.
- BOAST, L., B. CLIFFORD, AND D. DOYLE (2020): “Learning in Real Time: How Charter Schools Served Students during COVID-19 Closures,” *Public Impact*.
- BRANCH, G. F., E. A. HANUSHEK, AND S. G. RIVKIN (2012): “Estimating the effect of leaders on public sector productivity: The case of school principals,” Tech. rep., National Bureau of Economic Research.
- BRUHN, J., S. IMBERMAN, AND M. WINTERS (2022): “Regulatory arbitrage in teacher hiring and retention: Evidence from Massachusetts charter schools,” *Journal of Public Economics*, 215, 104750.
- BUDDE, R. (1988): “Education by Charter: Restructuring School Districts. Key to Long-Term Continuing Improvement in American Education,” Tech. rep., ERIC.
- CARTER, S. C. (2000): *No excuses: Lessons from 21 high-performing, high-poverty schools.*, ERIC.
- CENTER FOR EDUCATION POLICY RESEARCH (2022): “New Research Provides First Clear Picture of District-Level Learning Losses in Massachusetts as well as Nationally,” Educa-

tion Recovery Scorecard.

- CENTER FOR RESEARCH ON EDUCATION OUTCOMES (2022): “Charter Schools’ Responses to the Pandemic in California, New York, and Washington,” Tech. rep., Stanford University.
- CHABRIER, J., S. COHODES, AND P. OREOPOULOS (2016): “What can we learn from charter school lotteries?” *Journal of Economic Perspectives*, 30, 57–84.
- CLARK, M. A., P. M. GLEASON, C. C. TUTTLE, AND M. K. SILVERBERG (2015): “Do charter schools improve student achievement?” *Educational Evaluation and Policy Analysis*, 37, 419–436.
- CLOTFELTER, C. T., H. F. LADD, AND J. L. VIGDOR (2007): “Teacher credentials and student achievement: Longitudinal analysis with student fixed effects,” *Economics of education review*, 26, 673–682.
- COHODES, S. (2016): “Teaching to the student: Charter school effectiveness in spite of perverse incentives,” *Education Finance and Policy*, 11, 1–42.
- COHODES, S. AND J. FEIGENBAUM (2021): “Why does education increase voting? Evidence from Boston’s charter schools,” Tech. rep., National Bureau of Economic Research.
- COHODES, S. AND A. PINEDA (2024): “Diverse Paths to College Success: The Impact of Massachusetts’ Urban and Nonurban Charter Schools on College Trajectories,” Tech. rep., National Bureau of Economic Research.
- COHODES, S. AND S. ROY (2025): “Thirty years of charter schools: What does lottery-based research tell us?” *Journal of School Choice*, 19, 8–49.
- COHODES, S., E. SETREN, AND C. WALTERS (2021): “Can successful schools replicate? Scaling up Boston’s charter school sector,” *American Economic Journal: Economic Policy*, 13, 138–167.
- COVID-19 SCHOOL DATA HUB (2023): “Predominant Learning Models in Massachusetts in 2020–2021,” <https://www.covidschooldatahub.com/states/massachusetts>, accessed: 2026-03-06.
- CREDO (2022): “Coronavirus and School Research: A Major Disruption and Potential Opportunity,” *Center for Research on Educational Outcomes*, <https://credo.stanford.edu/wp-content/uploads/2022/02/Charter-School-COVID-Final.pdf>.
- (2023): “The National Charter School Study III,” *Center for Research on Educational Outcomes*, <https://ncss3.stanford.edu/wp-content/uploads/2023/06/Credo-NCS-S3-Report.pdf>.
- DI LIBERTO, A., F. SCHIVARDI, AND G. SULIS (2015): “Managerial practices and student performance,” *Economic Policy*, 30, 683–728.
- DOBBIE, W. AND R. G. FRYER JR (2013): “Getting beneath the veil of effective schools: Evidence from New York City,” *American Economic Journal: Applied Economics*, 5, 28–60.
- EPPLER, D., R. ROMANO, AND R. ZIMMER (2016): “Charter schools: A survey of research

- on their characteristics and effectiveness,” *Handbook of the Economics of Education*, 5, 139–208.
- FAHLE, E. M., T. J. KANE, T. PATTERSON, S. F. REARDON, D. O. STAIGER, AND E. A. STUART (2023): “School district and community factors associated with learning loss during the COVID-19 pandemic,” *Center for Education Policy Research at Harvard University*.
- FELIX, M. (2020): “Charter schools and suspensions: Evidence from Massachusetts Chapter 222,” *Blueprint Labs*.
- FRYER, R. G. ET AL. (2017): “Management and student achievement: Evidence from a randomized field experiment,” Tech. rep., National Bureau of Economic Research.
- FRYER JR, R. G. (2014): “Injecting charter school best practices into traditional public schools: Evidence from field experiments,” *The Quarterly Journal of Economics*, 129, 1355–1407.
- FRYER JR, R. G. AND M. HOWARD-NOVECK (2020): “High-dosage tutoring and reading achievement: evidence from New York City,” *Journal of Labor Economics*, 38, 421–452.
- GURYAN, J., J. LUDWIG, M. P. BHATT, P. J. COOK, J. M. DAVIS, K. DODGE, G. FARKAS, R. G. FRYER JR, S. MAYER, H. POLLACK, ET AL. (2023): “Not too late: Improving academic outcomes among adolescents,” *American Economic Review*, 113, 738–765.
- KHO, A., S. SMITH, AND R. ZIMMER (2025): “From Disruption to Recovery: Charter School Performance During and After the COVID-19 Pandemic,” .
- KRAFT, M. A. AND M. GOLDSTEIN (2020): “Getting tutoring right to reduce COVID-19 learning loss,” Brookings, accessed 2026-03-31.
- KRAFT, M. A., J. A. LIST, J. A. LIVINGSTON, AND S. SADOFF (2022): “Online tutoring by college volunteers: Experimental evidence from a pilot program,” in *AEA Papers and Proceedings*, American Economic Association, vol. 112, 614–618.
- KRAFT, M. A. AND S. NOVICOFF (2024): “Time in School: A conceptual framework, synthesis of the causal research, and empirical exploration,” *American Educational Research Journal*, 61, 724–766.
- LAVERTU, S. (2024): “Ohio Charter Schools after the Pandemic: Are Their Students Still Learning More than They Would in District Schools? Research Brief.” *Thomas B. Fordham Institute*.
- LYNCH, K., L. AN, AND Z. MANCENIDO (2023): “The impact of summer programs on student mathematics achievement: A meta-analysis,” *Review of Educational Research*, 93, 275–315.
- MA DESE (2022): “Massachusetts Charter School Waitlist Initial Report for 2022–2023,” Massachusetts Department of Elementary and Secondary Education.
- (2023a): “Press Release: 2023 MCAS Scores Show Progress in Math and ELA Academic Recovery,” Massachusetts Department of Elementary and Secondary Education Press Release.

- (2023b): “Spring 2022 MCAS Tests: Summary of State Results,” Massachusetts Department of Elementary and Secondary Education.
- (2024a): “Enrollment: Grade, Race/Ethnicity, Gender, and Selected Populations,” .
- (2024b): “Final FY2025 Charter School Tuition and Enrollment,” <https://www.doe.mass.edu/charter/finance/tuition/fy2025/q4-final.html>, accessed: 2026-03-05.
- (2025): “Charter School Fact Sheet, Directory, and Application History,” <https://www.doe.mass.edu/charter/factsheet.html>, accessed: 2026-03-13.
- MASSACHUSETTS CHARTER PUBLIC SCHOOL ASSOCIATION (2022): “Get the Facts,” Accessed: 2026-03-05.
- MERSETH, K. K. (2009): *Inside urban charter schools: Promising practices and strategies in five high-performing schools.*, ERIC.
- NAEP (2022a): “NAEP Report Card: 2022 NAEP Mathematics Assessment,” The Nation’s Report Card.
- (2022b): “NAEP Report Card: 2022 NAEP Reading Assessment,” The Nation’s Report Card.
- NICKOW, A., P. OREOPOULOS, AND V. QUAN (2024): “The promise of tutoring for PreK–12 learning: A systematic review and meta-analysis of the experimental evidence,” *American Educational Research Journal*, 61, 74–107.
- ROBINSON, C. D., M. A. KRAFT, S. LOEB, AND B. E. SCHUELER (2021): “Accelerating Student Learning with High-Dosage Tutoring. EdResearch for Recovery Design Principles Series.” *EdResearch for recovery project*.
- TORRES, C. (2022): “Classroom Management in “No-Excuses” Charter Schools,” in *Handbook of Classroom Management*, Routledge, 152–166.

Tables

Table 1. School Characteristics

	(1)	(2)	(3)	(4)
	All charters	Boston area	Other regions	Non charter
Years open	18.750	16.895	21.462	.
Years of teacher experience in Massachusetts	5.685	4.799	6.980	10.629
Student/teacher ratio	11.006	10.858	11.223	11.848
Average per-pupil expenditure	20082	22872	16433	20619
Title I eligible	0.781	1.000	0.462	0.369
Observations (schools)	32	19	13	1977

Notes: This table shows descriptive statistics of all charter schools in the lottery analysis sample, along with separate descriptive statistics for Boston-area charter schools in the sample and those in other regions. Boston-area charter schools are those located in Boston, Cambridge, Somerville, Watertown, Newton, Brookline, Milton, Winthrop, Chelsea, Revere, or Everett. Column 4 shows characteristics of non-charters for comparison. Charter characteristics are measured in the 2022-2023 school year, or the last year in which a school was open if it closed prior to 2022. Non-charter characteristics are measured in the 2022-2023 school year, and include traditional public schools that serve students in grades 5–12. Data on per-pupil expenditure and student-to-teacher ratio come from MA DESE school profiles, and data on years open come from the MA DESE Charter Fact Sheet.

Table 2. Student Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	Boston area				Other regions	
	Non Charter	Randomized applicants	Non Charter	Randomized applicants	Non Charter	Randomized applicants
Female	0.485	0.516	0.484	0.514	0.485	0.522
Black	0.089	0.399	0.255	0.462	0.066	0.143
Hispanic	0.178	0.357	0.338	0.387	0.156	0.232
Asian	0.061	0.029	0.085	0.029	0.057	0.030
White	0.647	0.191	0.297	0.100	0.696	0.558
FRPL	0.311	0.571	0.523	0.632	0.282	0.327
LEP	0.100	0.158	0.218	0.180	0.083	0.070
Special education	0.185	0.194	0.192	0.195	0.183	0.191
Baseline charter	0.009	0.128	0.014	0.151	0.009	0.036
Baseline ELA	.	-0.328	.	-0.426	.	0.042
Baseline math	.	-0.313	.	-0.388	.	-0.021
N	2064681	34569	252258	27679	1812423	6890

Notes: This table shows descriptive statistics of Massachusetts students. The non-charter sample includes all students in grades 5–9 between 2002 and 2022, recording student characteristics from the first time that they are observed during this period in grades 5–9. Randomized applicants are students in the lottery data, excluding those dropped from the analysis by being disqualified or having sibling priority. Students may be in both the non-charter and randomized applicants sample if they do not end up attending a charter school. FRPL indicates whether students are on free or reduced-price lunch and LEP indicates whether students have Limited English Proficiency. Not all race/ethnicity categories are listed in the table, and therefore do not sum to 1. Boston-area charter schools are those located in Boston, Cambridge, Somerville, Watertown, Newton, Brookline, Milton, Winthrop, Chelsea, Revere, or Everett. Baseline ELA and math test scores come from the MCAS exam and are normalized to have mean zero and standard deviation one in the state by subject, grade, and year.

Table 3. Charter Effects on Test Scores

	(1)	(2)	(3)	(4)	(5)
	All Lottery Years	Lotteries 2002-2009	Lotteries 2010-2014	Lotteries 2015-2019	Lotteries 2020-2022
<i>Panel A: Math</i>					
Charter Years	0.145*** (0.015)	0.144*** (0.021)	0.256*** (0.028)	-0.012 (0.029)	0.139* (0.072)
Test Scores	71065	20354	19038	19554	12119
Students	32897	9393	9383	9170	4951
<i>Panel B: English</i>					
Charter Years	0.081*** (0.014)	0.075*** (0.019)	0.177*** (0.027)	-0.052* (0.029)	0.102 (0.071)
Test Scores	71104	20192	19125	19616	12171
Students	33020	9434	9420	9200	4966
<i>Panel C: Science</i>					
Charter Years	0.215*** (0.019)	0.172*** (0.026)	0.307*** (0.034)	0.098** (0.046)	0.233** (0.093)
Test Scores	33105	8417	10425	8834	5429
Students	28009	6952	8693	7711	4653

Notes: This table shows 2SLS estimates of the effect of years of charter school attendance on MCAS exam scores. Each column shows effects corresponding to admissions lottery cohorts from the indicated years, with “All Years” including cohorts from 2002-2022. The endogenous variable is years in charter schools between the admissions lottery and the exam, and the instruments are immediate offers and waitlist offers for any charter school in the lottery data. Math and ELA scores are measured in grades 5-8 and grade 10. Science scores are measured in grades 5, 8, and 10. Scores are normalized to have mean 0 and standard deviation of 1 within each grade-subject-year. Each regression controls for lottery risk sets, gender, race, ethnicity, female-minority interactions, special education status, English language learner status, FRPL status, and grade and year indicators. Heteroskedasticity-robust standard errors are shown in parentheses, clustered by student. *: p-value < 0.1; **: p-value < 0.05; ***: p-value < 0.01.

Table 4. Charter Effects on SAT and Post-Secondary Outcomes

	(1)	(2)	(3)	(4)
	All Lottery Years	Lotteries 2002-2009	Lotteries 2010-2014	Lotteries 2015-2019
<i>Panel A: Attempted SAT</i>				
Charter Years	0.008*** (0.002)	0.001 (0.001)	0.012** (0.005)	0.027** (0.013)
Control Mean	0.559	0.590	0.540	0.505
Students	17418	7307	5943	3921
<i>Panel B: SAT composite score</i>				
Charter Years	11.528*** (3.025)	12.918*** (3.084)	21.399*** (6.983)	-39.235** (17.368)
Control Mean	938.129	903.388	945.171	968.463
Tests	11249	4426	3746	2820
Students	9864	4413	3067	2127
<i>Panel C: Any post-secondary institution</i>				
Charter Years	0.013** (0.006)	0.016** (0.007)	0.012 (0.012)	-0.005 (0.025)
Control Mean	0.652	0.739	0.646	0.535
Students	18125	7304	5940	4881

Notes: This table shows 2SLS estimates of the effect of years of charter school attendance on SAT and post-secondary outcomes. Each column shows effects corresponding to admissions lottery cohorts from the indicated years, with “All Years” including cohorts from 2002-2020. The endogenous variable is years in charter schools between the admissions lottery and the outcome, and the instruments are immediate offers and waitlist offers for any charter school in the lottery data. In Panel B, SAT composite scores are only measured among students who take the SAT. In Panel C, the outcome is an indicator for ever enrolling in a 2-year or 4-year post-secondary institution. Each regression controls for lottery risk sets, gender, race, ethnicity, female-minority interactions, special education status, English language learner status, FRPL status, and grade and year indicators. Heteroskedasticity-robust standard errors are shown in parentheses; in Panel B, these are clustered by student. *: p-value < 0.1; **: p-value < 0.05; ***: p-value < 0.01.

Table 5. Charter Effects on Test Scores, by Location

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Boston Area					Other Regions				
	All Lottery Years	Lotteries 2002-2009	Lotteries 2010-2014	Lotteries 2015-2019	Lotteries 2020-2022	All Lottery Years	Lotteries 2002-2009	Lotteries 2010-2014	Lotteries 2015-2019	Lotteries 2020-2022
<i>Panel A: Math</i>										
Charter Years	0.239*** (0.018)	0.346*** (0.027)	0.274*** (0.030)	-0.052 (0.039)	0.243* (0.126)	0.024 (0.021)	0.014 (0.026)	0.094 (0.083)	0.035 (0.044)	0.037 (0.082)
Test Scores	63445	19147	18163	18225	7910	63445	19147	18163	18225	7910
Students	30728	8757	8897	8885	4189	30728	8757	8897	8885	4189
<i>Panel B: English</i>										
Charter Years	0.136*** (0.017)	0.173*** (0.025)	0.183*** (0.029)	-0.056 (0.039)	0.251** (0.125)	-0.019 (0.018)	-0.012 (0.022)	0.059 (0.074)	-0.064 (0.040)	0.014 (0.079)
Test Scores	63379	18963	18207	18271	7938	63379	18963	18207	18271	7938
Students	30797	8786	8909	8907	4195	30797	8786	8909	8907	4195
<i>Panel C: Science</i>										
Charter Years	0.283*** (0.023)	0.319*** (0.033)	0.320*** (0.037)	0.113** (0.055)	-0.013 (0.173)	0.064** (0.027)	0.038* (0.022)	0.153* (0.085)	0.031 (0.072)	0.283** (0.123)
Test Scores	30164	7846	9882	8565	3871	30164	7846	9882	8565	3871
Students	26063	6472	8239	7481	3871	26063	6472	8239	7481	3871

Notes: This table shows 2SLS estimates of the effect of years of charter school attendance on MCAS exam scores, separately by Boston-area charters and charters in other regions. The 2SLS procedure is estimated in a single regression and sample sizes indicate the total sample size from the pooled regression. Boston-area charter schools are those located in Boston, Cambridge, Somerville, Watertown, Newton, Brookline, Milton, Winthrop, Chelsea, Revere, or Everett. Each column shows effects corresponding to admissions lottery cohorts from the indicated years, with “All Years” including cohorts from 2002-2022. The endogenous variable is years in charter schools between the admissions lottery and the exam, and the instruments are immediate offers and waitlist offers for any charter school in the data. ELA and math test scores are measured in grades 5-8 and 10. Scores are normalized to have mean 0 and standard deviation of 1 within each grade-subject-year. Each regression controls for lottery risk sets, gender, race, ethnicity, female-minority interactions, special education status, English language learner status, FRPL status, and grade and year indicators. Heteroskedasticity-robust standard errors are shown in parentheses, clustered by student. *: p-value < 0.1; **: p-value < 0.05; ***: p-value < 0.01.

Table 6. Charter Effects on SAT and Post-Secondary Outcomes, by Location

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Boston Area				Other Regions			
	All Lottery Years	Lotteries 2002-2009	Lotteries 2010-2014	Lotteries 2015-2019	All Lottery Years	Lotteries 2002-2009	Lotteries 2010-2014	Lotteries 2015-2019
<i>Panel A: Attempted SAT</i>								
Charter Years	0.011*** (0.003)	0.000 (0.001)	0.017** (0.007)	0.035** (0.014)	-0.001 (0.002)	-0.000 (0.001)	0.001 (0.004)	-0.020 (0.033)
Students	13208	5670	4467	3070	13208	5670	4467	3070
<i>Panel B: SAT composite score</i>								
Charter Years	17.795*** (4.022)	21.882*** (4.165)	25.651*** (8.024)	-43.147** (20.732)	2.340 (4.033)	3.679 (4.360)	-1.802 (9.837)	6.941 (38.221)
Tests	10299	4179	3591	2518	10299	4179	3591	2518
Students	8954	4167	2933	1843	8954	4167	2933	1843
<i>Panel C: Any post-secondary</i>								
Charter Years	0.013* (0.008)	0.023** (0.010)	0.009 (0.013)	-0.023 (0.030)	0.011* (0.006)	0.009 (0.006)	0.046** (0.019)	-0.111 (0.113)
Students	13203	5667	4464	3070	13203	5667	4464	3070

Notes: This table shows 2SLS estimates of the effect of years of charter school attendance on SAT and college outcomes, separately by Boston-area charters and charters in other regions. The 2SLS procedure is estimated in a single regression and sample sizes indicate the total sample size from the pooled regression. Boston-area charter schools are those located in Boston, Cambridge, Somerville, Watertown, Newton, Brookline, Milton, Winthrop, Chelsea, Revere, or Everett. Each column shows effects corresponding to admissions lottery cohorts from the indicated years, with “All Years” including cohorts from 2002-2020. The endogenous variable is years in charter schools between the admissions lottery and the outcome, and the instruments are immediate offers and waitlist offers for any charter school in the lottery data. In Panel B, SAT composite scores are only measured among students who take the SAT. In Panel C, the outcome is an indicator for ever being observed enrolling in a 2-year or 4-year post-secondary institution. Each regression controls for lottery risk sets, gender, race, ethnicity, female-minority interactions, special education status, English language learner status, FRPL status, and grade and year indicators. Heteroskedasticity-robust standard errors are shown in parentheses; in Panel B, these are clustered by student. *: p-value < 0.1; **: p-value < 0.05; ***: p-value < 0.01.

Table 7. Charter Effects on Test Scores, by Student Characteristics

	(1)	(2)	(3)	(4)	(5)
	Hispanic	White	Black	LEP	FRPL
<i>Panel A: Math</i>					
Charter Years	0.220*** (0.024)	0.012 (0.022)	0.286*** (0.027)	0.259*** (0.034)	0.255*** (0.020)
Test Scores	25122	15190	26930	11264	39270
Students	11713	6416	12988	5151	18737
<i>Panel B: English</i>					
Charter Years	0.156*** (0.023)	-0.031 (0.019)	0.128*** (0.026)	0.202*** (0.035)	0.156*** (0.020)
Test Scores	25184	15238	26857	11322	39323
Students	11770	6434	13034	5172	18835
<i>Panel C: Science</i>					
Charter Years	0.353*** (0.034)	0.025 (0.028)	0.295*** (0.031)	0.314*** (0.045)	0.337*** (0.026)
Test Scores	11929	6488	12922	5492	18961
Students	10203	5672	10638	4636	15927

Notes: This table shows 2SLS estimates of the effect of years of charter school attendance on MCAS exam scores, from lottery years 2002–2022, separately by student characteristics. Each column shows effects estimated within a different demographic group. The endogenous variable is years in charter schools between the admissions lottery and the exam, and the instruments are immediate offers and waitlist offers for any charter school in the lottery data. Test scores are measured in grades 5–8 and grade 10, normalized to have mean 0 and standard deviation of 1 within each grade-subject-year. Each regression controls for lottery risk sets, gender, race, ethnicity, female-minority interactions, special education status, English language learner status, FRPL status, and grade and year indicators. Heteroskedasticity-robust standard errors are shown in parentheses, clustered by student. *: p-value < 0.1; **: p-value < 0.05; ***: p-value < 0.01.

Table 8. Survey Responses

	(1)	(2)	(3)	(4)	(5)
	2026 Mean	2012 Mean (Overlap Sample)	2026 Mean (Overlap Sample)	Difference (2026-2012)	P-Value
<i>Panel A: School Day</i>					
Years open+	22.621	9.125	23.125	14.000	
Days per year	183.964	185.312	184.625	-0.688	0.304
Average minutes per day	438.357	442.625	435.875	-6.750	0.630
Average math instruction (min)+	52.933	78.688	65.875	-12.812	0.143
Math instruction (share of day)+	0.119	0.176	0.151	-0.025	0.155
Average reading instruction (min)+	57.912	74.312	65.875	-8.438	0.212
Reading instruction (share of day)+	0.133	0.168	0.151	-0.017	0.320
<i>Panel B: School Practices</i>					
Uniforms+	0.690	0.875	0.625	-0.250	0.170
Saturday school+	0.172	0.375	0.000	-0.375*	0.080
Cold calling+	0.103	0.429	0.143	-0.286	0.356
Student contract	0.379	0.500	0.625	0.125	0.598
Parent contract+	0.621	0.750	0.750	0.000	1.000
Group projects	0.000	0.286	0.000	-0.286	0.172
DEAR or SSR	0.000	0.571	0.000	-0.571**	0.030
Reading aloud	0.034	0.286	0.000	-0.286	0.172
College icons in classroom	0.034	0.571	0.000	-0.571**	0.030
Teacher autonomy	0.103	0.667	0.167	-0.500*	0.076
Reward system	0.483	0.571	0.429	-0.143	0.604
<i>Panel C: School Philosophy</i>					
Traditional reading and math skills	0.414	0.429	0.286	-0.143	0.604
College preparation	0.345	0.857	0.429	-0.429*	0.078
STEM	0.069	0.000	0.143	0.143	0.356
Cultural awareness	0.103	0.429	0.143	-0.286	0.356
Strict adherence to school standards	0.138	0.714	0.143	-0.571**	0.030
Social and physical wellbeing	0.103	0.286	0.000	-0.286	0.172
Individually-tailored instruction	0.207	0.429	0.143	-0.286	0.356
Discipline and comportment	0.000	0.429	0.000	-0.429*	0.078
Speech and writing development	0.103	0.429	0.143	-0.286	0.172
Measurable results	0.103	0.429	0.143	-0.286	0.172
Qualitative achievement	0.103	0.000	0.000	0.000	
<i>Panel D: Teacher Profile</i>					
TFA novices+	0.069	0.286	0.143	-0.143	0.604
TFA alumni	0.241	0.429	0.429	0.000	1.000
Recent college graduates*	0.379	0.167	0.167	0.000	1.000
Lessons videotaped	0.655	0.714	0.857	0.143	0.356
Phone Responses	1		0		
Total Responses	18	8	8		
Observations	29	8	8		

Notes: The survey questions appear in Appendix B. The “Overlap Sample” corresponds to schools that responded to both the current survey (2026 mean) and the survey from Angrist et al. (2013) (2012 mean). + indicates questions that were asked in the phone survey; all other questions were only asked in the online survey. p-values in column (5) correspond to the test that the difference in column (4) is equal to 0. In column (4), stars correspond to significance levels. *: p-value < 0.1; **: p-value < 0.05; ***: p-value < 0.01.

Table 9. Use of Learning Practices Before and After Pandemic

	(1)	(2)	(3)	(4)
	Pre-pandemic	Post-pandemic	Change (post-pre)	P-Value
Virtual tools	0.200	0.533	0.333***	0.001
Hire additional educators	0.233	0.467	0.233***	0.006
Virtual activities	0.233	0.433	0.200**	0.012
Family engagement	0.767	0.900	0.133**	0.043
Attendance coaches	0.200	0.333	0.133**	0.043
Identify risk of chronic absenteeism	0.500	0.633	0.133**	0.043
Tailored instruction	0.367	0.467	0.100*	0.083
Virtual curriculum	0.133	0.233	0.100*	0.083
Remedial instruction	0.367	0.433	0.067	0.161
After-school tutoring	0.333	0.400	0.067	0.423
Diagnostic assessments	0.800	0.800	0.000	1.000
During-school tutoring	0.367	0.367	0.000	1.000
Summer school	0.467	0.433	-0.033	0.712
Formative assessments	0.867	0.800	-0.067	0.423
Responses	18	18		
Observations	29	29		

Notes: This table reports the share of charter school survey respondents indicating that they “Often” or “Always” use the indicated practices, both prior to the pandemic and after the pandemic. The survey questions appear in Appendix B. The stars in column (3) correspond to the significance level on the test that the difference between the post- and pre-values equals 0, with the p-values shown in column (4). *: p-value < 0.1; **: p-value < 0.05; ***: p-value < 0.01.

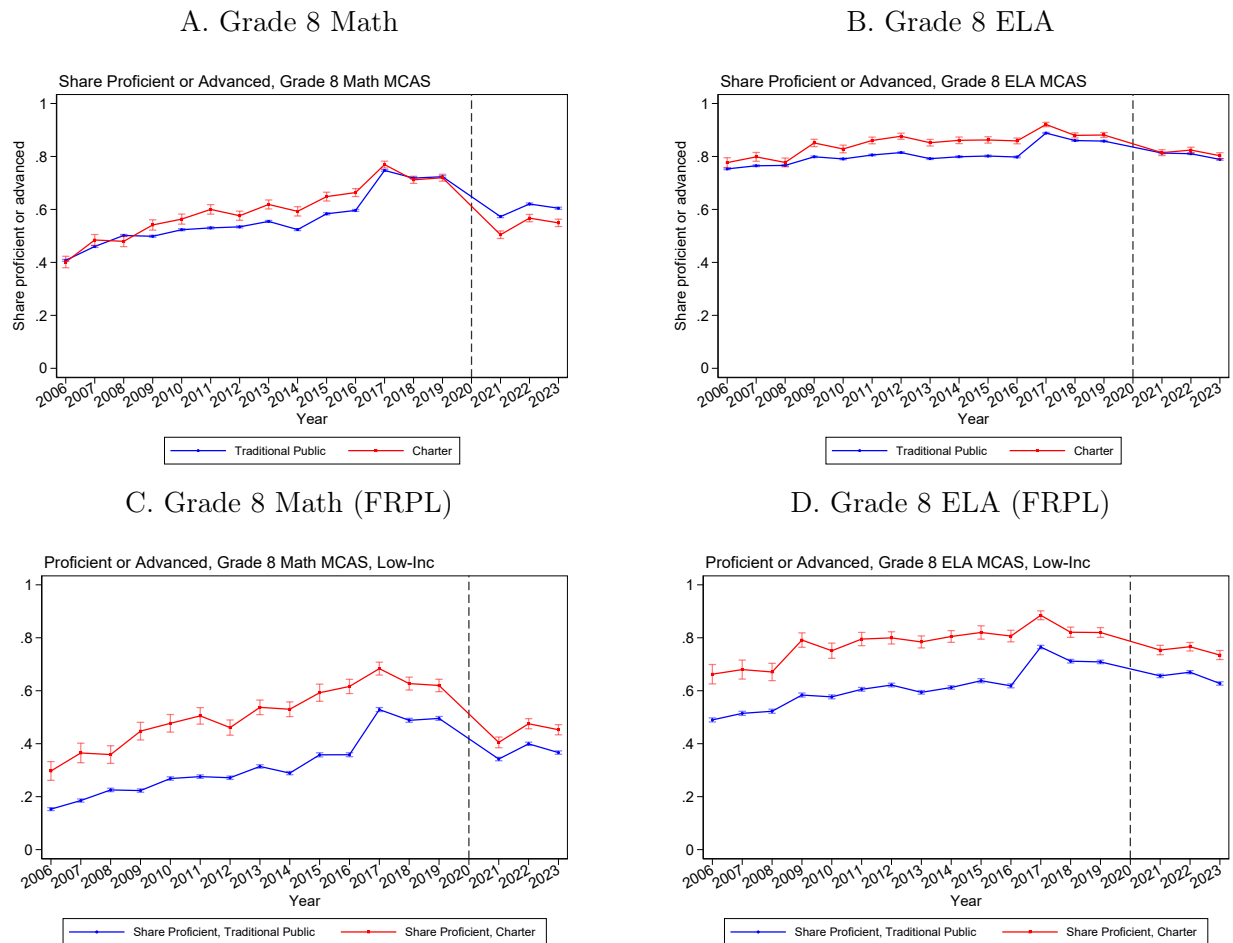
Table 10. Relationship Between COVID-Era Effectiveness and School Practices

	(1)	(2)	(3)	(4)
	Math, Pre-COVID Practice	Math, Post-COVID Practice	ELA, Pre-COVID Practice	ELA, Post-COVID Practice
Virtual tools	-0.046 (0.062)	-0.155* (0.084)	-0.039 (0.049)	-0.159*** (0.042)
Hire additional educators	-0.112 (0.075)	-0.042 (0.075)	-0.098 (0.061)	-0.065 (0.057)
Virtual activities	-0.091 (0.063)	-0.165** (0.075)	-0.083* (0.049)	-0.166*** (0.039)
Family engagement	-0.076 (0.080)	-0.031 (0.106)	-0.054 (0.059)	-0.014 (0.070)
Attendance coaches	-0.277*** (0.093)	-0.195*** (0.075)	-0.213*** (0.059)	-0.140** (0.066)
Identify risk of chronic absenteeism	-0.118 (0.085)	-0.180 (0.111)	-0.095 (0.066)	-0.169*** (0.054)
Tailored instruction	-0.135 (0.087)	-0.123 (0.102)	-0.103* (0.060)	-0.090 (0.067)
Virtual curriculum	-0.122 (0.094)	-0.080 (0.074)	-0.163*** (0.047)	-0.086 (0.067)
Remedial instruction	-0.135 (0.087)	-0.165** (0.077)	-0.103* (0.060)	-0.135*** (0.050)
After-school tutoring	0.031 (0.128)	-0.069 (0.103)	0.027 (0.090)	-0.086 (0.072)
Diagnostic assessments	0.017 (0.043)	0.124*** (0.036)	-0.099*** (0.012)	0.050 (0.075)
During-school tutoring	0.118 (0.114)	0.118 (0.114)	0.087 (0.085)	0.087 (0.085)
Summer school	-0.179*** (0.069)	-0.162** (0.072)	-0.105* (0.062)	-0.097 (0.063)
Formative assessments	-0.108 (0.118)	0.157** (0.067)	-0.095 (0.086)	0.175*** (0.038)

Notes: This table reports coefficients from regressions of post-COVID charter-specific value-added and indicators for whether schools report that they “often” or “always” use each listed practice, prior to the COVID pandemic and since the COVID pandemic. Each practice and column corresponds to a separate regression. The survey questions appear in Appendix B. Regressions include indicators for middle school, urban schools, and Boston-area schools. In each regression, observations are weighted by the inverse of the standard error on the value-added estimate. Practices are sorted by their change in reported adoption between the pre-pandemic and post-pandemic period, with the practices with the largest changes sorted at the top of the table. Heteroskedasticity-robust standard errors are reported in parentheses. *: p-value < 0.1; **: p-value < 0.05; ***: p-value < 0.01.

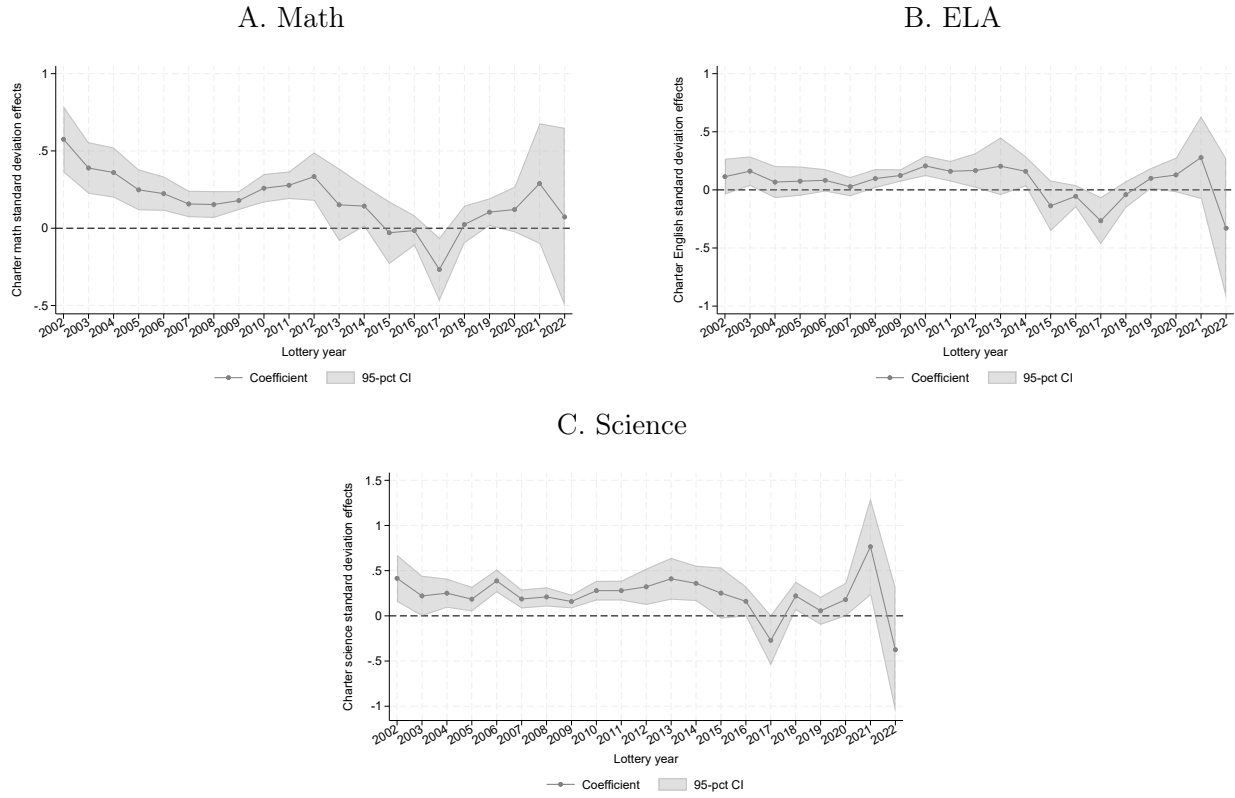
Figures

Figure 1. Proficiency Rates Over Time



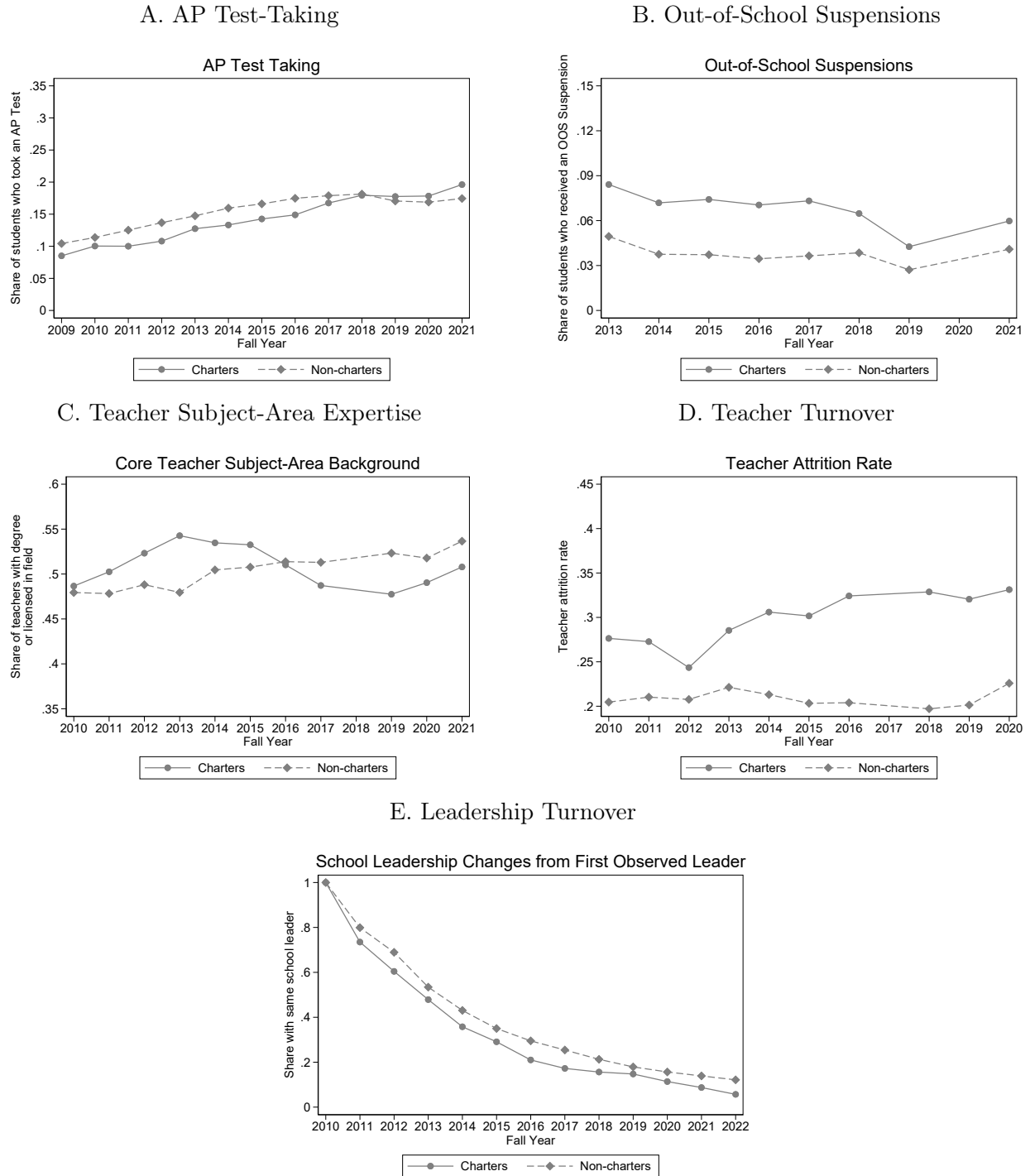
Notes: These graphs show the share of grade 8 students proficient in math and ELA in the spring of each year. Scores are not available in 2020 due to the COVID-19 pandemic. There is a jump in 2017 due to changes in proficiency measures from the adoption of the MCAS Next-Generation exam. Panels C and D restrict results to FRPL students.

Figure 2. Charter Effects on MCAS Scores Over Time



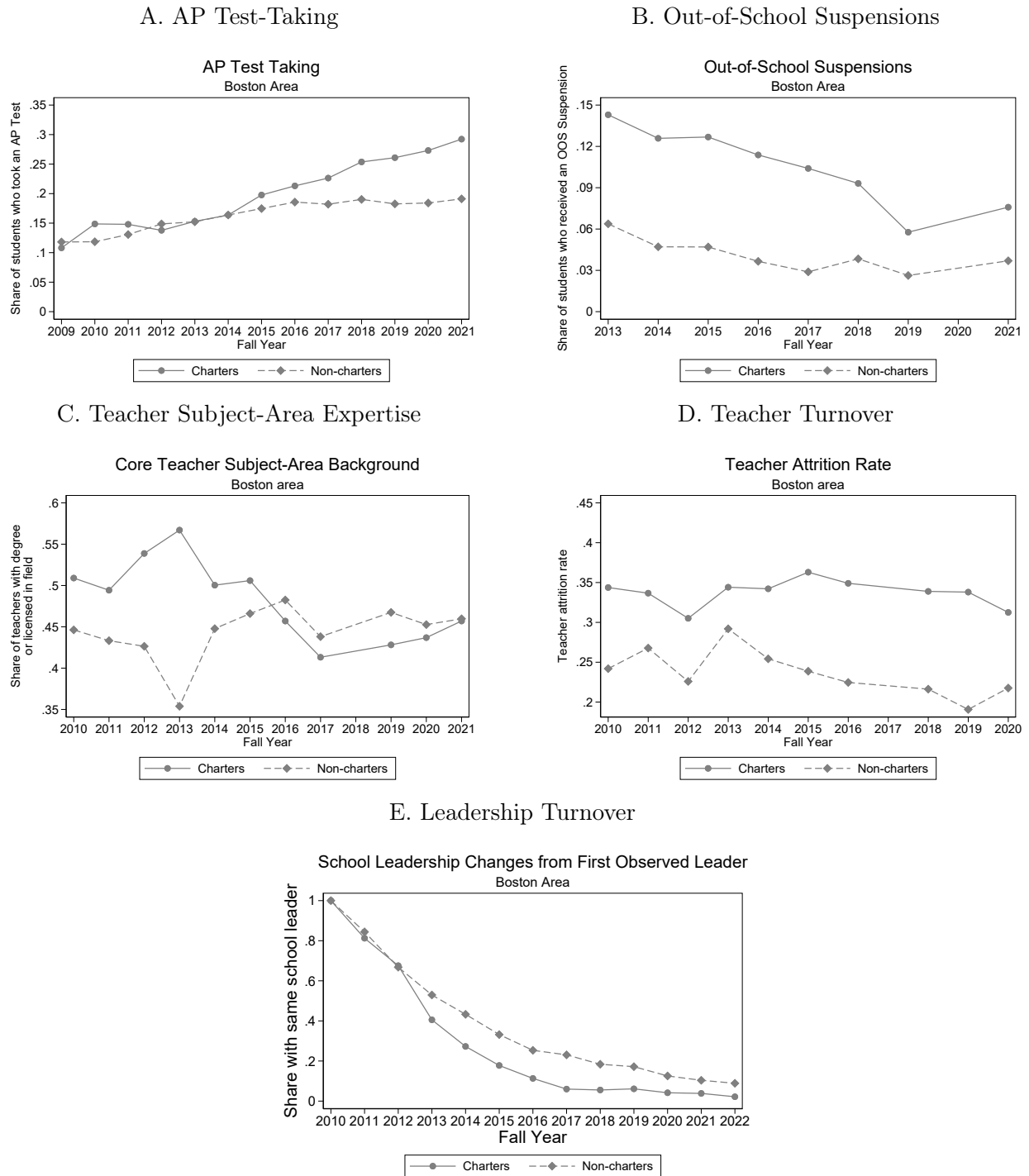
Notes: These figures show the time series of the 2SLS estimates of Massachusetts charter school effects on MCAS scores, separately by lottery year and subject area. Shaded areas correspond to 95% confidence intervals. The endogenous variable is years in charter schools between the admissions lottery and the outcome, and the instruments are immediate offers and waitlist offers for any charter school in the lottery data. Standard errors are clustered by student.

Figure 3. Charter and Non-Charter Characteristics Over Time



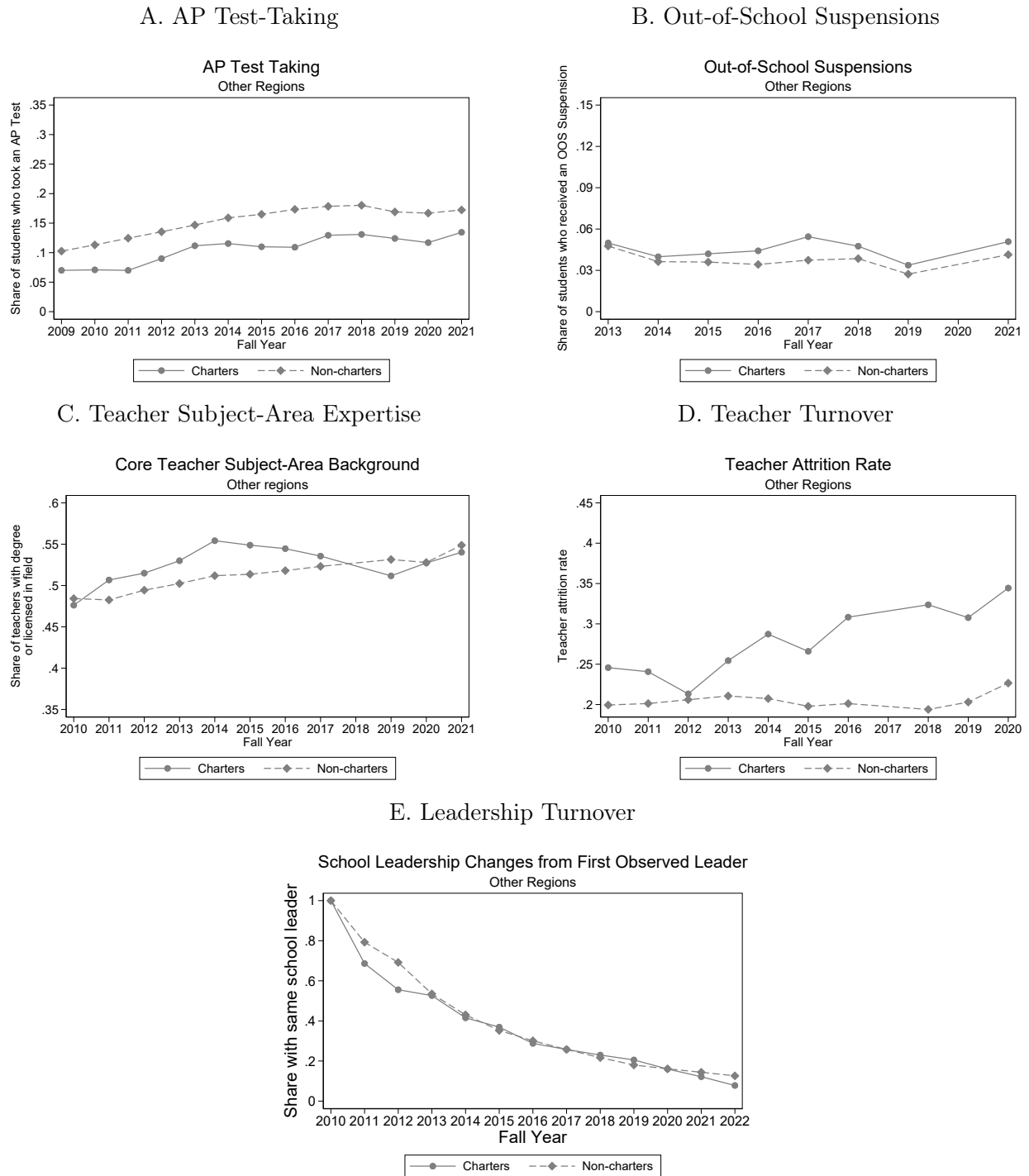
Notes: These graphs show the time series of the indicated school characteristics, among all charter schools in the state and among all non-charter schools. The series for AP test-taking is measured only among high school students. The series for out-of-school suspensions in Panel B only begins in 2013 due to changes in reporting standards in that year. Missing years of teacher turnover and qualifications are due to incomplete data. The leadership turnover graph in Panel E corresponds to the share of schools that have the same leader (principal/headmaster/headmistress/head of school) as when first observed.

Figure 4. Boston-Area Charter and Non-Charter Characteristics Over Time



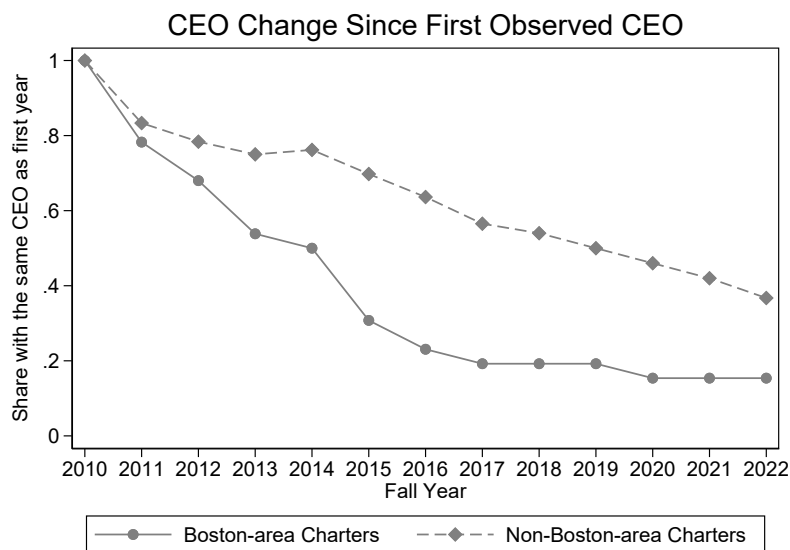
Notes: These graphs show the time series of the indicated school characteristics, among Boston-area charter schools in the state and among Boston-area non-charter schools. The series for AP test-taking is measured only among high school students. The series for out-of-school suspensions in Panel B only begins in 2013 due to changes in reporting standards in that year. Missing years of teacher turnover and qualifications are due to incomplete data. The leadership turnover graph in Panel E corresponds to the share of schools that have the same leader (principal/headmaster/headmistress/head of school) as when first observed.

Figure 5. Non-Boston Charter and Non-Charter Characteristics Over Time



Notes: These graphs show the time series of the indicated school characteristics, among charter schools and non-charter schools outside of the Boston area. The series for AP test-taking is measured only among high school students. The series for out-of-school suspensions in Panel B only begins in 2013 due to changes in reporting standards in that year. Missing years of teacher turnover and qualifications are due to incomplete data. The leadership turnover graph in Panel E corresponds to the share of schools that have the same leader (principal/headmaster/headmistress/head of school) as when first observed.

Figure 6. Charter CEO Attrition Over Time



Notes: This figure depicts the share of charter schools that have the same CEO as they did the first time that they are observed in the data. Series are shown separately for Boston-area charters and charters in other regions.

A Data Appendix

The datasets used in this paper are constructed using administrative data provided by DESE, linked to charter school lottery files. The administrative files contain data on student enrollment, demographics, achievement, and attendance. In addition, some administrative files are used to construct time series of school characteristics. Most of the data details are described in the text, with additional details below.

A.1 Student Enrollment and Demographics (SIMS)

The Student Information Management System (SIMS) data set contains student-level enrollment and demographic information for all Massachusetts public school students. This includes the school attended, grade level, demographics, and program participation, such as special education, English-language learner, and free or reduced-price lunch (FRPL) eligibility. Each student is assigned a unique identifier (SASID), which is used to merge across administrative datasets.

For enrollment, I assign students to the school where they attended for the majority of an academic year. Students are coded as attending a charter school if they attended any charter school for the majority of the given academic year.

A.2 State Standardized Test Scores

Data on standardized test scores come from the MCAS. The MCAS is given in math and ELA in grades 3–8 and grade 10, and in science in grades 5, 8, and 9. The state did not administer the MCAS exam in spring 2020 due to the COVID pandemic. In addition, different exams were given during different periods. In spring 2015 and 2016, districts had the option to use the Partnership for Assessment of Readiness for College and Careers (PARCC) exam. Starting in spring 2017, Massachusetts adopted a “next-generation MCAS” exam that incorporated some elements from the PARCC exam.

To harmonize test scores and ensure comparability over time across different assessments, I follow the approach from Bruhn et al. (2022). Specifically, each test score is standardized across the state within grade-year-subject groups to have mean zero and standard deviation one. Ideally, this would use raw scores across all exams, but these are not available for the PARCC exam in 2015 or 2016. Therefore, for the MCAS, raw scores are standardized in each year. For the PARCC in 2015, scaled scores to align with MCAS are provided, so these MCAS concordance scores are used. For the PARCC in 2016, “theta” scores are provided, which are based on item-response theory and adjust the raw scores based on item difficulty.

In robustness analyses, I examine sensitivity to other methods of harmonizing scores across assessments (Appendix Table C9). The first alternative method (Theta PARCC Scores) continues to use the raw scores for all MCAS years but uses the “theta” scores for both PARCC years. The main disadvantage of this approach is that most of the “theta” scores adjust for test mode (online vs. in-person), but these mode-adjusted scores are not always available in 2015. The second alternative method (Scaled Scores) uses scaled scores for both the MCAS and PARCC exams. While this method uses a single score metric

across assessments, DESE advises against using scaled scores for analysis, since the score transformations are nonlinear, piecewise, and vary across the score distribution, resulting in distortions to inference. Regardless of the alternative method used, the same estimated trends in charter effectiveness are observed.

A.3 Post-secondary Outcomes

Data on student post-secondary outcomes come from the National Student Clearinghouse (NSC) records provided by DESE. This information includes any college attendance and completion for Massachusetts public school students, at any point in time.

A.4 Educator and School Personnel Data

Data on school personnel are used to construct school-level measures of characteristics, including school leader turnover, teacher turnover, and teacher subject-area expertise. The primary dataset used in constructing these variables is the Educator Personnel Information Management System (EPIMS), which provides annual data on all public school employees. Additional information on teachers is available in the Educator Licensing and Renewal (ELAR) data.

To determine whether teachers have subject-area expertise in their teaching assignments, the following degree fields are used, from both undergraduate and graduate degrees:

ELA

- ELAR degree fields: English
- EPIMS degree fields: English/Literature/Composition

Math

- ELAR degree fields: Mathematics
- EPIMS degree fields: Mathematics

Science

- ELAR degree fields: Astronomy, Biochemistry, Biology, Chemistry, Earth Science, Physics
- EPIMS degree fields: Astronomy, Biochemistry, Biology, Chemistry, Earth Science/Geology, Physics, Aeronautical/Aerospace Science and Engineering, Agricultural/Forestry/Horticultural Studies/Wildlife Studies, Animal/Veterinary Science, Natural Sciences, Ecology, Marine/Environmental/Pharmaceutical Sciences, Physical Sciences

B Survey Appendix

This Appendix describes the questions asked in the survey of school administrators, conducted using Qualtrics. In a small number of cases, schools asked to complete the survey over the phone rather than on Qualtrics. The phone survey was shorter, and Table 8 indicates which questions were in the phone survey. The survey was based on the previous survey of Massachusetts charter schools conducted by Angrist et al. (2013), modified to include more recent practices, particularly those emerging since the start of the COVID-19 pandemic. Respondents received a small incentive for participation, and the recruitment procedures were approved by the MIT Institutional Review Board.

The survey consisted of seven sections: learning loss recovery, school day policies, classroom setting and practices, areas of emphasis, school structure, teacher profile, and respondent profile. Each of these sections is described below.

Learning Loss Recovery

Survey respondents were asked to rate the extent to which they used a variety of practices, asked separately for the period *before March 2020* and for the period *between March 2020 and June 2024*. For each practice, respondents selected “Never,” “Sometimes,” “Often or always,” or “I don’t know.” The practices were as follows:

- Tailored accelerated instruction (i.e., teacher-led individualized learning, using new, grade-level content to teach prior-grade concepts or skills)
- Remedial instruction (i.e., using content from prior years to teach concepts or skills)
- Identifying individual student academic needs with diagnostic assessment data
- Identifying individual student academic needs with formative assessment data
- Hiring additional educators to provide small-group and individual instruction
- Tutoring during the school day
- Tutoring after school
- Identifying students at risk of becoming chronically absent using attendance data
- Attendance coaches/officers
- Summer academic programs
- Family engagement/outreach activities (e.g., home visits, communicating via text apps, video conference meetings, etc.)
- Classroom use of virtual activities (Desmos, Quizizz, Kahoot, Nearpod, Prodigy, etc.)
- Classroom use of virtual curriculum (ABCya!, Khan Academy, etc.)

- Classroom use of virtual tools (Edpuzzle, Flipgrid, Google Classroom, etc.)

For several of the practices (tailored accelerated instruction, remedial instruction, tutoring during the school day, tutoring after school, and summer academic programs), if respondents indicated that they either “Sometimes” or “Often or always” used the practice between March 2020 and June 2024, they were asked to indicate which groups of students received the practice, selecting all that apply among the following options: all students, students who struggle with class work, students who struggle with MCAS, none, or other (and to specify, if other).

Finally, if schools indicated that they ever used tutoring, they were asked the following additional questions about their tutoring programs (separately for tutoring during the school day, tutoring after school, and summer programs):

- Source of tutors (selecting all that apply, among: Teach for America or AmeriCorps, community members, parents, teachers/staff, local college students, or “other”)
- Whether high-dosage tutoring was used (defined as “tutoring that takes place for at least 30 minutes per session, one-on-one or in small group instruction, offered three or more times per week, is provided by educators or well-trained tutors, aligns with an evidence-based core curriculum or program, and is also known as Evidence-based or High-quality tutoring”)
- Whether standard tutoring was used (defined as “a less intensive method of tutoring that may take place in one-on-one, small group, or large group settings, is offered less than three times per week, and is provided by educators who may or may not have received specific training in tutoring practices”)
- Whether self-paced tutoring was used (defined as “a method of tutoring in which students work on their own, typically online, where they are provided guided instruction that allows them to move onto new material after displaying mastery of content”)
- Subject areas for which students receive tutoring (selecting all that apply, among: Mathematics, English/Language Arts including Reading, Sciences, Computer Science, Social Studies/History, and Foreign Language)

School Day Policies

Survey respondents were asked the following questions about school day policies:

- Whether instructional activities begin and end at the same time each day of the school week for the typical student
- The typical start and end time of instructional activities for the typical student
- The start and end time of instructional activities for an alternate schedule (if applicable), and how often school days take on an alternate schedule (once per week, once per month, or “other,” with an option to specify)

- Whether certain students have longer or shorter school days (i.e. extended days for struggling students), with a prompt to explain, if “yes”
- The number of days in the school year for a typical student (excluding optional Saturdays)
- Whether the lengths of the school day or school year were shortened during each of the following school years: 2020-21, 2021-22, 2022-23, 2023-24, or 2024-25
- Whether students who needed them were provided with digital devices (e.g., laptops, tablets, Chromebooks, etc.) during each of the following school years: 2020-21, 2021-22, 2022-23, 2023-24, or 2024-25
- Whether certain groups of students (e.g., special education students, students with approved medical concerns, particular grade levels) were offered different learning modes (e.g., in-person, remote, or hybrid) during the 2020-2021 school year
- (if applicable) Which students were offered different learning modes during the 2020-2021 school year?
- (if applicable) Months in which students were offered different learning modes (separately for August 2020 – June 2021)

Survey respondents were also asked (yes or no) whether the school day had been modified in the following ways to support learning recovery for students:

- Extending class time spent on targeted subject areas during the school day
- Extending the school day to accommodate learning recovery activities
- Extending the school week to accommodate learning recovery activities
- Extending the school year to accommodate learning recovery activities

Next, survey respondents were asked (yes or no) whether the following behavioral expectations and disciplinary practices are used at the school:

- Students required to wear uniforms or follow a dress code
- Parents sign a contract explaining the school’s expectations for student conduct, discipline, student and parent responsibilities, and/or academic standards
- Students sign a contract explaining the school’s expectations for student conduct, discipline, student and parent responsibilities, and/or academic standards
- Detentions
- Positive behavior supports
- In-school suspensions

- Counseling sessions
- Behavior improvement plans
- Saturday schools
- Merit/demerit systems
- Timeout/quiet rooms
- Restorative justice student peer councils
- Student rewards for achievement or good behavior (e.g., small payments or redeemable points)

Finally, respondents were asked the following details about Saturday school, if applicable:

- Who attends Saturday school, selecting all that apply among: all students, students in certain grades, students who need academic help, or students being disciplined
- How often the typical Saturday school student attends Saturday school: monthly or less, bi-weekly, or weekly
- Average length of Saturday school sessions (in hours)
- Format of Saturday school instruction, selecting all that apply among: classroom instruction, small group tutoring, individualized tutoring, or other (and asking respondents to specify)

Classroom Setting and Practices

Survey respondents were asked to rate the extent to which a variety of settings and practices are present in classrooms in their schools. For each practice, respondents selected “Not at all,” “A little,” “Somewhat,” “To a large extent,” or “To a great extent.” The practices were as follows:

- Group projects
- Cold calling
- Checks for understanding (informal tests to gauge understanding during the lesson)
- DEAR or SSR (Drop Everything and Read/Sustained Silent Reading)
- Reading aloud
- Timed, repetitive practice of math skills
- College icons in the classroom (e.g. banner with name of teacher’s college, past students’ graduation years and college outcomes)

- Teacher autonomy

Next, survey respondents were asked to select among the ELA curriculum products that their school used between August 2020 and June 2024, selecting all that apply, with a free-response option for “other” and an option for “Don’t Know.” These ELA curriculum products were as follows:²² Amplify ELA, Appleseeds Foundational Skills, ARC Core, Benchmark Advance, Collaborative Literacy, Core Knowledge Language Arts, Developing Core Literary Proficiencies, EL Education, Fishtank, Foundations A-Z, From Phonics to Reading, Guidebooks, Imagine Learning, Into Reading, Into Literature, Magnetic Reading Foundations, MyPerspectives, myView Literacy, Odell Education, Paths to College and Career, Ready-Gen, Savvas Essentials: Foundational Reading, Springboard, StudySync, Wit and Wisdom, and Wonders.

Similarly, survey respondents were asked to select among the math curriculum products that their school used between August 2020 and June 2024, selecting all that apply, with a free-response option for “other” and an option for “Don’t Know.” These math curriculum products were as follows:²³ Agile Mind, Bridges in Mathematics, Carnegie Learning, CK-12, Core Connections, Core Curriculum, Core-Plus, CPM, Desmos, Discovering Mathematics, EdGems, enVision, Eureka, Everyday Math, Fishtank, Imagine Learning, Into Math, Investigations, iReady Classroom Math, Kendall Hunt’s Illustrative Math, Leap, LearnZillion’s Illustrative Math, Math Expressions, Mathspace, Math Techbook, Math Vision Project, McGraw-Hill Illustrative Math, My Math, OpenUp, Origo Stepping Stones, Reveal, Ready, Snippet Math, Walch CCSS, and Zearn.

Survey respondents were also asked to select among the science curriculum products that their school used between August 2020 and June 2024, selecting all that apply, with a free-response option for “other” and an option for “Don’t Know.” These science curriculum products were those designated as HQIM by MA DESE at the time of survey creation and were as follows: Amplify Science, BSCS, CREATE for STEM, mySci, OpenSciEd, and Twig Science.

Finally, survey respondents were asked the following questions about their curricula:

- Average length of a period of math instruction and number of these periods per week
- Average length of a period of reading instruction and number of these periods per week
- The extent to which MCAS preparation is a part of the curriculum, selecting all that apply among the following options: special classes before exams, regular weekly classes/study sessions, including MCAS questions in regular quizzes, after-school instruction for all students, after-school instruction for struggling students, and classes or meetings for parents on nights/weekends

²²The ELA products were those designated as High Quality Instructional Materials (HQIM) by MA DESE at the time of survey creation. These materials include those rated “Partially Meets Expectations” or “Meets Expectations” by CURriculum RATings by TEachers (CURATE), those rated “Green” on EdReports’ Gateways 1 and 2, and Appleseeds Foundational Skills.

²³The math products were those designated as HQIM by MA DESE at the time of survey creation. These materials include those rated “Partially Meets Expectations” or “Meets Expectations” by CURATE, those rated “Green” on EdReports’ Gateway 1, and those rated “Green” or “Yellow” on EdReports’ Gateway 2.

- (if the school serves students in grades 9-12) Whether the school offers extra preparation for the SAT and AP exams (Yes, No, or Not Applicable)
- Hours per week teachers typically spend on instructional activities (in the classroom)
- Hours per week teachers typically spend on instructional activities outside of the classroom (ex: preparing lesson plans, tracking student performance, etc.)

Areas of Emphasis

Survey respondents were asked to rate the degree to which their school's curriculum focuses on various areas of emphasis. For each area, respondents selected "Not at all," "Little," "Somewhat," "To a large extent," or "To a great extent." The areas of emphasis were as follows:

- Traditional reading and math skills
- College preparation
- Social justice and anti-racism
- Preparation for specific careers (for this option, respondents were also asked to list specific careers, if applicable)
- STEM (science, technology, engineering, mathematics)
- Fine arts
- Immersion/dual language
- Socio-emotional learning

Additionally, respondents were asked to rate the degree to which their school's educational program emphasizes various principles. For each area, respondents selected "Not at all," "Little," "Somewhat," "To a large extent," or "To a great extent." The areas of emphasis were as follows:

- Cultural awareness
- Strict adherence to a set of school-wide standards and practices
- Social and physical well-being
- Individually tailored instruction
- Project-based learning
- Discipline and comportment
- Restorative justice approach to student discipline

- Speech and writing development
- Measurable results (for example, gains on state achievement tests)
- Qualitative achievement (for example, leadership, creativity, and community involvement)

School Structure

Survey respondents were asked the following questions about their school's founding and funding structure:

- How did the charter school originate? Check all that apply, among: founded as a charter; charter restart of a traditional public school; another conversion model of an existing public school or a previously operating charter; or other (with a free response to specify)
- Who founded the school? Check all that apply, among: parents, teachers, business leaders, philanthropist, management company, nonprofit organization, community members, or other (with a free response to specify)
- Since the initial approval of the charter, has this leadership group changed? (No or Yes, with a free response to explain)
- In addition to state and local funding, has the school ever received funding from the following sources? Check all that apply, among: federal, foundations, individuals, corporations, none of these, or other (with a free response to specify)
- In addition to state and local funding, does the school regularly receive funding from the following sources? Check all that apply, among: federal, foundations, individuals, corporations, none of these, or other (with a free response to specify)

Teacher Profile

Survey respondents were asked to indicate the frequency with which their school hires various types of teachers. For each type of teacher, respondents selected "Frequently," "Occasionally," or "Rarely or Never." The types of teachers were the following:

- Teach for America novices
- Teach for America alumni
- MATCH Teacher Residency
- Recent college graduates
- Certified teachers
- Experienced teachers (more than 4 years of teaching)

- Graduates of educator preparation programs

Respondents were also asked the following questions about their teachers:

- How are full-time, year-round teachers hired? Check all that apply. [On a contract of specific length, At-will]
- Please estimate the hiring acceptance rate (i.e., 0.25 if 50 applicants are accepted of 200).
- Is there currently a teacher's union active at the school? [Yes, No]
- Has there ever been a teacher's union active at the school? [Yes, No]
- Please indicate the performance incentives available at the school. Check all that apply. [Merit pay, Higher salaries for hard to fill subjects, Yearly bonus, Within-school promotion, Recognition/non-monetary awards, Other (please specify)]
- How often do administrators and supervisors observe veteran teachers in the classroom to review their performance (periods/semester)?
- Are lessons ever videotaped and filmed as part of the teacher feedback process? [Yes, No]

Respondent Profile

Finally, survey respondents were asked basic information about their position at the school. First they were asked their role at the school [Principal, head of school, or executive director; Vice principal; Director of curriculum or instruction; or Other (please specify)]. Second, they were asked how long they have worked at the school (in academic years).

C Appendix Exhibits

Appendix Table C1. Charter School Sample

	Lottery Years	Survey	School Level	Boston Area
Abby Kelley Foster		X		No
Academy of the Pacific Rim	2005–2021		MS + HS	Yes
Atlantis		X		No
Benjamin Banneker		X		Yes
Boston Collegiate	2002–2014, 2016–2017		MS	Yes
Boston Green Academy	2011–2014		HS	Yes
Boston Preparatory	2005–2022	X	MS + HS	Yes
Bridge Boston	2020–2022		MS	Yes
CCSC		X		Yes
Cape Cod Lighthouse	2007–2010		MS	No
Christa McAuliffe		X		No
City on a Hill	2002, 2004–2017		HS	Yes
City on a Hill II	2013–2017		HS	Yes
Codman Academy	2004, 2008–2017		MS + HS	Yes
Dorchester Collegiate Academy	2012		MS	Yes
Edward Brooke	2006–2009, 2011–2022	X	MS	Yes
Excel Academy	2008–2013, 2016–2022	X	MS + HS	Yes
Four Rivers	2003–2010		HS	No
Foxborough Regional		X		No
Francis W. Parker	2006–2010	X	HS	No
Global Learning	2006–2007, 2009		MS	No
Grove Hall Prep	2011		MS	Yes
Health Careers Academy	2003–2006		HS	Yes
Hill View Montessori	2019–2022	X	MS	No
Innovation Academy	2007–2010		MS	No
KIPP Boston	2012–2014, 2018–2022		MS	Yes
KIPP Lynn	2005–2009, 2018–2022		MS + HS	No
Map Academy		X		No
Marblehead Community	2005–2007, 2009–2010		MS	No
Match	2002–2022		MS + HS	Yes
Neighborhood House	2016–2021	X	MS + HS	Yes
Phoenix Academy Chelsea		X		Yes
Pioneer Charter School of Science	2019–2022	X	MS + HS	Yes
Pioneer Charter School of Science II	2019–2022	X	HS	No
Pioneer Valley Performing Arts	2006–2010		HS	No
Rising Tide	2009, 2016–2022	X	MS + HS	No
River Valley		X		No
Roxbury Preparatory	2002–2022		MS + HS	Yes
Salem Academy	2010		MS	No
Springfield Preparatory		X		No
Sturgis	2004, 2006, 2008–2009		HS	No
Up Academy	2011–2017		MS	Yes

Notes: This table shows the charter schools included in either the survey or lottery sample, as well as grade levels served. MS indicates that the school served any grades within 5-8 during the years of the data and HS indicates that the school served any grades within 9-12 during the years of the data. Boston-area charter schools are those located in Boston, Cambridge, Somerville, Watertown, Newton, Brookline, Milton, Winthrop, Chelsea, Revere, or Everett.

Appendix Table C2. First Stage Estimates

	(1)	(2)	(3)	(4)	(5)
	All Lottery Years	Lotteries 2002-2009	Lotteries 2010-2014	Lotteries 2015-2019	Lotteries 2020-2022
<i>Panel A: Math</i>					
Initial Offer	1.049*** (0.019)	1.331*** (0.037)	0.924*** (0.033)	0.967*** (0.039)	0.620*** (0.059)
Waitlist Offer	0.854*** (0.018)	1.035*** (0.027)	0.622*** (0.034)	0.863*** (0.039)	0.610*** (0.053)
Obs (Test Scores)	71065	20354	19038	19554	12119
Obs (Students)	32897	9393	9383	9170	4951
<i>Panel B: English</i>					
Initial Offer	1.048*** (0.019)	1.331*** (0.037)	0.926*** (0.033)	0.963*** (0.039)	0.618*** (0.059)
Waitlist Offer	0.853*** (0.018)	1.035*** (0.027)	0.623*** (0.033)	0.864*** (0.039)	0.610*** (0.053)
Obs (Test Scores)	71104	20192	19125	19616	12171
Obs (Students)	33020	9434	9420	9200	4966
<i>Panel C: Science</i>					
Initial Offer	0.863*** (0.022)	1.160*** (0.044)	0.787*** (0.037)	0.657*** (0.044)	0.465*** (0.065)
Waitlist Offer	0.696*** (0.020)	0.903*** (0.033)	0.504*** (0.035)	0.642*** (0.047)	0.526*** (0.061)
Obs (Test Scores)	33105	8417	10425	8834	5429
Obs (Students)	28009	6952	8693	7711	4653

Notes: This table reports first-stage estimates of charter lottery offers on charter enrollment, within the sample corresponding to each regression of charter effects on MCAS scores. The outcome is number of years of charter enrollment between the admissions lottery and the exam. Each regression controls for lottery risk sets, gender, race, ethnicity, female-minority interactions, special education status, English language learner status, FRPL status, and grade and year indicators. Heteroskedasticity-robust standard errors are shown in parentheses, clustered by student. *: p-value < 0.1; **: p-value < 0.05; ***: p-value < 0.01.

Appendix Table C3. Balance Tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Asian	Black	Hispanic	White	Other Race	FRPL	LEP	SPED	Base ELA	Base Math
Initial Offer	0.002 (0.003)	-0.007 (0.008)	0.005 (0.008)	-0.001 (0.006)	0.002 (0.003)	0.008 (0.009)	-0.002 (0.007)	0.003 (0.008)	-0.013 (0.020)	0.010 (0.019)
Waitlist Offer	0.002 (0.003)	-0.001 (0.007)	0.003 (0.007)	-0.004 (0.005)	0.000 (0.002)	0.014* (0.007)	0.013** (0.005)	-0.001 (0.006)	-0.013 (0.018)	-0.002 (0.016)
Students	34569	34569	34569	34569	34569	34569	34569	34569	26759	28709

Notes: This table shows balance tests resulting from regressing the indicated student characteristics on charter initial offers and waitlist offers, controlling for lottery risk set indicators. Base ELA and Base Math refer to the MCAS scores during the year prior to application. *: p-value < 0.1; **: p-value < 0.05; ***: p-value < 0.01.

Appendix Table C4. Charter Effects on Test Scores for 6th-Grade Applicants

	(1)	(2)	(3)	(4)	(5)
	All Lottery Years	Lotteries 2002-2009	Lotteries 2010-2014	Lotteries 2015-2019	Lotteries 2020-2022
<i>Panel A: Math</i>					
Charter Years	0.191*** (0.015)	0.245*** (0.022)	0.277*** (0.030)	-0.007 (0.030)	0.126 (0.081)
Control Mean	-0.296	-0.212	-0.384	-0.270	-0.283
Test Scores	58596	14142	16089	17559	10806
Students	22225	4667	6745	7175	3638
<i>Panel B: English</i>					
Charter Years	0.095*** (0.015)	0.103*** (0.020)	0.186*** (0.029)	-0.046 (0.029)	0.106 (0.080)
Control Mean	-0.264	-0.189	-0.448	-0.181	-0.180
Test Scores	58475	13889	16146	17598	10842
Students	22220	4649	6752	7182	3637
<i>Panel C: Science</i>					
Charter Years	0.254*** (0.019)	0.247*** (0.025)	0.336*** (0.034)	0.081* (0.045)	0.216** (0.100)
Control Mean	-0.478	-0.390	-0.705	-0.383	-0.267
Test Scores	25080	5577	8216	7049	4238
Students	20385	4475	6522	5926	3462

Notes: This table shows 2SLS estimates of the effect of years of charter school attendance on MCAS exam scores, only for 6th grade applicants. Each column shows effects corresponding to admissions lottery cohorts from the indicated years, with “All Years” including cohorts from 2002-2022. The endogenous variable is years in charter schools between the admissions lottery and the exam, and the instruments are immediate offers and waitlist offers for any charter school in the lottery data. Test scores are measured in grades 6-8 and grade 10, normalized to have mean 0 and standard deviation of 1 within each grade-subject-year. Each regression controls for lottery risk sets, gender, race, ethnicity, female-minority interactions, special education status, English language learner status, FRPL status, and grade and year indicators. Heteroskedasticity-robust standard errors are shown in parentheses, clustered by student. *: p-value < 0.1; **: p-value < 0.05; ***: p-value < 0.01.

Appendix Table C5. Charter Effects on Test Scores for 9th-Grade Applicants

	(1)	(2)	(3)	(4)	(5)
	All Lottery Years	Lotteries 2002-2009	Lotteries 2010-2014	Lotteries 2015-2019	Lotteries 2020-2022
<i>Panel A: Math</i>					
Charter Years	0.062** (0.030)	0.060* (0.033)	0.033 (0.080)	-0.156 (0.194)	0.166 (0.128)
Control Mean	-0.190	-0.057	-0.273	-0.355	-0.330
Test Scores	12469	6212	2949	1995	1313
Students	10672	4726	2638	1995	1313
<i>Panel B: English</i>					
Charter Years	0.041 (0.027)	0.043 (0.029)	0.068 (0.075)	-0.202 (0.216)	0.063 (0.133)
Control Mean	-0.202	-0.058	-0.390	-0.336	-0.202
Test Scores	12629	6303	2979	2018	1329
Students	10800	4785	2668	2018	1329
<i>Panel C: Science</i>					
Charter Years	0.097* (0.053)	0.092* (0.050)	-0.326 (0.247)	0.395 (0.305)	0.261 (0.231)
Control Mean	-0.450	-0.263	-0.572	-0.580	-0.431
Test Scores	8025	2840	2209	1785	1191
Students	7624	2477	2171	1785	1191

Notes: This table shows 2SLS estimates of the effect of years of charter school attendance on MCAS exam scores, only for 9th grade charter applicants. Each column shows effects corresponding to admissions lottery cohorts from the indicated years, with “All Years” including cohorts from 2002-2022. The endogenous variable is years in charter schools between the admissions lottery and the exam, and the instruments are immediate offers and waitlist offers for any charter school in the lottery data. Test scores are normalized to have mean 0 and standard deviation of 1 within each grade-subject-year. Each regression controls for lottery risk sets, gender, race, ethnicity, female-minority interactions, special education status, English language learner status, FRPL status, and grade and year indicators. Heteroskedasticity-robust standard errors are shown in parentheses, clustered by student. *: p-value < 0.1; **: p-value < 0.05; ***: p-value < 0.01.

Appendix Table C6. Charter Effects on Test Scores in Urban/Non-Urban Areas

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Urban					Non-Urban				
	All Lottery Years	Lotteries 2002-2009	Lotteries 2010-2014	Lotteries 2015-2019	Lotteries 2020-2022	All Lottery Years	Lotteries 2002-2009	Lotteries 2010-2014	Lotteries 2015-2019	Lotteries 2020-2022
<i>Panel A: Math</i>										
Charter Years	0.229*** (0.016)	0.317*** (0.024)	0.273*** (0.030)	−0.020 (0.033)	0.146 (0.117)	−0.029 (0.025)	−0.061** (0.030)	0.101 (0.080)	−0.045 (0.064)	0.088 (0.092)
Test Scores	63389	19147	18163	18200	7879	63389	19147	18163	18200	7879
Students	30688	8757	8897	8876	4158	30688	8757	8897	8876	4158
<i>Panel B: English</i>										
Charter Years	0.128*** (0.016)	0.158*** (0.022)	0.182*** (0.029)	−0.032 (0.034)	0.137 (0.116)	−0.058*** (0.022)	−0.056** (0.025)	0.063 (0.072)	−0.181*** (0.056)	0.073 (0.088)
Test Scores	63321	18963	18207	18243	7908	63321	18963	18207	18243	7908
Students	30758	8786	8909	8898	4165	30758	8786	8909	8898	4165
<i>Panel C: Science</i>										
Charter Years	0.288*** (0.022)	0.339*** (0.031)	0.319*** (0.037)	0.127** (0.051)	−0.109 (0.164)	0.001 (0.029)	−0.057** (0.025)	0.161** (0.082)	−0.059 (0.086)	0.441*** (0.142)
Test Scores	30160	7846	9882	8561	3871	30160	7846	9882	8561	3871
Students	26059	6472	8239	7477	3871	26059	6472	8239	7477	3871

Notes: This table shows 2SLS estimates of the effect of years of charter school attendance on MCAS exam scores, separately by charters in urban and non-urban areas. The 2SLS procedure is estimated in a single regression and sample sizes indicate the total sample size from the pooled regression. Urban areas are defined following Cohodes and Pineda (2024) as those where the local school district participated in the Massachusetts Urban Superintendents Network. Each column shows effects corresponding to admissions lottery cohorts from the indicated years, with “All Years” including cohorts from 2002-2022. The endogenous variable is years in charter schools between the admissions lottery and the exam, and the instruments are immediate offers and waitlist offers for any charter school in the data. ELA and math test scores are measured in grades 5-8 and 10. Scores are normalized to have mean 0 and standard deviation of 1 within each grade-subject-year. Each regression controls for lottery risk sets, gender, race, ethnicity, female-minority interactions, special education status, English language learner status, FRPL status, and grade and year indicators. Heteroskedasticity-robust standard errors are shown in parentheses, clustered by student. *: p-value < 0.1; **: p-value < 0.05; ***: p-value < 0.01.

Appendix Table C7. Charter Effects on Test Scores for Schools with 2010-14 Lotteries

	(1)	(2)	(3)	(4)	(5)
	All Lottery Years	Lotteries 2002-2009	Lotteries 2010-2014	Lotteries 2015-2019	Lotteries 2020-2022
<i>Panel A: Math</i>					
Charter Years	0.187*** (0.016)	0.210*** (0.021)	0.256*** (0.028)	-0.028 (0.038)	0.182 (0.137)
Test Scores	71065	20354	19038	19554	12119
Students	32897	9393	9383	9170	4951
<i>Panel B: English</i>					
Charter Years	0.100*** (0.015)	0.087*** (0.019)	0.177*** (0.027)	-0.045 (0.038)	0.187 (0.142)
Test Scores	71104	20192	19125	19616	12171
Students	33020	9434	9420	9200	4966
<i>Panel C: Science</i>					
Charter Years	0.230*** (0.019)	0.195*** (0.024)	0.307*** (0.034)	0.130** (0.055)	0.104 (0.161)
Test Scores	33105	8417	10425	8834	5429
Students	28009	6952	8693	7711	4653

Notes: This table shows 2SLS estimates of the effect of years of charter school attendance on MCAS exam scores, only among the set of schools with lottery records in the data for any year between fall 2010 and 2014. Each column shows effects corresponding to admissions lottery cohorts from the indicated years, with “All Years” including cohorts from 2002-2022. The endogenous variable is years in any charter school between the admissions lottery and the exam, and the instruments are immediate offers and waitlist offers for any of the early charter schools. Test scores are measured in grades 5-8 and grade 10, normalized to have mean 0 and standard deviation of 1 within each grade-subject-year. Each regression controls for lottery risk sets, gender, race, ethnicity, female-minority interactions, special education status, English language learner status, FRPL status, and grade and year indicators. Heteroskedasticity-robust standard errors are shown in parentheses, clustered by student. *: p-value < 0.1; **: p-value < 0.05; ***: p-value < 0.01.

Appendix Table C8. Charter Effects on Suspensions

	(1)	(2)
	Lotteries 2015-2019	Lotteries 2020-2021
<i>Panel A: Out-of-school suspension</i>		
Charter Years	0.013*	0.018**
	(0.007)	(0.008)
Students	27869	10691
<i>Panel B: In-school suspension</i>		
Charter Years	0.012***	0.003
	(0.005)	(0.006)
Students	27869	10691

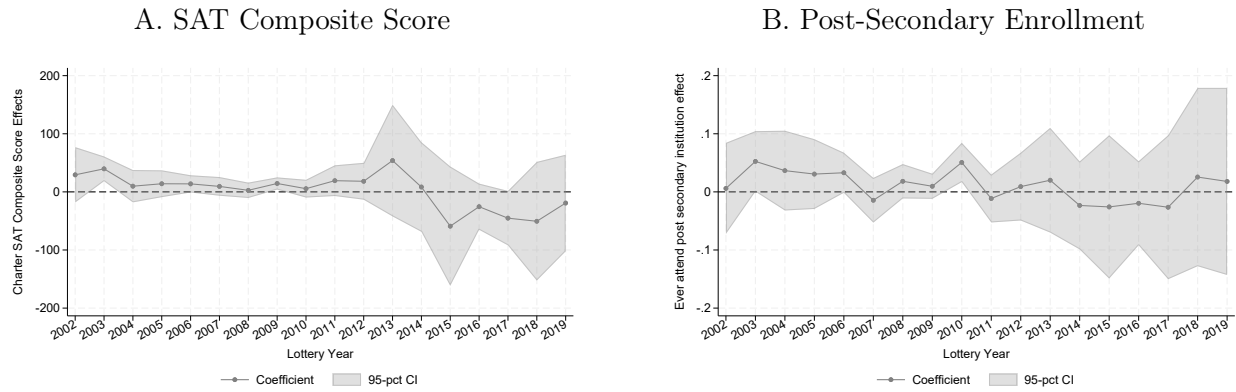
Notes: This table shows 2SLS estimates of the effect of years of charter enrollment on ever receiving the indicated type of suspension. Each column shows effects corresponding to admissions lottery cohorts from the indicated years. The endogenous variable is years in charter schools between the admissions lottery and the exam, and the instruments are immediate offers and waitlist offers for any charter school in the lottery data. Each regression controls for lottery risk sets, gender, race, ethnicity, female-minority interactions, special education status, English language learner status, FRPL status, and grade and year indicators. Heteroskedasticity-robust standard errors are shown in parentheses. *: p-value < 0.1; **: p-value < 0.05; ***: p-value < 0.01.

Appendix Table C9. Achievement Effects (Spring 2015-2016), Alternative Harmonizations

	(1)	(2)	(3)
	Baseline	Theta PARCC Scores	Scaled Scores
<i>Panel A: Math</i>			
Charter Years	0.201*** (0.051)	0.186*** (0.051)	0.219*** (0.050)
Test Scores	4170	4089	4702
Students	4086	4005	4596
<i>Panel B: English</i>			
Charter Years	0.092* (0.050)	0.074 (0.050)	0.116** (0.050)
Test Scores	4198	4126	4730
Students	4115	4043	4628

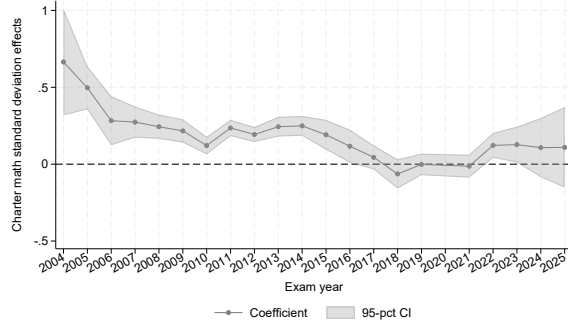
Notes: This table shows 2SLS estimates of the effect of years of charter school attendance on exam scores for exams taken in spring 2015 or 2016, using the alternative harmonization methods between the MCAS and PARCC exam described in Appendix A. The endogenous variable is years in charter schools between the admissions lottery and the exam, and the instruments are immediate offers and waitlist offers for any charter school in the lottery data. Test scores are measured in grades 5-8 and grade 10 normalized to have mean 0 and standard deviation of 1 within each grade-subject-year. Each regression controls for lottery risk sets, gender, race, ethnicity, female-minority interactions, special education status, English language learner status, FRPL status, and grade and year indicators. Heteroskedasticity-robust standard errors are shown in parentheses, clustered by student. *: p-value < 0.1; **: p-value < 0.05; ***: p-value < 0.01.

Appendix Figure C1. Charter Effects on SAT and Post-Secondary Outcomes Over Time



Notes: These figures show the time series of the 2SLS estimates of Massachusetts charter school effects on SAT scores and any post-secondary enrollment, separately by lottery year. Shaded areas correspond to 95% confidence intervals. The endogenous variable is years in charter schools between the admissions lottery and the outcome, and the instruments are immediate offers and waitlist offers for any charter school in the lottery data.

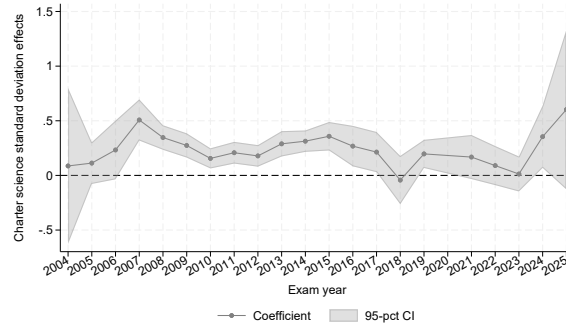
Appendix Figure C2. Charter Effects on MCAS Scores by Exam Year Over Time



A. Math



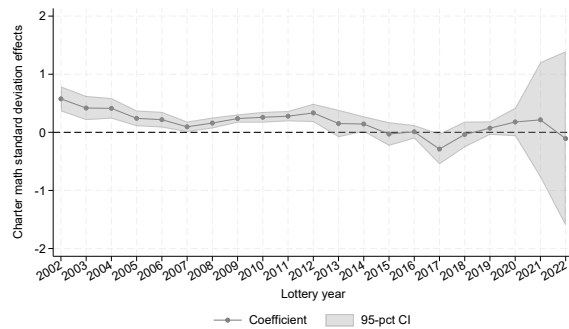
B. ELA



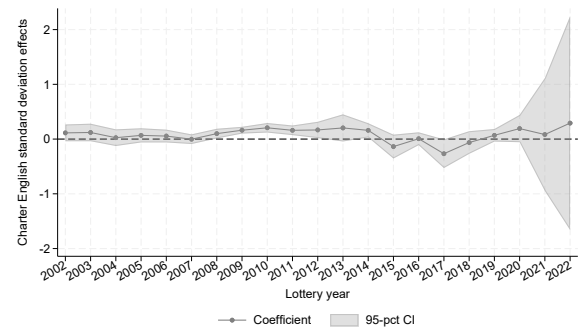
C. Science

Notes: These figures show the time series of the 2SLS estimates of Massachusetts charter school effects on MCAS scores, separately by MCAS exam year and subject area. Shaded areas correspond to 95% confidence intervals. The endogenous variable is years in charter schools between the admissions lottery and the outcome, and the instruments are immediate offers and waitlist offers for any charter school in the lottery data. Standard errors are clustered by student. Point estimates are not shown in 2020 because the state did not administer the MCAS exam in spring 2020 due to the COVID pandemic.

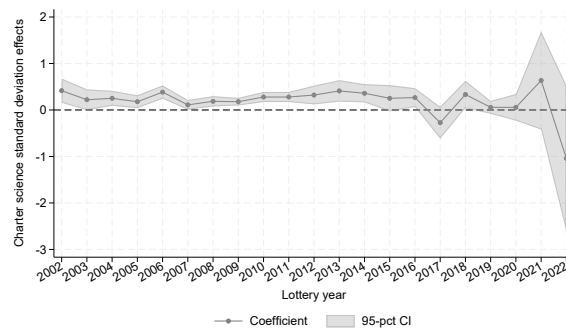
Appendix Figure C3. Charter Effects on MCAS Scores Over Time, for Schools with 2010-14 Lotteries



A. Math



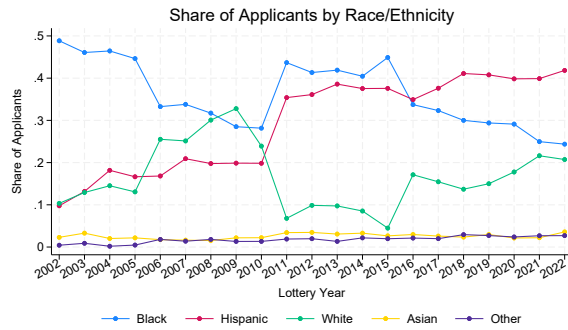
B. ELA



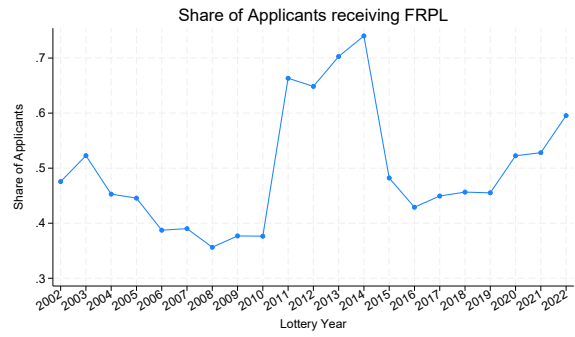
C. Science

Notes: These figures show the time series of the 2SLS estimates of Massachusetts charter school effects on MCAS scores, separately by lottery year and subject area, only among the set of schools with lottery records in the data for any year between fall 2010 and fall 2014. Shaded areas correspond to 95% confidence intervals. The endogenous variable is years in any charter school between the admissions lottery and the exam, and the instruments are immediate offers and waitlist offers for any of the early charter schools. Standard errors are clustered by student.

Appendix Figure C4. Charter Applicant Characteristics Over Time



A. Race/Ethnicity



B. FRPL

Notes: These figures plot the characteristics of applicants in the lottery data based on race/ethnicity (Panel A) and free- or reduced-price lunch status (Panel B).