Abstract Title Page

Title: Using school admissions lotteries to measure effects of an integrated student support model on students' academic achievement

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Background/Context

Out-of-school factors can significantly impact students' readiness to learn and thrive in school, accounting for up to two-thirds of the variance in achievement (Coleman et al., 1966; Rothstein, 2010; Berliner, 2013). Research has found that comprehensive, school-based student support interventions can be helpful in addressing out-of-school factors that can interfere with achievement and thriving (Walsh, et al., 2014). This study contributes to the research regarding the efficacy of comprehensive student support by using admissions lotteries to compare those who did and did not win a random offer to attend schools implementing an integrated student support model. The comparison of lottery winners and losers estimates causal effect free of selection bias (Angrist, Pathak, & Walters, 2013; Cohodes, Setren, & Walters, 2016).

Purpose/Objective

The current study evaluates whether participating in City Connects during elementary school as a result of a random lottery leads to improved academic outcomes.

Setting

The setting is a large urban public school district. During the years of this study, 2006-07 through 2013-14, the intervention was implemented in 27 elementary and K-8 schools in several geographic areas across the city; students from all other elementary and K-8 schools in the district who faced the same risk of assignment to treatment serve as comparisons.

Intervention

City Connects is an approach to addressing out-of-school barriers to academic success and thriving grounded in best practices for student support (Marx, Wooley & Northrop 1998; Adelman & Taylor 2006) and guided by contemporary understandings of child development (Masten 2001; Bronfenbrenner & Morris 1998; Lerner, 1995). At the core of the intervention is the Coordinator, a full-time licensed school psychologist or social worker in the school. Elements of the practice include: working with every teacher to identify strengths and needs of each student; connecting each student to a tailored set of supports and enrichments in the school and community; developing a plan for at-risk students with the support of a wider team; implementing prevention programs; and maintaining relationships with community partners and families.

Participants

The sample was drawn from 13,432 students applying to attend Kindergarten during 2006-7 to 2013-14 who participated in a school admissions lottery process. In this district, families could provide up to 10 choices for a school they would like their Kindergarten student to attend. These preferences, along with "priority" variables such as having a sibling already attending the school and proximity to the student's home, were used to assign students to schools via a deferred acceptance algorithm. If applicants outnumbered available spots in a particular school, an assignment mechanism including a random component was used to break priority ties. By capitalizing on the random component embedded within the system, this study identified groups of students who faced the same risk of assignment to the treatment condition yet received different treatment offers. Of the total sample, 4,119 students had a random chance of being assigned to a school implementing City Connects.

Data Collection and Analysis

Anonymized data were provided by the district, including student characteristics (gender, race/ethnicity, lunch subsidy eligibility, language learner status, country of origin and special education status); standardized achievement test scores in mathematics and ELA; and enrollment lottery records such as information on students' school preferences, priority ranking within each school (e.g., sibling enrollment and proximity/walk zone status), lottery numbers randomly generated by the district, and eventual school placement.

In a first analysis, the deferred acceptance algorithm was run with district-provided random lottery numbers and school preference data in order to confirm the school assignment process and assess classification accuracy. The assignment process was replicated with a high degree of classification accuracy (95%).

Next, lottery numbers were randomly sampled from a uniform distribution 100,000 times for each school year 2006-7 to 2013-14 (total=800,000) and the deferred acceptance algorithm was run with each of these simulated lottery draws to assign students to schools using the district assignment system rules (Abdulkadiroglu, Angrist, Narita, & Pathak, 2017). The frequency of assignment to schools implementing City Connects was calculated across simulated lottery draws, resulting in a ***deferred acceptance propensity score*** (Abdulkadiroglu et al., 2017). The set of students with deferred acceptance propensity scores in the interval (0, 1) were identified as those subject to lottery randomization (N=4,119).

Given that school preference and student ranking information is encoded within the deferred acceptance propensity score, any offer to a school implementing City Connects is random, conditional on the propensity score. The deferred acceptance propensity score and an indicator for whether the offer was to a school implementing or not implementing City Connects were included in intention-to-treat and instrumental variable regression models. Additionally, robust standard errors were adjusted for school clustering. By estimating achievement effects for students facing the same risk of assignment yet receiving different random offers, potential internal validity issues such as selection bias that could be present in quasi-experimental studies are minimized.

Findings/Results

Table 1 presents student characteristics by category of enrollment offer (intervention school vs. not) and coefficients from a logistic regression of offer on student characteristics. No student characteristic was significantly related to the type of school offer, suggesting the two groups were comparable.

Tables 2 and 3 provide results from analyses comparing standardized mathematics and ELA assessment scores for students receiving City Connects and comparison students not receiving City Connects across grades 3 to 6. In Table 2, regression coefficients represent standardized group mean differences and capture the impact of City Connects on students eligible to receive City Connects**,** regardless of compliance with their random offer. In Table 3, the standardized group mean differences represent average treatment effect for compliers (students actually attending intervention schools after receiving an offer to do so), highlighting the impact of being randomly assigned to City Connects.

The intention-to-treat analysis reveals that students assigned and not assigned to intervention schools score similarly in both math and ELA in grade 3. Starting in grade 4, intervention students score higher than their comparison peers in both domains, significantly so in 5^{th} and 6^{th} grade. Results from the instrumental variable analysis were similar; intervention students consistently score higher in both mathematics and ELA than non-treatment peers, significantly outperforming non-treatment students in 5^{th} and 6^{th} grade mathematics and reading.

Conclusion

For entering kindergarten students, random assignment to a school implementing City Connects resulted in better academic performance, with these benefits being most notable at later grades. The results from this natural experiment confirm results of quasi-experimental studies: receiving a comprehensive student support intervention during elementary school leads to positive academic impacts.

Appendix

Table 1. Logistic regression covariate balance for entering kindergarten students

Student Characteristics	% in Not Offered Intervention Sample	% in Offered Intervention Sample	Estimate (log-odds)	Std. Error	*p*-value
Male	51%	52%	0.10	0.11	0.37
Black	32%	28%	-0.28	0.21	0.18
Hispanic	44%	47%	0.002	0.19	0.99
Asian	10%	13%	-0.12	0.23	0.62
Multi-racial/ Other	2%	2%	-0.27	0.35	0.44
Special Educational Needs Level 1 (primarily regular classroom)	2%	2%	0.22	0.37	0.56
Special Educational Needs Level 2 (<25% of time out regular classroom)	4%	4%	0.02	0.27	0.95
Special Educational Needs Level 3 (25-60% of time out regular classroom)	< 1%	< 1%	-0.62	0.91	0.50
Born outside US	7%	10%	0.21	0.20	0.30
Eligible free lunch	73%	74%	-0.14	0.17	0.43
Eligible reduced-price lunch	4%	4%	-0.38	0.30	0.20
Missing lunch subsidy status	10%	11%	-0.12	0.22	0.59
English Language Learner	18%	24%	-0.12	0.16	0.47

Table 2. Intention-to-Treat Estimates

	Math (SE)	ELA (SE)
3rd grade	0.04 (.08)	0.004 (.06)
4th grade	0.08 (.08)	0.10 (.08)
5th grade	0.21 (.10) **	0.21 (.12)*
6th grade	0.27 (.11)**	0.36 (.14)**

*** Significant at $p < .01$ ** Significant at $p < .05$ * Significant at $p < .10$

Note: Models include school year and student characteristics as covariates (gender, race, Special Education, free/ reduced price lunch, ELL status). Standard errors adjusted for school clusters.

Table 3. Instrumental Variable Estimates

	Math	ELA
3rd	0.12 (.21)	0.01 (.16)
4th	0.24 (.24)	0.29 (.24)
5th	0.59* (.32)	0.60* (.32)
6th	0.62** (.28)	0.81** (.37)

*** Significant at $p < .01$ ** Significant at $p < .05$ * Significant at $p < .10$

Note: Models include school year and student characteristics as covariates (gender, race, Special Education, free/ reduced price lunch, ELL status). Standard errors adjusted for school clusters.

Figure 1. Intention-to-Treat Model Specification

$$Z\ MCAS_{it} = \tau_t + \sum_j \rho_j d_{ij} + X_i'\theta + \theta_{Offer} Random\ Offer_{it} + \upsilon_{it},$$

where τ_t are year effects, X_i' is a vector of student characteristics, and υ_{it} is an error term.

The set of d_{ij} includes a dummy variable for each deferred acceptance propensity score rounded to the nearest 100th; these propensity scores represent risk of assignment to the treatment condition, and lottery offers are randomly assigned within these strata, but not unconditionally.

The variable of interest, *random offer*, represents a random offer to a school implementing Intervention ABC.

Figure 2. Instrumental Variable Model Specification

Second stage: $ZMCAS_{it} = \alpha_{2t} + \sum_j \delta_j d_{ij} + X_i'\beta + \beta_{Intervention} \widehat{Intervention}\ ABC_{it} + \varepsilon_{it}$

First stage: $Intervention\ ABC_{it} = \alpha_{1t} + \sum_j \kappa_j d_{ij} + X_i'\Pi + \Pi_{Offer} RandomOffer_{it} + \eta_{it}$

In the first stage model, a_{1t} are year effects, X_i' is a vector of student characteristics, and η_{it} is an error term. The set of d_{ij} includes a dummy variable for each deferred acceptance propensity score rounded to the nearest 100th; these propensity scores represent risk of assignment to the treatment condition, and lottery offers are randomly assigned within these strata, but not unconditionally.

In this first stage equation, the *random offer* variable, representing a random offer to a school implementing Intervention ABC, is used to identify exogenous variation in the treatment, *Intervention ABC*, which is the outcome variable for the first stage regression model.

In the second stage regression model, predicted values from the first stage model, $\widehat{Intervention}\ ABC$, are used as a predictor variable in order to identify the causal effect of the intervention on compliers, given by $\beta_{Intervention}$. In this second stage model, a_{2t} are year effects, X_i' is a vector of student characteristics, ε_{it} is an error term, and d_{ij} are a set of deferred acceptance propensity scores rounded to the nearest 100th.

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