

Inputs and Impacts in Charter Schools: KIPP Lynn

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The charter school landscape includes a variety of organizational models and a few national franchises. The nation's largest network of charter schools is the Knowledge is Power Program (KIPP), with 80 schools operating or slated to open soon. KIPP schools target low income and minority students and subscribe to an approach some have called *No Excuses* (Abigail Thernstrom and Stephen Thernstrom 2003). No Excuses schools feature a long school day and year, selective teacher hiring, strict behavior norms, and encourage a strong student work ethic.

KIPP schools have often been central in the debate over whether schools alone can substantially reduce racial achievement gaps. Descriptive accounts of KIPP suggest positive achievement effects (see, e.g., Jay Mathews 2009), but critics argue that the apparent KIPP advantage reflects differences between students who attend traditional public schools and students that choose to attend KIPP schools (see, e.g., Martin Carnoy, Rebecca Jacobsen, Lawrence Mishel, and Richard Rothstein 2005). There are few well-controlled studies of KIPP schools that might help sort out these competing claims, and none that focus on KIPP.¹

This paper reports on a quasi-experimental evaluation of the only KIPP school in New England, KIPP Academy Lynn. KIPP Lynn opened in the fall of 2004 and is the only charter school in Lynn, Mass., a low income city north of

Boston. KIPP Lynn is a middle school that serves about 300 students in grades 5–8. Like most other Massachusetts charter schools, KIPP Lynn is funded primarily through tuition paid by students' home districts. Tuition is typically set to match sending districts' average per pupil expenditure, though this is offset by state subsidies to the sending district when a student first transfers.

Each KIPP school sets its own curriculum, but KIPP Lynn shares many features with other KIPP schools. KIPP Lynn has a long school year, starting in August and including some Saturdays, and a long school day, running from 7:30 in the morning to 5:00 in the afternoon. Students are expected to conform to a behavioral code and receive "paychecks," points awarded for good work that can be spent on field trips and other perks. Parents or guardians, students, and teachers are asked to sign a "Commitment to Excellence," a promise to come to school on time and work hard, among other things.

As at other KIPP schools, KIPP Lynn's non-union teachers work long hours and are expected to be on call to assist their students in the evening. Many KIPP Lynn teachers are graduates of the national Teach For America (TFA) internship program. KIPP Lynn teachers are much younger than middle school teachers in the Lynn Public Schools (LPS), and more likely to be African American.

Most KIPP Lynn students live in Lynn and would otherwise attend an LPS school. The population of Lynn is more than two-thirds white, but 70 percent of the 13,000 students in LPS are nonwhite. This is documented in Table 1, the first two columns of which show average characteristics of fifth graders, the entry grade for KIPP Lynn. (Some applicants who have already completed fifth grade enter KIPP Lynn by repeating a grade, as do a small number of sixth graders.) LPS fifth graders are 42 percent Hispanic, 17 percent black, and 11 percent Asian. KIPP fifth graders are 57 percent Hispanic and 24 percent black, with few Asians. Roughly 19 percent of students are classified as special education at both LPS and KIPP. LPS has a moderately

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¹ See, for example, the studies linked at <http://www.kipp.org/01/independentreports.cfm>. Caroline M. Hoxby and Sonali Murarka's (2009) quasi-experimental study of New York City charters includes four KIPP schools. Will Dobbie and Roland G. Fryer Jr. (2009) use quasi-experimental methods to study charter schools in Harlem.

TABLE 1—DESCRIPTIVE STATISTICS AND COVARIATE BALANCE

	Means for 2005–2008			Balance regression
	Lynn 5th graders (1)	KIPP Lynn 5th graders (2)	KIPP Lynn applicants (3)	Winners vs. Losers (4)
Hispanic	0.418	0.565	0.538	–0.052 (0.053)
Black	0.173	0.235	0.254	0.027 (0.044)
Asian	0.108	0.021	0.022	0.026* (0.015)
Female	0.480	0.474	0.484	–0.010 (0.054)
Free/reduced price lunch	0.770	0.842	0.825	–0.030 (0.041)
Special education	0.185	0.189	0.197	–0.013 (0.042)
Limited English proficient	0.221	0.172	0.206	–0.075 (0.047)
Baseline (4th grade) math score	–0.307	–0.336	–0.390	0.097 (0.114)
Baseline (4th grade) ELA score	–0.356	–0.399	–0.438	0.054 (0.118)
Fourth grade applicant			0.768	0.056 (0.046)
<i>p</i> -value from joint <i>F</i> -test				0.671

Notes: Column (4) reports coefficients from regressions of the variable indicated in each row on an indicator variable equal to one if the student won an admissions lottery. Covariates include dummies for application year interacted with a contemporaneous sibling applicant dummy as well as application grade. The regression sample is restricted to randomized applicants with baseline demographics.

higher proportion classified as having limited English proficiency (LEP), 22 percent versus 17 percent at KIPP. Many charter schools in the Northeast are disproportionately nonwhite, but KIPP Lynn is unusual in enrolling such a high proportion of Hispanic, LEP, and special education students. This is significant, because critics have charged that charter schools ignore or have been unsuccessful with these populations.²

Statewide regulations require Massachusetts charter schools to use a lottery when oversubscribed. KIPP Lynn was undersubscribed when it opened in the fall of 2004 and only marginally oversubscribed in 2005. More recently, however, more than 200 students have applied for about 90 seats. The 2005–2008 admissions lotteries are used here to develop a quasi-experimental research design. These randomized lotteries allow us to estimate the causal effect of KIPP Lynn on

achievement, solving the problem of selection bias that plagues most studies of school effectiveness.

I. Data and Empirical Framework

A. Data

We started with lists of applicants to KIPP Lynn for 2005 through 2008. These four applicant cohorts were matched to the Massachusetts Student Information Management System (SIMS), a database with demographic and other information for all public school students in the state. We found 91 percent of KIPP applicants in the SIMS database, though winners are somewhat more likely to be matched than losers.³ Applicants' SIMS records were then matched

² For example, this United Federation of Teachers report: http://www.uft.org/news/issues/uft_report-separate_and_unequal.pdf

³ Controlling for year of application and whether the applicant comes from LPS, the match differential is about ten percent. Looking at LPS applicants only, however, the differential falls to 0.029 (SE = 0.027). An analysis using only applicants from LPS generates results almost identical to those reported here.

to fifth–eighth grade scores on Massachusetts Comprehensive Assessment System (MCAS) tests given in the Spring of 2006–2009. We standardized math and English language arts (ELA) scores to a statewide reference population by subject, grade, and year. Excluding applicants with siblings already enrolled in KIPP (who are guaranteed a slot), late applicants (who miss the lotteries), unmatched applicants, and a few others leaves 457 in the lottery analysis sample.⁴ Of these, 69 percent were offered a spot at KIPP Lynn, and 54 percent enrolled.

Older cohorts contribute more follow-up data to our analysis than do more recent cohorts. For example, the 2005 applicant cohort was tested in fifth through eighth grades, while the 2008 cohort was tested in fifth grade only. The 2005 cohort is the only one observed in eighth grade. Lottery winners spent an average of about 1.85 years at KIPP Lynn in our sample period.

Table 1 reports descriptive information for samples of fifth graders attending LPS and KIPP Lynn during our study period, and for our sample of KIPP Lynn lottery applicants. LPS students are poor and mostly nonwhite, but students at KIPP Lynn tend to be poorer and are even more likely to be nonwhite. LPS students had low fourth grade math and ELA scores, about a third of a standard deviation below the state average. KIPP Lynn applicants and enrolled students were even further behind.

Lottery winners and losers are similar, a fact documented in column (4) of Table 1, which reports differences in demographic characteristics and baseline scores between winners and losers.⁵ By virtue of random assignment, we should expect these differences to be small. In practice, however, our reconstruction of the KIPP lotteries is based on spreadsheets with some missing information. We corrected most of the entries by reviewing the lottery records with school staff but may not have fixed the problem entirely. It is therefore especially encouraging that most pre-treatment

characteristics come out balanced. Only one variable (proportion Asian) shows a marginally significant difference between winners and losers. The *F*-statistic for a joint test of balance on all characteristics gives little cause for concern.

Although lottery winners and losers look similar at the time the lotteries were held, subsequent attrition may lead to important differences in the follow-up sample if the attrition process is nonrandom (attrition here means exit to a private school or a move out of state). Of particular concern is whether we are more likely to have test score outcomes for winners than for losers. We observe math and ELA scores for about 85 percent of charter lottery losers. Lottery winners are about five points more likely to have follow-up scores, but these differences shrink and become insignificant with controls. These small follow-up differentials seem unlikely to impart substantial selection bias in our impact analysis.

B. 2SLS Strategy

We're interested in the causal effect of KIPP Lynn on MCAS scores, where this effect is modeled as a function of time spent in KIPP. The equation of interest is

$$(1) \quad y_{igt} = \alpha_t + \beta_g + \sum_j \delta_j d_{ij} + \gamma' X_i + \rho s_{igt} + \epsilon_{igt}$$

where y_{igt} denotes the scores of student i tested in year t in grade g . The variable s_{igt} records years spent at KIPP Lynn as of the test date, counting any repeated grades. The (average) causal effect of interest is ρ . The terms α_t and β_g are year-of-test and grade-of-test effects, while X_i is a vector of demographic controls with coefficient γ , and ϵ_{igt} is an error term that captures random fluctuation in test scores. The dummies d_{ij} indicate three of the four KIPP Lynn application cohorts, indexed by j .

The first stage uses the randomly assigned lottery offers as an instrument for s_{igt} and takes the form:

$$(2) \quad s_{igt} = \lambda_t + \kappa_g + \sum_j \mu_j d_{ij} + \Gamma' X_i + \pi Z_i + \eta_{igt}$$

where λ_t and κ_g are year-of-test and grade effects. The excluded instrument is the lottery offer

⁴ We look at first time applicants only. We also exclude applicants from sixth or seventh grade as few of these end up attending KIPP.

⁵ These are from regressions that control for year and grade of application, applicants' sibling status (siblings who apply together are more likely to get in, since a winning sibling improves the loser's position on the waiting list), and interaction of sibling status with year of application. Note applicants with siblings *already* enrolled are excluded from our sample.

TABLE 2: LOTTERY RESULTS

	First stage (1)	Reduced form (2)	2SLS (3)
<i>Panel A. Math (N=856 w/baseline scores)</i>			
Basic	1.222*** (0.063)	0.431*** (0.116)	0.353*** (0.095)
Demographics & baseline scores	1.228*** (0.066)	0.425*** (0.066)	0.346*** (0.052)
<i>Panel B. ELA (N=856 w/baseline scores)</i>			
Basic	1.223*** (0.063)	0.183 (0.117)	0.150 (0.094)
Demographics & baseline scores	1.234*** (0.066)	0.149** (0.073)	0.120** (0.058)

Notes: Grades are pooled. Basic controls include those from the regressions in Table 1 as well as year-of-test and grade-of-test dummies. Robust standard errors (clustered at the student level) are reported in parentheses.

dummy Z_i , with first stage effect π . The reduced form generated by this system comes from substituting (2) for s_{igt} in (1). The reduced form effect is the coefficient on Z_i in a regression of y_{igt} on Z_i with the same controls and data structure as in equations (1) and (2). Because the model is just-identified, 2SLS estimates of ρ are given by the ratio of reduced form to first stage coefficients.

II. Results

A. Lottery Results

The lottery first stage coefficient is a little over 1.2 years, as can be seen in the first column of Table 2. In other words, by the time they were tested, lottery winners had spent an average of 1.2 years more at KIPP than lottery losers. The addition of demographic variables and baseline scores has almost no effect on the first stage estimates.⁶ In a world with perfect lottery compliance, no late entry or grade repetition, and no loss to follow-up, the first stage in our sample would be 1.75, but this is reduced by the fact that some winners never enroll in KIPP or leave before finishing, and some losers end up in KIPP later.⁷ On the other hand, although KIPP schools

⁶ We report separate first stages for math and ELA because samples differ slightly by subject.

⁷ The 2005 cohort contributes one score after one year (in fifth grade), one after two years (in sixth grade), one after three years (in seventh grade), and one after four years (in eighth grade) for an average of 2.5 years in KIPP across

are sometimes said to encourage weaker students to leave (see, e.g., the discussion in chapter 46 of Mathews, 2009), we found that lottery winners were about as likely as losers to change schools in grades 6–8, a result discussed more fully in our working paper (Joshua D. Angrist, Susan M. Dynarski, Thomas J. Kane, Parag A. Pathak and Christopher R. Walters 2010).

Lottery winners score about 0.4 standard deviations (hereafter, σ) higher than losers on math, a robust, reduced-form result reported in column (2) in the top half of Table 2. The reduced forms for ELA, reported in the bottom half of the table, are more variable across specifications, ranging from 0.15–0.18 σ as the set of controls varies. This variability probably reflects the modest imbalance between winners and losers in the proportion LEP documented in Table 1. The estimated effect on ELA is marginally significant in models with demographic and baseline score controls.

Because the first stage coefficients are larger than one, the 2SLS estimates are smaller than the reduced-form estimates, though they also have a different interpretation. The 2SLS estimates imply that math scores increase by about 0.35 σ for each year at KIPP Lynn. The 2SLS estimates for ELA show per year gains on the order of 0.12–0.15 σ . The most precise of these is 0.12 σ , estimated in models with demographic and baseline score controls (standard error = 0.058). These effects are remarkably similar to the middle school results in Atila Abdulkadiroğlu et al. (2009) estimated using lotteries from a sample of charter schools in Boston. Measured against Lynn’s Hispanic-white score gaps of about 0.5 σ in math and 0.6 σ in ELA, both the math and ELA effects are substantial.

B. Hispanic Subgroups and Interactions

KIPP Lynn serves more Hispanic students than is typical of charter schools in the Northeast. Table 3 looks at effects in the Hispanic and non-Hispanic subgroups. Concerns about access for Hispanics notwithstanding, effects are reasonably similar for Hispanic and non-Hispanic students, though ELA estimates for the latter are imprecise.

grades. A similar calculation for the other cohorts, which are seen in fewer grades, produces 2.0 potential years in KIPP for the 2006 cohort, 1.5 potential years in KIPP for the 2007 cohort, and 1 year of potential years in KIPP for the 2008 cohort. The average of these is 1.75.

TABLE 3: SUBGROUPS AND INTERACTIONS

	Math (1)	ELA (2)
<i>Panel A. Hispanic Subgroups</i>		
Hispanic	0.346*** (0.074)	0.121 (0.075)
Non-Hispanic	0.331*** (0.076)	0.086 (0.099)
<i>Panel B. Baseline Score Interactions</i>		
Main effect	0.367*** (0.054)	0.139** (0.057)
Interaction	-0.106*** (0.041)	-0.157*** (0.045)

Notes: Estimates are 2SLS coefficients analogous to those in Table 2. Panel B instruments years at KIPP Lynn and its interaction with baseline score using the lottery offer and offer \times baseline score. Covariates include demographics and baseline scores.

Charter skeptics have sometimes argued that while relatively motivated and able students may benefit from charter school attendance, weaker students lose out. We briefly explored this type of treatment effect heterogeneity by estimating a model that adds an interaction between applicants' baseline (fourth grade) scores and years at KIPP Lynn, normalized so that the main effect of years at KIPP Lynn is evaluated at the mean of the baseline score distribution. Panel B of Table 3 shows that KIPP Lynn raises achievement *more* for weaker students. Children with baseline scores half a standard deviation below the applicant mean appear to get a rough 0.06σ additional achievement boost from each year they spend at KIPP Lynn. This finding echoes a similar negative interaction with baseline scores reported in our Boston study (Abdulkadiroğlu et al., 2009).

III. Concluding Comments

Our estimates suggest that KIPP Lynn generated substantial score gains for lottery winners, with effects on the order of 0.35σ for math and 0.12σ for ELA. The characteristics of lottery winners and losers are similar and lottery based 2SLS estimates are insensitive to controls for demographic variables and baseline scores.

KIPP Lynn benefits Hispanic and non-Hispanic applicants about equally, with larger gains for students with low baseline scores. Our estimates for KIPP Lynn are also remarkably similar to those reported for Boston charters in Abdulkadiroğlu et al. (2009). The results reported here are for a single school, but KIPP runs many similar schools across the country. The key elements of KIPP's No Excuses model feature in other charter schools, such as those in our Boston sample. Our results suggest the major elements of this model combine to produce noteworthy achievement gains, at least as measured on statewide standardized tests.

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