Leveraging Lotteries To Gauge Charter Effectiveness

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The Big Picture

- Massachusetts charters are ...
  - Funded by sending districts
  - Typically outside local collective bargaining agreements
  - Subject to review, revocation; some have been closed
  - Expanding, especially in Boston, but still a modest share of total enrollment
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- A consistent but nuanced picture emerges
  - Urban (mostly *No Excuses*) charters generate impressive achievement and post-secondary gains for their (mostly low income minority) students, including for special education and English language learners
  - Statewide, effects are mixed: on average, the non-urban charters we studied reduce achievement
An alternative estimate of the KIPP attendance effect appears in columns (4) and (5) in Table 3.1. Column (4) reports means for KIPP students, while column (5) shows the contrast between KIPP students and everyone else in the applicant pool. The differences in column (5) ignore randomized lottery offers and come from a regression of post-enrollment math scores on a dummy variable for KIPP attendance, along with the same controls used to construct the win/loss differences in column (3). The variation in KIPP attendance in this regression comes mostly, but not entirely, from the lottery. Because KIPP enrollment involves random assignment as well as individual choices (made, for example, when winners opt out), comparisons between those who do and don’t enroll may be compromised by selection bias. However, the estimate for math scores is $0.48\sigma = \frac{0.355\sigma}{0.741}$.

**Figure 3.2**
IV in school: the effect of KIPP attendance on math scores

- **Offered a seat (253)**
  - Average score: $-0.003$
  - Proportion enrolled in KIPP: $0.787$

- **Not offered a seat (118)**
  - Average score: $-0.358$
  - Proportion enrolled in KIPP: $0.046$

*Note: The effect of Knowledge Is Power Program (KIPP) enrollment described by this figure is $0.48\sigma = 0.355\sigma/0.741$.***
Lottery Offer Effects at Boston High Schools

FIGURE 2:
Results for Charter High Schools by Grade: Lottery Winners vs. Lottery Losers

Source: Abdulkadiroglu et al. (2009) and Abdulkadiroglu et al. (2011)
Lottery Offer Effects at Boston Middle Schools

FIGURE 4:
Results for Charter Middle Schools by Grade: Lottery Winners vs. Lottery Losers

Source: Abdulkadiroglu et al. (2009) and Abdulkadiroglu et al. (2011)
Charter Enrollment FX for Boston Sped and ELL

Source: Setren (2016); Estimates for Boston charter high schools – elementary and middle estimates are similar
HS Grad and Adams FX for Boston Sped and ELL

Source: Setren (2016)
No Excuses Drives Urban Charter Success

Panel A. Observational estimates

Panel B. Lottery estimates

Figure 2. School-Specific Treatment Effects

Notes: This figure plots school-specific math effects against school-specific ELA effects. The sample used to construct lottery estimates contains fewer schools than the observational sample. The figure plots both middle and high school estimates.

Source: Angrist et al. (2013)
Boston In-Districts Take Over

The in-district model

✓ A traditional public school–building, staff, and students–come under charter management; typically all staff are replaced
✓ These charter takeovers *grandfather* (guarantee) seats for students at the legacy school
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  - Effects on low achievers who haven’t sought charter seats: *unlike lottery applicants, in-district students are passively enrolled*
  - In-districts offer an inexpensive alternative to the insertion of effective charter practices in traditional public schools (as explored in Houston)
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  - ✓ We compare *changes* in achievement for students enrolled in legacy schools with changes in achievement of students in similar schools not taken over, controlling for student characteristics and pre-takeover scores
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  - We compare *changes* in achievement for students enrolled in legacy schools with changes in achievement of students in similar schools not taken over, controlling for student characteristics and pre-takeover scores
- We studied UP Academy Boston, the first in-district middle school, which replaced Gavin in South Boston
Achievement Growth: Gavin Grandfathered vs. Control

Figure 4b: UP grandfathering DD

Source: Abdulkadiroglu et al. (2016); Estimates for UP’s later cohorts are similar
Beyond MCAS
College Enrollment Effects (2SLS Using Lotteries)

Source: Angrist et al. (2016); Estimates for Boston charter high schools
FIG. 3.—Comparisons of lottery estimates of effects on earlier and later outcomes. This figure plots within-risk-set lottery estimates of the effects of charter school attendance. Panel A plots effects on SAT Reasoning (verbal and math) against effects on MCAS composite scores. Panel B plots effects on the probability of enrollment in a 4-year college within 6 months of projected graduation against effects on MCAS composite scores. The sample in panel A includes students projected to graduate between 2007 and 2013, while the sample in panel B includes students projected to graduate between 2006 and 2012. Samples in both panels are further restricted to students with available data for both outcomes. Circles indicate risk sets in which students applied to one school, while squares indicate risk sets in which students applied to two. Marker sizes are proportional to the inverse of the standard errors of the MCAS estimates. Estimates for a given risk set use the instrument (immediate or ever offer) with the larger first-stage $t$-statistic. The sample excludes risk sets with first-stage $t$-statistics less than 1. Lines show weighted least squares regressions with weights inversely proportional to standard errors. The slopes are $87.9 \text{(SE) } 16.9$ for the SAT plot and $0.133 \text{(SE) } 0.053$ for the 4-year enrollment plot.

Source: Angrist et al. (2016)

Note: Circles indicate risk sets in which students applied to one school, while squares indicate risk sets in which students applied to two.
MCAS Effects Predict: Four-Year College Enrollment

Panel B: MCAS Composite-Four-year College Enrollment

Source: Angrist et al. (2016)

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References


