The Effect of Attending a Charter School in Newark, New Jersey on Student Test Scores

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Abstract

I exploit information about parental preference and a randomized component in the assignment of students to schools within a deferred acceptance (DA) mechanism to estimate the causal effect of enrolling in a charter school in Newark, New Jersey on student test scores. Newark's charter school sector is among the most expansive in the U.S. with charters now enrolling about a third of the city's public school students. The estimates incorporate variation from students attending about 70% of the city's charter schools, accounting for about 85% of charter school enrollment. Enrolling in a Newark charter school that participated in the DA assignment process leads to a large and statistically significant increase in math and English Language Arts (ELA) scores. Students appear to maintain these gains over time. Enrolling in a charter school that is operated by either the KIPP or Uncommon charter school networks has an especially large effect.

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1 Introduction

Charter schools have gained significant market share in several localities including the large urban areas of New Orleans, Washington D.C., Detroit, and Kansas City. At least a third of public school students attend charter schools in 16 districts, and at least a quarter of public school students enroll in charters in another 19 districts (Gerstenfeld et al. 2019). If charter schools are to revitalize public education in the way that some of their advocates envision, then they must maintain their effectiveness as the sector grows within localities. And yet, it is reasonable to suspect that local charter sectors might not scale well. For instance, large charter sectors might dig deeper into the local market for teachers and school leaders, necessitate more bureaucracy, or lead to changes in the characteristics of students who enroll in charter schools. Much of the prior charter school literature presents estimates that are limited to data from a selective subset of charter schools operating within the locality and/or take place in areas where charter schools enroll only a small minority of students (Clark et al. 2015; Furgeson et al. 2012; Dobbie and Fryer Jr. 2011, 2013, 2015; Hoxby et al. 2009). Studies that both take advantage of exogeneous variation in charter school enrollments and incorporate the large majority of charter schools operating within a highly concentrated charter sector are currently limited to Denver (Abdulkadiroglu et al. 2017) and Boston (Abdulkadiroglu et al. 2011; Cohodes et al. 2013; Angrist et al. 2013; Cohodes et al. 2019).

I contribute to the charter school literature by producing causal estimates for the effect of attending a charter school in Newark, New Jersey on student standardized test scores. Newark's charter school sector is among the most expansive in the U.S. with charters now enrolling about a third of the city's public school students. Legislatively-approved growth is projected to increase the proportion of the city's public school students attending charters to 44% by 2022.[1] Newark provides an especially salient policy setting in which to consider charter school impacts. Expanding the city's charter sector was among several reforms driven

[1] https://chalkbeat.org/posts/newark/2018/03/27/over-40-percent-of-newark-students-could-attend-charter-schools-within-five-years-heres-how/

by a $100 million matching gift in 2010 from Facebook CEO Mark Zuckerberg and his wife Priscilla Chan aimed at reforming public education in the city. The couple announced the gift on the Oprah Winfrey show alongside then-governor Chris Christie and then-mayor and current U.S. Senator Cory Booker. These reforms were met with a mixed public reaction.[2]

I apply the approach for producing causal estimates within a deferred acceptance (DA) assignment mechanism recently developed by Abdulkadiroglu et al. (2017), which takes advantage of information about parental schooling preferences and a randomized component in school assignments. This approach allows me to produce causal estimates while employing variation from 70% of the city's charter schools, enrolling 85% of its charter school students.

I find that enrolling in a Newark charter school leads to a large[3] and statistically significant increase in math and English Language Arts (ELA) scores on average. Students appear to maintain these test score improvements over time. I find the potential for differences in the effect of enrolling in a charter school by student subgroup, though these models are estimated too imprecisely to detect such differences as significant.

I find meaningful differences in the impact of attending charter schools based on the school's operator. I find especially large test-score impacts from attending a participating charter school operated by one of two well-known Charter Management Organizations that operate schools in several localities across the nation: Knowledge is Power Program (KIPP) and Uncommon Public Schools. Charter schools operated by these providers are especially interesting because of their national reach, because they account for about half of Newark's charter school students, and because they both have previously been described as applying the "no excuses" approach that prior studies have found to be especially effective at improving student test scores (Dobbie and Fryer Jr. 2013; Abdulkadiroglu et al. 2011; Cohodes et al. 2013; Angrist et al. 2013; Cohodes et al. 2019; Abdulkadiroglu et al. 2017). I find that, taken together, enrolling in a charter school not operated by one of these two networks has on average no significant effect on ELA scores and a positive but more modest effect in

[2]For a detailed narrative account of Newark's school reforms following the Zuckerberg/Chan gift see Russakoff (2015).

[3]The magnitude of the main effect is considered "large" according to the framework suggested by Kraft (Working Paper).

math.

The remainder of this paper proceeds as follows. Section 2 describes the data used for the analysis. Section 3 first describes the DA mechanism used by Newark to assign students to schools and then the method that I use to incorporate information from that process to estimate the causal effect of enrolling in a charter school. Section 4 reports the results from the estimations. Section 5 concludes.

2 Data

I combine data from two sources. First, I acquired from the New Jersey Department of Education longitudinal administrative data for students attending traditional public and charter schools in Newark from 2013-14 through 2017-18. Relevant data elements include student test scores, demographics, and school enrollments.

The administrative data is matched to records from Newark Enrolls, the city's common enrollment assignment mechanism. My analysis relies on the data that the city used to match students to schools for the 2014-15 and 2015-16 school years, which were the first two years of the system. These data include school preference orderings and the school assignments resulting from a deferred acceptance algorithm. Participants in the common enrollment system were matched to the state administrative data by first and last name, date of birth, race/ethnicity, gender, and the grade level to which they were applying for enrollment.

The dependent variable in my analysis is each student's test score on the state's math or ELA exam, standardized by subject, grade, and year. Newark students were typically tested in grades three through nine prior to the 2014-2015 school year; thereafter, testing was expanded to include most students enrolled in grades nine through 11.[4] The estimation sample includes students who participated in the initial assignment round of the Newark

[4] In the 2014-2015 school year, New Jersey transitioned its mathematics and ELA standardized testing from the New Jersey Assessment of Skills and Knowledge (NJASK) to exams provided by the Partnership for Assessment of Readiness for College and Careers (PARCC).

Enrolls process that are successfully matched to records in the NJDOE data with non-missing test scores.[5] All students in the estimation sample also have valid test scores in the year prior to assignment for use as a control, which excludes students seeking seats in grade three.

I report results from the primary analysis that combines students from the first and second years of the DA system into a single regression. The dependent variable is thus the student's standardized score a given number of years following initial assignment. For example, the analysis of test scores one year following assignment uses the spring 2015 score for students who participated in the 2014-15 DA process and the spring 2016 score for students who participate in the 2015-16 DA process. The Appendix reports results for each of the cohorts separately.

3 Empirical Strategy

3.1 Deferred Acceptance Assignment to Schools

My approach takes advantage of information about parental preferences and student assignments under the city's common enrollment system that applies the DA mechanism for assigning students to schools first developed by Abdulkadiroglu and Sonmez (2003). Newark first used this enrollment system, branded Newark Enrolls, to assign students to all traditional public and magnet schools as well as a large subset of charter schools that chose to participate for the 2014-15 school year.[6] Appendix Table 1 lists and classifies the participation status of each charter school by assignment year.

Each spring, parents submit to the centralized school district a rank-ordered list of school preferences for their child's enrollment the following year. Students are guaranteed admission to their current school if it offers the necessary grade level. Schools submit their

[5] Newark Enrolls included a second round for students who had not initially participated, were unmatched in the first round, or were unsatisfied with their initial assignment. As re-entry into the second round is potentially endogenous, I only consider participants in the first round.

[6] Early in its history, Newark Enrolls was branded as One Newark. Newark Enrolls replaced lotteries or other selection mechanisms previously used by participating charter schools.

number of available seats in each grade. Schools also have ranked priorities for students based on a few factors. Siblings of students currently enrolled in a school are given first priority, followed by students who live in the neighborhood surrounding a school. In Newark, schools with below average enrollments of students in special education and students eligible for free or reduced priced lunch give a priority to the number of students with those characteristics necessary to bring their proportion within the school up to the citywide average. Magnet schools additionally provide a rank ordered list of applicants based on interviews and other criteria. Finally, students are provided with a randomly generated lottery number that is used to break ties for students whose characteristics give them equal priority status.

Newark Enrolls then uses the parental preferences and student priority categories to assign students to schools via a DA algorithm. Each student is considered for their first preference school, and students are ranked according to their priority status and assigned random number. If the number of students listing a school is less than or equal to the number of seats available in a given grade, these students are provisionally assigned to that school. If instead the number of applicants exceeds the number of available seats, those students below the allocation cutoff are then considered for their next most preferred school via the same process along with the students provisionally assigned in the first step. Thus, a student may "bump" another student provisionally assigned a seat in the first stage if they have a higher school priority category, or the same priority category combined with a more preferred lottery number. This process is repeated iteratively until all students are assigned to a school or have exhausted their list of schools. If a student fails to obtain a seat at any of their listed schools and their current school offers their grade, they are reseated at their current school or a "guaranteed" school most often based on their residence.

Unfortunately, the district was unable to provide the specific algorithm used to assign students, and thus I was forced to replicate the assignment mechanism. Some data limitations prevent me from fully replicating the process. First, due to not knowing the number of available seats for each school-grade combination, I instead estimate this based on the number of seats assigned less those that appear to be assigned based on re-seating for students who exhausted their preferred school list. Second, the district did not provide the preferences of magnet schools. I instead infer these based on actual student assignments to magnet schools. Third, I did not have access to the exact details of priority assignment for special education or free lunch students; no attempt to replicate it improved assignment accuracy so this priority is omitted. Lastly, for the spring 2015 lottery, I do not have the results of the initial round of the algorithm; I instead use the final results after the second round and any manual adjustments made by Newark Enrolls. Despite these limitations, I am able to replicate the true seating assignments for 85% of participating students.[7]

3.2 Estimating the Effect of Enrolling in a Newark Charter School

I am interested in estimating the effect of enrolling in a charter school on later student test scores. In the absence of endogeneity in the relationship between charter assignment and eventual enrollment, the causal relation of interest could be found via the coefficient β in the equation:

$$y_{it} = \alpha + \beta C_{iT} + \gamma X_{iT} + \epsilon_{it} \tag{1}$$

Where y_{it} is the test score of student i at time t, X_{iT} is a vector of demographic controls and prior test score, C_{iT} is an indicator for student enrollment in a charter school in the year following participation in Newark Enrolls in year T, and ϵ_{it} is an error term. Direct estimation of (1) via OLS, however, may be biased in the scenario that enrollment in a charter school at time T is correlated with unobserved student characteristics that also affect y_{it}.

The first step to account for this concern is to instrument for enrollment using assignment to a charter school under the Newark Enrolls DA algorithm. The second step to control for unobserved student type is to use the propensity score control method developed in Abdulkadiroglu et al. (2017)'s estimation of the effect of attending a charter school in Denver.

[7]The results are not sensitive to changes in how student assignments are modeled. The preferred results reported in the paper use the version of the assignment algorithm for each cohort year that assigned the highest percentage of students to the school to which they were actually assigned when using lottery numbers used by the city for student assignments.

This method allows me to parsimoniously control for student type as indicated by their submitted preferences while still recovering the full range of quasi-experimental variation in the data. To do this, I run 500 simulations in each cohort where I generate new random lottery numbers for each student and estimate the likelihood of a given student being assigned to a charter school with the proportion of simulations resulting in charter assignment. This propensity score is then used as a control variable. Intuitively, this takes advantage of the fact that conditional on a student's priority status and submitted preferences, actual assignment is determined by the randomly generated lottery number. Controlling for the propensity score allows me to exploit this conditionally random variation in assignment; in effect, it compares students who did or did not enroll in a charter school while holding constant any differences in likelihood of enrollment stemming from their preferences and priority status at each charter school.

This process thus modifies (1) to:

$$y_{it} = \alpha + \beta \hat{C}_{iT} + \gamma X_{iT} + \delta p_{iT} + \epsilon_{it} \tag{2}$$

Where $\hat{C}_{iT}$ instruments for charter enrollment C_{iT} with charter assignment and p_{iT} is the student's simulated propensity score for charter assignment. The exclusion restriction assumes that conditional on assignment propensity and the other covariates, assignment to a charter school is associated with charter enrollment but has no other impact on student outcomes. I estimate (2) using 2-stage least squares.

The coefficient β from (2) can be interpreted as the local average treatment effect of attending a Newark charter school for applicants who enroll in a charter school following an offer through Newark Enrolls. This estimate treats as non-compliers students who decline an original charter school assignment or who enroll in a participating charter school due to participating in a subsequent Newark Enrolls round or other avenues. The central assumption for interpreting β as the causal effect of charter school attendance is that the DA mechanism assigns applicants with the same preferences and priorities for assignment to a school with equal probability.

Following Abdulkadiroglu et al. (2017), I also look for heterogeneity in treatment effects across different school types. I estimate models that follow the same procedure as (2) but that instead of generating a single propensity score for attending a charter school, generates multiple propensity scores for attending a charter school run by either KIPP or Uncommon or a charter school run by a different entity.

The use of a centralized enrollment system allows me to use identifying variation from a much broader set of charter schools than is often available when measuring the effect of attending a charter school in other localities. First, the availability of a centralized data set removes the need to acquire historical lottery records from each charter school individually, which often leads to the exclusion of many charter schools in a locality. In addition, the estimated charter school impact is not limited to only students attending charter schools that are oversubscribed. All students with a probability of charter school assignment between zero and one contribute to the identification of β.

3.3 Covariate Balance

Accounting for the propensity score is intended to control for potential bias from unobserved characteristics that are associated with both charter assignment and later student test scores. I test the plausibility of this method by evaluating whether the covariates are balanced between those offered and not offered a charter seat when controlling for the propensity score.

Columns 1 through 4 of Table 1 show that there are large differences in the characteristics of all Newark students, students who participate in Newark Enrolls, and participating students with propensity scores strictly between zero and one. Columns 5 and 7 report the coefficient from a regression of charter assignment and a cohort indicator on each respective characteristic with and without controlling for students' propensity scores, and Columns 6 and 8 report the p-values for inference on those coefficients, respectively.

[Table 1 about here.]

Restricting the sample to students with charter propensity between zero and one and conditioning on charter propensity greatly diminishes many of the baseline differences between those offered or not offered a charter school seat. After conditioning on the propensity score there remain no significant differences at the 5% level, though there are marginally significant differences in the probability that the student is female and the probability that the student attends a charter school in the previous year. The unadjusted pre-assignment differences in other important attributes such as the student's race/ethnicity, eligibility for free lunch or reduced priced lunch, and baseline math and ELA score are statistically insignificant. A joint F-test on all of the covariates listed fails to find an overall significant difference in the adjusted baseline characteristics of those offered or not offered a charter school seat, though it is somewhat disconcerting that the test only slightly misses the threshold for marginal significance at the 10% level.

The existence of some marginally significant differences in the baseline characteristics of those students who are or are not assigned to charter schools even after conditioning on the propensity score is likely due to the incomplete modeling of the assignment process described in Section 3.1. Even these slight differences in covariate balance are cause for some caution when applying a causal interpretation to the estimates. The primary regressions directly account for the differences in the above observed characteristics. The potential concern, however, is that the existence of these observed differences imply that there could also be unobserved differences between the charter and non-charter groups for which the model does not account.

In the results described below, I address the potential that the propensity score does not sufficiently create like comparison groups by showing that the estimated effect of attending a participating charter school is very similar in models that control for the propensity score and other observed covariates listed in Table 1 and in models that control only for the propensity score. This pattern of results implies that the propensity score itself sufficiently controls for the observed characteristics in the comparison for students attending a participating school. It is reasonable, then, to assume that the propensity score also accounts for unobserved differences between charter school and non-charter school students.

4 Results

Tables 2 and 3 report the results for the estimated effect of enrolling in a participating charter school on student math and ELA scores one through three years later. The tables report results from models that evaluate the effect of enrolling in any participating charter school according to (2), and from models that separate the effect of attending a charter school operated by either KIPP or Uncommon or another participating charter school. The latter specification includes separate propensity scores for each charter school subcategory. Tables in the Appendix demonstrate that the results are qualitatively similar when each cohort is analyzed separately.

[Table 2 about here.]

[Table 3 about here.]

Let us focus first on the main set of results in the top panel, which are derived from models that control for the propensity score and baseline observed characteristics. In columns 1, 4, and 7, I first consider the results from models that aggregate all participating charter schools. Enrolling in a charter school that participated in Newark Enrolls rather than a traditional public school leads to an average increase of 0.263 and 0.246 standard deviations in a student's score that spring in math and ELA, respectively. Students appear to maintain these effects into later years.

Columns 2, 5, and 8 separate participating charter schools according to whether or not they are operated by KIPP or Uncommon. Attending a charter school operated by KIPP or Uncommon leads to substantial test score improvements in both subjects. Taken together, enrolling in a participating charter school that is not operated by one of those networks has an initial positive effect on student math performance, though the effect is less than a third of the size of the impact of attending a school operated by KIPP or Uncommon. In aggregate, I find no significant effect from attending a school not operated by KIPP or Uncommon.

Though it cannot be given the same causal interpretation, it is notable that the results suggest a positive relationship between attending a charter that did not participate in the Newark Enrolls process and later student outcomes. This result is useful if only because it suggests that the main results for the impact of attending a participating charter school are not likely to be driven by the most effective charters choosing to participate in the common enrollment system while the least effective schools are removed from the analysis.

The results reported in the bottom of Tables 2 and 3 derive from models that control for charter assignment propensity but do not directly control for other baseline student characteristics. These analyses serve as a robustness test for the causal interpretation of the estimates. As expected, removing the baseline covariates decreases the precision of the estimate relative to the respective estimate reported in the top panel. However, removing the control for baseline characteristics has very little impact on any of the estimates for the effect of attending a charter school that participated in the DA enrollment system. In contrast, removing these control variables leads to a dramatic increase in the estimated effect of attending a non-participating charter school. This pattern of results is consistent with providing a causal interpretation to my main estimates. In particular, the propensity score itself sufficiently accounts for the potentially confounding influence of observed baseline differences between those offered or not offered charter school enrollment (including baseline test score and race/ethnicity). Thus, it is reasonable to suspect that controlling for the propensity score also sufficiently accounts for other baseline differences between the groups that I do not directly observe.

Table 4 reports the results from models that restrict the analysis to include students in particular subgroups of interest. There appear to be some differences in the effect of enrolling in a charter school by student subgroup, though the models are estimated too imprecisely to detect the differences as significant. Notably, the estimates from the one-year effects are uniformly positive and in several cases are statistically significant. Indeed, with the exception of the very imprecisely estimated effect for Hispanic students on the math exam, the 95% confidence intervals suggest that the analysis can credibly rule out that enrolling in a charter school negatively impacted student test scores.

[Table 4 about here.]

5 Conclusion

Newark is one of a growing number of urban areas where the charter school sector is now operating at a large enough scale to have fundamentally altered the local educational landscape. I exploit a random component in the assignment of students to charter and traditional public schools in Newark by a deferred acceptance algorithm to estimate the causal effect of attending a Newark charter school on student test scores.

I find evidence that enrolling in a Newark charter school leads to large and sustained improvements in student math and ELA test scores. Students especially benefit from attending a charter school run by either the KIPP or Uncommon national charter school networks. However, I also find some evidence of positive impacts from attending a participating school that is not run by one of those two networks. Further, when interpreting the effect of attending a participating charter school other than one operated by KIPP or Uncommon it should be kept in mind that this necessary categorization likely mixes together schools that operate differently and thus might have different effects.

My results from Newark are generally similar to recent findings of charter school impacts in Denver and Boston where the researchers were similarly able to incorporate data from nearly all of the city's charter schools. Taken together, these findings strongly suggest that charter school sectors that enroll a substantial share of local students are capable of producing large effects on student outcomes relative to local traditional public schools. Notably, in each of these cities a large portion of students attending charter schools enroll in a charter that employs principles found by prior studies to have significant positive effects on student test score outcomes. Charter school growth in several other cities has not been as targeted to a similar subset of providers. Thus future research that uses causal methods to measure the impact of attending charter sectors with a larger variety of providers once they have reached a meaningful scale is necessary.

Table 1: Test for Covariate Balance

			Propensity score between 0 and 1					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	All Newark	All Matched Applicants	Non-Offered Mean	Offered Mean	w/o Propensity	p-value	w/ Propensity	p-value
Baseline Math	-0.00	-0.08	-0.21	-0.10	0.12	0.03	0.01	0.84
Baseline ELA	-0.00	-0.11	-0.20	-0.10	0.10	0.05	0.00	0.94
Previous Charter Student	0.18	0.06	0.05	0.09	0.04	0.01	0.03	0.07
Female	0.49	0.50	0.53	0.51	-0.03	0.33	-0.06	0.06
African-American	0.56	0.58	0.81	0.81	0.00	1.00	0.02	0.46
Hispanic	0.37	0.36	0.18	0.19	0.01	0.64	-0.01	0.84
Free Lunch	0.63	0.56	0.79	0.80	0.01	0.62	0.03	0.33
Reduced Price Lunch	0.05	0.05	0.07	0.08	0.01	0.52	0.01	0.56
Special Education	0.16	0.31	0.12	0.11	-0.01	0.48	0.03	0.21
Limited English Proficiency	0.07	0.05	0.04	0.03	-0.00	0.63	0.00	0.68
f-stat					1.68	.08	1.58	0.11

Note: Column (2) includes all students in who can be matched to a record in the 2014 or 2015 Newark Enrolls first round lottery. Columns (3) and (4) are restricted to students in the Year 1 Mathematics regression sample with propensity scores strictly between 0 and 1.

Column (5) reports the coefficient of charter attendance in a regression of charter attendance and a cohort indicator on the variable listed at left. Column (7) reports the same coefficient when propensity score is added as an additional control.

Free and Reduced Lunch Status and Special Education Status are measured using indicators from the NJDOE rather than NPS in order to obtain mean values for Column (1).

The F-statistics and p-values at the bottom of the table jointly test balance for all baseline covariates for the unadjuted and adjusted differences, respectively.

Table 2: Regression Results: Mathematics

	(1)	(2)	(3)	(4)	(5)	(6)
	Year 1		Year 2		Year 3	
	Mathematics					
	Controls: Propensity Score & Baseline Characteristics					
Participating Charter	0.263***		0.183***		0.283***	
	(0.050)		(0.059)		(0.058)	
KIPP or Uncommon		0.389***		0.288***		0.459***
		(0.054)		(0.063)		(0.064)
Other Participating Charter		0.108*		0.051		0.066
		(0.064)		(0.077)		(0.075)
Non-Participating Charter	0.230***	0.240***	0.116**	0.116**	-0.001	0.014
	(0.059)	(0.060)	(0.057)	(0.058)	(0.076)	(0.076)
Observations	5,731	5,731	5,742	5,742	4,658	4,658
	Controls: Propensity Score, Exclude Baseline Characteristics					
Participating Charter	0.279***		0.194**		0.296***	
	(0.073)		(0.078)		(0.078)	
KIPP or Uncommon		0.409***		0.274***		0.451***
		(0.083)		(0.086)		(0.088)
Other Participating Charter		0.059		0.028		0.051
		(0.088)		(0.099)		(0.099)
Non-Participating Charter	0.653***	0.606***	0.524***	0.459***	0.473***	0.422***
	(0.088)	(0.089)	(0.091)	(0.093)	(0.100)	(0.101)
Observations	5,731	5,731	5,742	5,742	4,658	4,658

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

In addition to students' propensity score, the top set of tables includes controls for students' baseline test scores, previous school type, race, gender, neighborhood, grade, free lunch status, special education status, LEP status, and cohort. The second set only controls for propensity score and cohort. Robust standard errors are reported in the parentheses.

Table 3: Regression Results: English Language Arts

	(1)	(2)	(3)	(4)	(5)	(6)
	Year 1		Year 2		Year 3	
	English and Language Arts					
	Controls: Propensity Score & Baseline Characteristics					
Participating Charter	0.246***		0.227***		0.260***	
	(0.046)		(0.054)		(0.060)	
KIPP or Uncommon		0.395***		0.391***		0.439***
		(0.053)		(0.059)		(0.067)
Other Participating Charter		0.064		0.012		0.038
		(0.056)		(0.069)		(0.078)
Non-Participating Charter	0.189***	0.204***	0.179***	0.188***	0.233***	0.250***
	(0.062)	(0.061)	(0.068)	(0.068)	(0.077)	(0.076)
Observations	5,748	5,748	5,680	5,680	5,043	5,043
	Controls: Propensity Score, Exclude Baseline Characteristics					
Participating Charter	0.260***		0.234***		0.235***	
	(0.066)		(0.075)		(0.079)	
KIPP or Uncommon		0.386***		0.339***		0.387***
		(0.078)		(0.084)		(0.091)
Other Participating Charter		0.054		0.029		-0.007
		(0.079)		(0.093)		(0.099)
Non-Participating Charter	0.451***	0.407***	0.419***	0.355***	0.433***	0.392***
	(0.084)	(0.085)	(0.088)	(0.089)	(0.090)	(0.090)
Observations	5,748	5,748	5,680	5,680	5,043	5,043

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

In addition to students' propensity score, the top set of tables includes controls for students' baseline test scores, previous school type, race, gender, neighborhood, grade, free lunch status, special education status, LEP status, and cohort. The second set only controls for propensity score and cohort. Robust standard errors are reported in the parentheses.

Table 4: Regression Results by Demographic Subgroups

	(1)	(2)	(3)	(4)	(5)	(6)
	Mathematics			English Language Arts		
Group	1yr	2yr	3yr	1yr	2yr	3yr
African-American	0.269***	0.171***	0.296***	0.227***	0.192***	0.285***
	(0.053)	(0.063)	(0.064)	(0.050)	(0.060)	(0.067)
Hispanic	0.060	0.046	0.009	0.218*	0.140	-0.056
	(0.133)	(0.169)	(0.151)	(0.119)	(0.134)	(0.140)
Female	0.254***	0.214***	0.207***	0.278***	0.210***	0.206**
	(0.066)	(0.079)	(0.078)	(0.062)	(0.072)	(0.086)
Male	0.270***	0.148*	0.367***	0.218***	0.249***	0.315***
	(0.075)	(0.087)	(0.085)	(0.069)	(0.081)	(0.083)
IEP	0.183	-0.076	0.247*	0.169	0.125	0.198
	(0.136)	(0.174)	(0.137)	(0.110)	(0.154)	(0.145)
No IEP	0.287***	0.223***	0.285***	0.272***	0.251***	0.274***
	(0.053)	(0.062)	(0.063)	(0.050)	(0.057)	(0.066)
Free Lunch	0.295***	0.195***	0.295***	0.269***	0.270***	0.324***
	(0.054)	(0.065)	(0.065)	(0.050)	(0.059)	(0.066)
No Free Lunch	0.171	0.199	0.288*	0.178	0.076	0.039
	(0.131)	(0.155)	(0.147)	(0.119)	(0.144)	(0.157)

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

All regressions include controls for students' propensity scores, baseline test scores, previous school type, race, gender, neighborhood, grade, free lunch status, special education status, LEP status, and cohort. Robust standard errors are reported in the parentheses.

References

Atila Abdulkadiroglu and Tayfun Sonmez. School choice: A mechanism design approach. *American Economic Review*, 93(3):729–747, June 2003.

Atila Abdulkadiroglu, Joshua D. Angrist, Susan M. Dynarski, Thomas J. Kane, and Parag A. Pathak. Accountability and flexibility in public schools: Evidence from boston's charters and pilots. *The Quarterly Journal of Economics*, 126(2):699–748, May 2011.

Atila Abdulkadiroglu, Joshua D. Angrist, Yusuke Narita, and Parag A. Pathak. Research design meets market design: Using centralized assignment for impact evaluation. *Econometrica*, 85(5):1373–1432, September 2017.

Joshua D. Angrist, Parag A. Pathak, and Christopher R. Walters. Explaining charter school effectiveness. *American Economic Journal: Applied Economics*, 5(4):1–27, October 2013.

Melissa A. Clark, Philip M. Gleason, Christina Clark Tuttle, and Marsha K. Silverberg. Do charter schools improve student achievement? *Educational Evaluation and Policy Analysis*, 37(4):419–436, December 2015.

Sarah Cohodes, Elizabeth Setren, and Christopher R. Walters. Can successful schools replicate? scaling up boston's charter school sector. Working Paper 25796, National Bureau of Economic Research, May 2019.

Sarah R. Cohodes, Elizabeth M. Setren, Christopher R. Walters, Joshua D. Angrist, and Parag A. Pathak. Charter school demand and effectiveness: A boston update. Research report, The Boston Foundation and NewSchools Venture Fund, October 2013.

Will Dobbie and Roland G. Fryer Jr. Are high-quality schools enough to increase achievement among the poor? evidence from the harlem children's zone. *American Economic Journal: Applied Economics*, 3(3):158–187, July 2011. doi: 10.1257/app.3.3.158.

Will Dobbie and Roland G. Fryer Jr. Getting beneath the veil of effective schools: Evidence from new york city. *American Economic Journal: Applied Economics*, 5(4):28–60, October 2013. doi: 10.1257/app.5.4.28.

Will Dobbie and Roland G. Fryer Jr. The medium-term impacts of high-achieving charter schools. *Journal of Political Economy*, 123(5):985–1037, October 2015. doi: 10.1086/682718.

Joshua Furgeson, Brian Gill, Joshua Haimson, Alexandra Killewald, Moira McCullough, Ira Ira Nichols-Barrer, Bing-ru Teh, Natalya Verbitsky-Savitz, Melissa Bowen, Allison Demeritt, Paul Hill, and Robin Lake. Charter-school management organizations: Diverse strategies and diverse student impacts. Technical report, Mathematica Policy Research and the Center on Reinventing Public Education, January 2012.

Adam Gerstenfeld, Kevin Hesla, and Jamison White. A growing movement: America's largest charter public school communities. Technical report, National Alliance for Public Charter Schools, January 2019.

Caroline M. Hoxby, Jenny Kang, and Sonali Murarka. How new york city's charter schools affect achievement. Technical report, New York City Charter Schools Evaluation Project, Cambridge, MA, September 2009.

Matthew A. Kraft. Interpreting effect sizes of education interventions. Technical report, EdWorkkingPaper, August Working Paper.

Dale Russakoff. *The Prize: Who's in Charge of America's Schools?* Houghton Mifflin Harcourt, New York, 2015.

Appendix to The Effect of Attending a Charter School in Newark, New Jersey on Student Test Scores

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In this appendix, I detail the data and specifications discussed in Sections 2 and 3.

1 NJDOE and NPS Student Information

I acquired administrative data for students attending traditional public and charter schools in Newark from 2013-2014 through 2017-2018. These were used for test scores (see Section 2) and the following information about each student and as of the year following their Newark Enrolls participation:

- School attended.
- Date of birth.
- Gender.
- Race. Students are marked as American Indian, Asian, Black, Hispanic, Pacific Islander, or White. These categories are not strictly mutually exclusive.
- Ethnicity. Students are marked as Hispanic / non-Hispanic.
- Limited English Proficiency status. Students were considered to have LEP status if they have ever been in an LEP program.

- Special education status. Students with a code of "X" were assumed to be non-special education students. All other codes were assumed indicate that a student had special education status.
- Free and reduced lunch status.

These files sometimes contain multiple records per student; this could happen if the student changed schools. I filtered the data to a single record per student per year, under the assumption that the most accurate record for any student was the school with the most recent school entry date.

I supplemented these controls with the following information from the Newark Enrolls data files:

- Grade applied for.
- IEP status at time of Newark Enrolls participation.
- Free lunch status at time of Newark Enrolls participation.
- Geographic neighborhood at time of Newark Enrolls participation.

2 Student Test Scores

I used test scores in mathematics and language arts literacy (LAL) in the year of Newark Enrolls participation as a baseline control. Subsequent years' test scores were used as outcome variables. In 2013-2014, the relevant test scores were students' NJ ASK Mathematics Scaled Scores and NJ ASK LAL Scaled Scores. For later years, New Jersey began using PARCC exams. For these years, I used the NJ PARCC Mathematics, Algebra I, Algebra II, Geometry, and LAL Scaled Scores.

Test scores were standardized to have a mean value of 0 and standard deviation of 1 within each grade, subject and year, with the exception of Algebra I, Algebra II, and Geometry scores. In the case of these scores, they were standardized within subject and year but across all grades.

3 Charter Schools and Magnet High Schools

For each student in each year, I obtained the school most recently entered according to the NJDOE data. This was used to mark charter school attendance status in the year following Newark Enrolls participation. For analyses 2 or 3 years following Newark Enrolls participation, the relevant treatment variable was still assumed to be attendance in the year following participation.

Table 1 includes all Newark charter schools, and their participation status in Newark Enrolls in 2014 and 2015.

Newark Public Schools operates six magnet high schools that all use the Newark Enrolls system. None of the six are charter schools. These schools are permitted to use additional criteria to rank students in the Newark Enrolls process, including standardized test scores, attendance records, course grades, interviews, writing samples, and auditions. They are listed in Table 2.

4 Newark Enrolls School Assignments, Lottery Simulation, and Propensity Scores

The following procedure was applied for 2014 and 2015 Newark Enrolls participants:

Student School Assignments For both cohorts, I only consider students who participated in the initial round of Newark Enrolls for the reasons detailed in Section 3For students in the 2014 cohorts, I directly observe their first round assignment. For students in the 2015 cohort, I only have their final assignment after all rounds. Thus, this variable is noisy, and may not accurately represent the first round assignment in the student chooses to reenter in the second round and receives a different assignment.

Student School Preferences and Guaranteed Schools: Students' choices were rearranged to remove any blank spots in their ordering between their first and last choice. This

Table 1: Newark Charter Schools

School	2014-2015 Newark Enrolls Participant?	2014-2015 Newark Enrolls School Code	NJDOE District & School Code
Great Oaks Charter School[1]	Yes	711	6053-917
Lady Liberty Academy Charter School	Yes	713	7100-936
Marion P. Thomas Charter School	Yes	715	7210-940
Merit Prep Charter School[2]	Yes	716	6091-974
Newark Educators' Community Charter School	Yes	718	6029-911
Newark Legacy Charter School[1]	Yes	719	6037-922
Newark Prep Charter School[2]	Yes	720	6059-941
North Star Academy Charter School (Uncommon)	Yes	721	7320-960
People's Preparatory Charter School	Yes	722	6057-938
Philip's Academy Charter School	Yes	723	6094-968
Roseville Community Charter School	Yes	725	6058-939
TEAM Charter Schools (KIPP)	Yes	726	7325-965
The Paulo Freire Charter School[2]	Yes	728	6090-977
University Heights Charter School	Yes	729	8065-980
Vision Academy Charter School[3]	Yes	730	6038-923
Achieve Community Charter School[4]	No	N/A	6110-902
Discovery Charter School	No	N/A	6320-920
LEAD Charter School [4]	No	N/A	6109-953
Link Community Charter School	No	N/A	6099-986
Maria L. Varisco-Rogers Charter School	No	N/A	7735-975
M.E.T.S. Charter School[5]	No	N/A	6068-951
New Horizons Community Charter School[5]	No	N/A	7290-957
Robert Treat Academy Charter School	No	N/A	7730-970
The Gray Charter School	No	N/A	6665-930

[1] Great Oaks Charter School and Newark Legacy Charter School merged in 2016 and became known as Great Oaks Legacy Charter School, with Newark Enrolls School Code 731.

[2] Merit Prep Charter School, Newark Prep Charter School, and the Paulo Freire Charter School were ordered to close in 2017 by NJDOE due to poor performance, and did not participate in Newark Enrolls from 2017 onward.

[3] Vision Academy Charter was subsumed by Marion P. Thomas Charter School after the 2013-2014 school year and did not appear in later cohorts of Newark Enrolls.

[4] Achieve Community Charter School and LEAD Charter School opened in 2017. Achieve Community Charter School participated in the 2017 cohort of Newark Enrolls with the Newark Enrolls School Code 732; LEAD charter school remains a non-participating charter school.

[5] M.E.T.S. Charter School and New Horizons Community Charter School became participating schools in the 2017 cohort of Newark Enrolls with the Newark Enrolls School Codes of 733 and 717.

Table 2: Newark Magnet High Schools

School	2014-2015 Newark Enrolls School Code	NJDOE District & School Code
American History High School	43	3570-087
Arts High School[1]	26	3570-010
Bard Early College High School	11	3570-304
University High School	24	3570-057
Science Park High School	25	3570-055
Technology High School	38	3570-056

[1] Arts High School includes several different programs. Prior to 2017, the Newark Enrolls data marks each of these separately (i.e., 26TR for students wishing to study in the trumpet program.

could occur if a student's submission included a school for which that student was not eligible. For example, if a first grade applicant submitted a listing of Park Elementary School, Malcolm X. Shabazz High School, and Hawkins Street Elementary School, they would be treated as if Hawkins Street Elementary School was their second choice school. Students could list up to eight schools, but were not required to list multiple schools.

If applicable, students were assigned a guaranteed school. Should a student receive a seat at none of the schools on their list, their current school was assumed to be guaranteed unless they were marked as being in a transition grade for their school (i.e., a sixth grade applicant currently attending a school offering grades K through 5) or their school was closing.

Seat Allocations The number of seats available for each grade-school combination was not available. I estimated this for every grade-school combination for which I observed an assigned student. For a given grade-school combination, the number of seats available was assumed to be the greater of students assigned to that school in the first round or after both rounds, less any seats that appeared to have been allocated as a result of being a student's guaranteed school. Assignments were assumed to be the result of guaranteed school status when students were matched back to their current school. Students from the geographic neighborhood of each school were assumed to have priority for 75% of available seats as described below, with the exception of students applying to high schools, multi-campus charters, or Philip's Academy Charter School.[1]

Propensity Score Calculation Newark Enrolls assigns students to schools based on students' preferred list of schools, the number of seats available, a priority system, and a randomly generated lottery number. To generate the likelihood that a particular student would be assigned to a charter school holding constant all students' preferences, I simulated this process 500 times with new randomly generated lottery numbers.

For each simulated round of this process, the following algorithm was completed after generating new lottery numbers distributed uniformly between 0 and 1, with lower numbers granting higher probability of admission:

1. Assign all students to a school. For the first iteration, use the first choice school for all students. For all later iterations, use the same school as the previous iteration if they were temporarily assigned admission; otherwise use the next school on the student's list.
2. Assign all students two priority numbers.
   (a) Students' non-geographic priority number is their lottery number plus 0 if their current school is closing, 1 if they have a sibling at their applied school, and 2 otherwise.
   (b) Students' geographic priority number is their lottery number plus 0 if their current school is closing, 1 if they have a sibling at their applied school, 2 if they reside in the same neighborhood as their applied school, and 3 otherwise.
3. For magnet schools, assign temporary admission if they were eventually assigned to their applied school and 0 otherwise.
4. For non-magnet schools, rank all students by geographic priority number at each grade-school combination, with the lowest number assigned a rank of 1. Assign temporary

[1] Based on discussions with NPS employees familiar with the process, Philip's Academy Charter School was unable to apply geographic preferences due to rules regarding funding received from the federal government.

admission if their numerical rank is less than 75% of available seats for that grade-school combination.

5. For students applying to non-magnet schools and not assigned admission in the previous step, re-rank them within each grade-school combination by non-geographic priority number, and assign temporary admission if their numerical rank is less than 25% of available seats for that grade-school combination.
6. Repeat this process until all students have been assigned to a school or have exhausted all schools on their list without being assigned a seat.
7. For students still unassigned at the end of this process, assign them to their guaranteed school if applicable. Otherwise, classify them as unassigned.

At the end of this process, there are three possible outcomes for each student: they are assigned to a school on their list, they are assigned to their guaranteed school, or they are unassigned.

For each student, their charter school propensity score was calculated as the proportion of instances where their assigned school was one of the participating charter schools in Table 1. For example, if a student was assigned to a charter school in 200 of the 500 simulations, their charter propensity score would be 0.4. Correspondingly, for the analysis that separates charters by their operators, each student's charter school propensity score was the proportion of instances where their final assigned school was either TEAM Charter Schools (KIPP) or North Star Academy Charter School (Uncommon Schools).

5 Data Merge

All students who participated in the first round of Newark Enrolls received a charter school propensity score and a propensity score for attending a school operated by KIPP or Uncommon. These scores (and control variables found in the Newark Enrolls data) were merged to NJDOE administrative records for the year of and the year following assignment using students' Statewide Student Identifier (SID) numbers. 21.65% and 18.28% of students in the 2014 and 2015 Newark Enrolls data respectively are missing an SID code. 14.3% and 16.9% of students in the 2014 and 2015 Newark Enrolls data have an SID code, but cannot be matched to records in one or both NJDOE files.

6 Regression Samples

To be included in my regression sample for n years after assignment, a student must have participated in that year's Newark Enrolls first round assignments, successful merge to NJDOE records by SID number, possess a valid test score in the year prior to assignment, and possess a valid test score in the same subject (Math, LAL) in the n^{th} year after assignment. I do not require that students in the math regressions have valid current or prior LAL test scores and vice versa. Similarly, for regressions on test scores 2, 3, or 4 years after assignment, I do not require that students have valid test scores for the intervening years.

All regressions, unless noted otherwise, contain the following control variables:

- Charter school propensity score or KIPP/Uncommon charter school propensity score.
- Test score in the year prior to assignment.
- An indicator for whether they were previously attending a charter school.
- An indicator for whether they were previously attending a magnet school.
- A set of indicators for student race.
- Gender.
- Grade applied for.
- Neighborhood at the time of Newark Enrolls assignment.
- IEP status at the time of Newark Enrolls assignment.
- Free lunch status at the time of Newark Enrolls assignment.
- LEP status as of the year following Newark Enrolls assignment.
- Special education status as of the year following Newark Enrolls assignment.
- Free and reduced lunch status as of the year following Newark Enrolls assignment.
- A set of cohort indicators.

7 Individual Year Regressions

Below are the results analogous to Table 2 and 3 for the 2014 and 2015 cohorts separately.

	Year 1		Year 2		Year 3		Year 4	
	Mathematics							
Participating Charter	0.293***		0.210***		0.162**		0.304***	
	(0.064)		(0.076)		(0.077)		(0.096)	
KIPP or Uncommon		0.442***		0.314***		0.408***		0.425***
		(0.075)		(0.082)		(0.085)		(0.102)
Other Participating Charter		0.133		0.122		-0.089		0.069
		(0.081)		(0.100)		(0.101)		(0.142)
Non-Participating Charter	0.258***	0.275***	0.154*	0.166*	0.013	0.040	0.189*	0.194*
	(0.089)	(0.089)	(0.084)	(0.085)	(0.096)	(0.095)	(0.109)	(0.108)
Observations	2,875	2,875	3,111	3,111	2,551	2,551	1,440	1,440
	English and Language Arts							
Participating Charter	0.261***		0.242***		0.252***		0.377***	
	(0.060)		(0.070)		(0.081)		(0.094)	
KIPP or Uncommon		0.449***		0.452***		0.488***		0.524***
		(0.068)		(0.077)		(0.092)		(0.096)
Other Participating Charter		0.050		-0.004		-0.006		0.041
		(0.076)		(0.090)		(0.105)		(0.145)
Non-Participating Charter	0.162*	0.178**	0.212**	0.228***	0.256**	0.279***	0.175	0.174
	(0.086)	(0.085)	(0.089)	(0.087)	(0.105)	(0.103)	(0.128)	(0.128)
Observations	2,919	2,919	3,101	3,101	2,810	2,810	1,454	1,454

Table 3: 2014 Regressions

	Year 1		Year 2		Year 3	
	Mathematics					
Participating Charter	0.254***		0.137		0.443***	
	(0.080)		(0.092)		(0.091)	
KIPP or Uncommon		0.338***		0.246**		0.512***
		(0.083)		(0.098)		(0.105)
Other Participating Charter		0.098		-0.071		0.280**
		(0.099)		(0.110)		(0.114)
Non-Participating Charter	0.219***	0.205**	0.036	0.022	0.012	-0.004
	(0.082)	(0.083)	(0.081)	(0.083)	(0.117)	(0.119)
Observations	2,856	2,856	2,631	2,631	2,107	2,107
	English and Language Arts					
Participating Charter	0.222***		0.210**		0.319***	
	(0.074)		(0.085)		(0.089)	
KIPP or Uncommon		0.334***		0.293***		0.401***
		(0.088)		(0.099)		(0.097)
Other Participating Charter		0.071		0.026		0.149
		(0.083)		(0.106)		(0.117)
Non-Participating Charter	0.220**	0.231**	0.143	0.119	0.234**	0.222**
	(0.090)	(0.092)	(0.102)	(0.104)	(0.113)	(0.113)
Observations	2,829	2,829	2,579	2,579	2,233	2,233

Table 4: 2015 Regressions

8 Observation Counts for Tables 2-4

Combined 2014-2015 Mathematics Regression

School Attended	Year 1	Year 2	Year 3
KIPP	312	380	358
Uncommon Schools	449	486	465
Other Participating Charter	823	813	684
Non-Participating Charter	112	89	71
Non-Charter	4,035	3,974	3,080
Total	5,731	5,742	4,658

Table 5: Observations by Category, Table 2

Combined 2014-2015 English and Language Arts Regression

School Attended	Year 1	Year 2	Year 3
KIPP	328	396	370
Uncommon Schools	453	488	469
Other Participating Charter	856	823	685
Non-Participating Charter	112	89	71
Non-Charter	3,999	3,884	3,448
Total	5,748	5,680	5,043

Table 6: Observations by Category, Table 3

Combined 2014-2015 Regressions

	Mathematics			English and Language Arts		
Demographic Category	Year 1	Year 2	Year 3	Year 1	Year 2	Year 3
African-American	3,530	3,514	2,967	3,649	3,529	3,126
Hispanic	1,951	1,955	1,534	1,878	1,899	1,704
Female	2,885	2,907	2,324	2,918	2,900	2,554
Male	2,846	2,835	2,334	2,830	2,780	2,489
IEP	911	930	804	951	905	816
No IEP	4,820	4,812	3,854	4,797	4,775	4,227
Free Lunch	4,413	4,437	3,689	4,440	4,386	3,958
No Free Lunch	1,318	1,305	969	1,308	1,294	1,085
Total	5,731	5,742	4,658	5,748	5,680	5,043

Table 7: Observations by Category, Table 4