Who Chooses and Who Benefits? The Limits of Decentralized School Choice*

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Abstract

The majority of U.S. public school districts now offer school choice programs that allocate seats using a centralized algorithm but with voluntary participation. The optional nature of public school choice segments public education and raises critical questions: who chooses, who benefits, and what policy alternatives can produce better outcomes for children? This paper provides new evidence on these questions by studying the Los Angeles Unified School District, the largest opt-in system in the country. Analyzing two decades of lottery records, we find that students living closer to choice options are both more likely to participate and to experience larger achievement gains. The proximity-based treatment effect heterogeneity is not explained by other observable treatment effect heterogeneity, suggesting a potential role for unobserved demand-side factors. To assess the empirical relevance of this hypothesis, we rely on quasi-experimental variation in distance to schools due to large expansions in choice programming and lottery-based admission lotteries to estimate a generalized Roy model that links families' decisions to apply and enroll to achievement gains. Our estimates indicate that the families least likely to apply under the current system would realize the largest test score benefits if they participated. In other words, decentralized, opt-in systems not only segment public education markets based on student ability and socioeconomic status but also exacerbate existing inequalities in educational outcomes. Policy interventions—such as targeted information interventions that cultivate broader participation or mandate participation as is done in cities such as New York—could produce achievement benefits that are 80% as large as highly-touted programs such as the Harlem Children's Zone Charters at low additional cost.

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1 Extended Abstract

In the United States, students who attend the lowest performing schools in their district fall behind their peers who attend the highest performing schools by 20% of a standard deviation of standardized exam achievement per year— a gap that education researchers equate to two-thirds of a grade level in annual learning progress.[1] To address such inequities in education, public school districts have spent the last two decades expanding school choice by introducing new magnet schools, dual language programs, theme-based academies, selective admissions "exam" schools, and creating a variety of alternative intra-district choice options. Proponents argue that public school choice has the potential to improve student outcomes by both fostering competition in the marketplace for students (Campos and Kearns, 2024, Neilson, 2021) and allowing families to more effectively select into schools that best suit their children's needs (Bruhn et al., 2023, Hoxby, 2003, Ovidi, 2025). Yet, this logic relies on the hope that parents of the children who stand to gain will actually take advantage of the options provided to them.

This paper studies public school choice systems and U.S. educational inequality. As motivation, we provide new descriptive evidence on the landscape of school choice based on an original survey of the nation's 120 largest school districts. The survey reveals that enrollment in non-neighborhood public schools of choice has quadrupled over the past 25 years. In fact, enrollment shares now closely rival the charter sector (see Figure 1). In addition to documenting a rise in public school choice, we find there is substantial heterogeneity in how families with school-age children are incentivized to participate. The vast majority of these districts (75%) have adopted algorithms to assign students to schools and a majority utilize a decentralized system that requires parents to proactively "opt-in" and submit school applications. Less than 25% of districts require all students to submit preferences through a fully centralized system, as is done in cities like New York and Boston (Abdulkadiroğlu and Sönmez, 2003, Abdulkadiroğlu et al., 2017). Finally, we show that economically disadvantaged students are underrepresented in choice schools. The under-representation is more pronounced in districts that are decentralized and require students to opt-in. This pattern highlights the concern that voluntary participation in school choice programs may segment the public schooling system by allowing the most advantaged students to leave behind their less advantaged peers.

Motivated by these findings, our main analysis seeks to answer three research questions: First, who chooses? More precisely, which families choose to take advantage of decentralized choice systems, and which families do not? Second, who benefits? In other words, conditional

[1] We calculate this statistic by averaging the 90-10 differential of within-district school test score growth across all US districts that have at least 10 schools reported in the Stanford Education Data Archive (SEDA). SEDA harmonized test scores to be comparable across states and districts (Fahle et al., 2024).

on opting-in, which students stand to gain the most from attending an option school? Third, can districts do better? More concretely, we aim to quantitatively evaluate the impact of various hypothetical enrollment policies with the goal of learning how to produce improved outcomes for the average child in a decentralized system.

To study these questions, we focus on the Los Angeles Unified School District (LAUSD), the largest decentralized public school choice system in the U.S. If treated as an independent district, the LAUSD choice program schools would have the 23rd-highest enrollment in the country with roughly 110,000 students annually. Notably, the number of choice options in the LAUSD has expanded in recent years, with a remarkable trend break starting in the mid 2010s (See Figure 2). Our analysis relies on two-decades worth of detailed application records that we combine with district-wide administrative student data containing achievement and other key outcomes. We focus on applications to middle school choice programs to maximize our ability to study achievement outcomes that can be immediately observed after schooling enrollment decisions.

Our study of "who chooses" combines a descriptive characterization of applicants with a quasi-experimental analysis of the supply of choice program options over time. We find that, while more academically advantaged students tend to sort into choice programs, there is scope for policies that improve access to create a more equitable allocation of students to schools. Table 1 shows that choice programs tend to reach a more racially diverse student body who are also more economically and academically advantaged. The baseline achievement differences are roughly 0.8σ, indicating stark gaps in academic preparation between choice students and the rest of the district. Proximity also appears to play an important role as distance to choice programs is also a strong predictor of participation (see Figure 3). To better understand how access matters, we ask how *changes* in distance—driven by the unprecedented expansion of choice programs in LAUSD (see Figure 2)—shift participation. Figure 4 illustrates how distance to the nearest choice program has substantially declined for students between 2004 and 2017. Event study results reported in Figure 5 show that a one-mile reduction in relative distance boosts participation rates by roughly 17%. These findings demonstrate that while more academically advantaged students tend to sort into choice programs, there is scope for policy to create a more equitable allocation of students to schools. Yet, whether increasing participation will improve student outcomes and reduce inequality, depends critically on which students stand to gain from attending a choice program.

We analyze who benefits by estimating the impacts on participants using 20 years of lottery data. The results show that students who stand to gain the most are those who are also

the least likely to apply when access is costly (as proxied by distance). The lottery data are generated by the random number tie-breaking embedded in the district-run assignment algorithm that allocates students to schools. Since the lotteries are random, we can be confident that differences in outcomes among lottery winners and losers are better attributed to the causal effect of the choice program rather than observed and unobserved differences among applicants. This approach allows us to better understand which students most benefit among those who choose to apply. Figure 6 combines insights from our motivating descriptive analysis with lottery variation to show that proximity is strongly associated with reduced form impacts of receiving a lottery admission offer. The difference in reduced form effects between students in the first quintile of relative distance and the fifth is roughly 0.09σ. The distance-based treatment effect heterogeneity is unexplained by variation in the first stage enrollment effects as they only range between 0.45 and 0.41. Other observable treatment effect heterogeneity, including but not limited to achievement, socioeconomic status, and student neighborhood quality, do not explain the distance-based heterogeneity as shown in Figure 7. If relative distance is an important shifter of demand, as is implied by our first set of results, then these findings demonstrate that students with the lowest unobserved demand also stand to gain the most. The intuition is that students who live far distances from choice programs face higher costs of choice program enrollment, so students that apply to choice programs from farther relative distance must have relatively stronger idiosyncratic tastes for choice programs.

Our analysis of whether districts can do better is based on a structural model that links application and enrollment to achievement to study the district-wide impact of inducing more students to participate in LAUSD's public school choice program.[2] The model allows us to isolate a component of taste heterogeneity that we can associate with causal effects and explore the prospective impact of alternative enrollment policies. The average treatment effect and the parameters governing selection on levels and gains in the student outcome model are identified using variation in distance and offers. Relative to the existing literature using structural models to understand treatment effects, we provide two innovations. First, we rely on policy variation in distance depicted in Figure 2 to identify key parameters of a student outcome equation. Second, we use the lottery variation to assess whether the model-implied LATEs match the

[2]In the model, families treat the decision to apply as a choice over a lottery and consider their admissions probabilities. The decision is governed by preferences for schools that depend on student attributes, idiosyncratic choice school heterogeneity, and distance and application costs that depend on student attributes and idiosyncratic costs. After students apply, considering their expected utility from different applications, offers are made via a centralized algorithm. Students who face a decision—those that applied and received an offer—must decide where to enroll. This decision depends on their preferences, as in the application stage, and a post-lottery shock that rationalizes why some families apply, receive offers, but do not ultimately enroll in the program where they applied. After students enroll, they take achievement exams that we study in the final part of the analysis. The idiosyncratic tastes that shift preferences for choice programs are present in both application and enrollment stages.

reduced form lottery LATEs in similar spirit to Angrist et al. (2017) and Kline and Walters (2019). Equipped with validated taste-based heterogeneous causal estimates, we return to policy implications and simulate the prospective impact of counterfactual policies that would reduce application costs, including information interventions meant to increase parental engagement, as well as mandating participation in the spirit of the systems currently in place in New York City and Boston.

Simulations from our structural model indicate that choice programs could generate substantial improvements for the average student (0.18σ). Figure 8 displays estimates of expected achievement gains and how they vary with parental demand. These results reveal that students do not sort into choice programs on the basis of comparative advantage in academic achievement. The test score gains are larger for students with weaker idiosyncratic preferences for choice programs, denoted as "Inclination to Treatment" in Figure 8. We test and statistically reject the restrictions implied by a version of our model that implies students choose schools to maximize test scores net of distance and application costs. Figure 9 reports the results from a validation exercise comparing the model-implied LATEs against lottery-based LATEs. We estimate subgroup-specific lottery LATEs and associate them with our mode-implied subgroup-specific LATE and find a forecast coefficient of 0.95, underscoring the internal validity of our approach (Kline and Walters, 2019). Overall, the pattern of selection and treatment effects that we document bears similarity to the findings of negative selection on treatment effects observed in health markets (Chandra and Staiger, 2007) and other education markets, such as charter schools (Walters, 2018) and early childhood care (Cornelissen et al., 2018, Kline and Walters, 2016).

A key policy implication of our result is that the decentralized nature of participation significantly limits the benefits of public school choice. To put our findings in context, we note that highly touted (and expensive) educational interventions like the Harlem Children's Zone tend to improve test scores by roughly 0.2σ. Our results suggest that LAUSD could obtain 80-90% of the Harlem Children Zone gains by expanding outreach efforts or mandating students to apply as is done in New Orleans, Newark, Long Beach Unified, Garland ISD, and several other large districts (Lincove and Valant, 2023). Our findings suggest that there is substantial scope to improve the efficacy of the public education system with simple, low-cost policy changes.

In on-going analysis, we formally evaluate the prospective impact of alternative enrollment policies. The structural model of application and enrollment decisions allows us to assess achievement and inequality in two counterfactual policy scenarios. The first is a policy that targets students with weak idiosyncratic tastes for choice programs and weakly induces them to

apply and enroll. A second scenario eliminates application costs and mandates participation as in districts such as New Orleans and Newark. While our key results suggest these policies can improve outcomes for disadvantaged students, potential capacity constraints and other frictions may prove to limit the potential gains, underscoring the need to conduct a formal counterfactual analysis.

The main contribution of this paper is to the literature on education market design and student outcomes. Important previous work has shown that uncoordinated school choice assignment policies generate substantial mismatch, and reforms that coordinate and centralize assignment mechanisms—what we refer to as centralized unified enrollment—generate important gains (Abdulkadiroğlu et al., 2017). Centralized unified enrollment systems have also been shown to substantially elevate student outcomes, leading to reductions in inequality, and spurring competition between schools (Campos and Kearns, 2024). While mounting evidence reveals that centralized unified enrollment systems produce substantial benefits relative to other options with less centralization, we know surprisingly little about how the opt-in design—which is the most common in the United States—affects student outcomes. This paper is a step forward in understanding this subtle feature of the design of markets that has strong implications for inequality.

A related literature has sought ways to improve the overall effectiveness of systems with centralized assignment systems. This includes work related to improving the quality of information about schools and one's admissions chances (Ainsworth et al., 2023, Andrabi et al., 2017, Arteaga et al., 2022, Campos, 2024, Corcoran et al., 2018, Corradini, 2023) and the potential impacts of strategy-proof mechanisms versus the ability to convey cardinal preferences (Agarwal and Somaini, 2018, Calsamiglia et al., 2020, Kapor et al., 2020). Our original survey uncovers wide variation in information availability and mechanism adoption across districts in the United States, underscoring the importance of the existing work, but also uncovers an overlooked design feature that has natural implications for inequality, the opt-in feature. We therefore contribute to the existing literature by highlighting an additional design feature with substantial scope for improvements in student outcomes.

References

Abdulkadiroğlu, Atila and Tayfun Sönmez, "School choice: A mechanism design approach," *American economic review*, 2003, *93* (3), 729–747.

_ , Nikhil Agarwal, and Parag A Pathak, "The welfare effects of coordinated assignment: Evidence from the New York City high school match," *American Economic Review*, 2017, *107* (12), 3635–3689.

Agarwal, Nikhil and Paulo Somaini, "Demand analysis using strategic reports: An application to a school choice mechanism," *Econometrica*, 2018, *86* (2), 391–444.

Ainsworth, Robert, Rajeev Dehejia, Cristian Pop-Eleches, and Miguel Urquiola, "Why do households leave school value added on the table? The roles of information and preferences," *American Economic Review*, 2023, *113* (4), 1049–1082.

Andrabi, Tahir, Jishnu Das, and Asim Ijaz Khwaja, "Report cards: The impact of providing school and child test scores on educational markets," *American Economic Review*, 2017, *107* (6), 1535–1563.

Angrist, Joshua D, Peter D Hull, Parag A Pathak, and Christopher R Walters, "Leveraging lotteries for school value-added: Testing and estimation," *The Quarterly Journal of Economics*, 2017, *132* (2), 871–919.

Arteaga, Felipe, Adam J Kapor, Christopher A Neilson, and Seth D Zimmerman, "Smart matching platforms and heterogeneous beliefs in centralized school choice," *The Quarterly Journal of Economics*, 2022, *137* (3), 1791–1848.

Bruhn, Jesse M, Christopher Campos, Eric Chyn, and Anh Tran, "Who Benefits from Remote Schooling? Self-Selection and Match Effects," Technical Report, National Bureau of Economic Research 2023.

Calsamiglia, Caterina, Chao Fu, and Maia Güell, "Structural estimation of a model of school choices: The boston mechanism versus its alternatives," *Journal of Political Economy*, 2020, *128* (2), 642–680.

Campos, Christopher, "Social Interactions, Information, and Preferences for Schools: Experimental Evidence from Los Angeles," Technical Report, National Bureau of Economic Research 2024.

_ and Caitlin Kearns, "The Impact of Public School Choice: Evidence from Los Angeles's Zones of Choice," *The Quarterly Journal of Economics*, 10 2024, *139* (2), 1051–1093.

Chandra, Amitabh and Douglas O Staiger, "Productivity spillovers in health care: evidence from the treatment of heart attacks," *Journal of political Economy*, 2007, *115* (1), 103–140.

Corcoran, Sean P, Jennifer L Jennings, Sarah R Cohodes, and Carolyn Sattin-Bajaj, "Leveling the playing field for high school choice: Results from a field experiment of informational interventions," Technical Report, National Bureau of Economic Research 2018.

Cornelissen, Thomas, Christian Dustmann, Anna Raute, and Uta Schönberg, "Who benefits from universal child care? Estimating marginal returns to early child care attendance," *Journal of Political Economy*, 2018, *126* (6), 2356–2409.

Corradini, Viola, "Information and access in school choice systems: Evidence from new york city," Technical Report, Technical report, working paper 2023.

Fahle, Erin M, Demetra Kalogrides, Benjamin R Shear, Sean F Reardon, and Andrew D Ho, "Stanford Education Data Archive Technical Documentation Version 5.0 March 2024," 2024.

Hoxby, Caroline Minter, "School choice and school productivity. Could school choice be a tide that lifts all boats?," in "The economics of school choice," University of Chicago Press, 2003, pp. 287–342.

Kapor, Adam J, Christopher A Neilson, and Seth D Zimmerman, "Heterogeneous beliefs and school choice mechanisms," *American Economic Review*, 2020, *110* (5), 1274–1315.

Kline, Patrick and Christopher R Walters, "Evaluating public programs with close substitutes: The case of Head Start," *The Quarterly Journal of Economics*, 2016, *131* (4), 1795–1848.

_ **and** _ , "On Heckits, LATE, and numerical equivalence," *Econometrica*, 2019, *87* (2), 677–696.

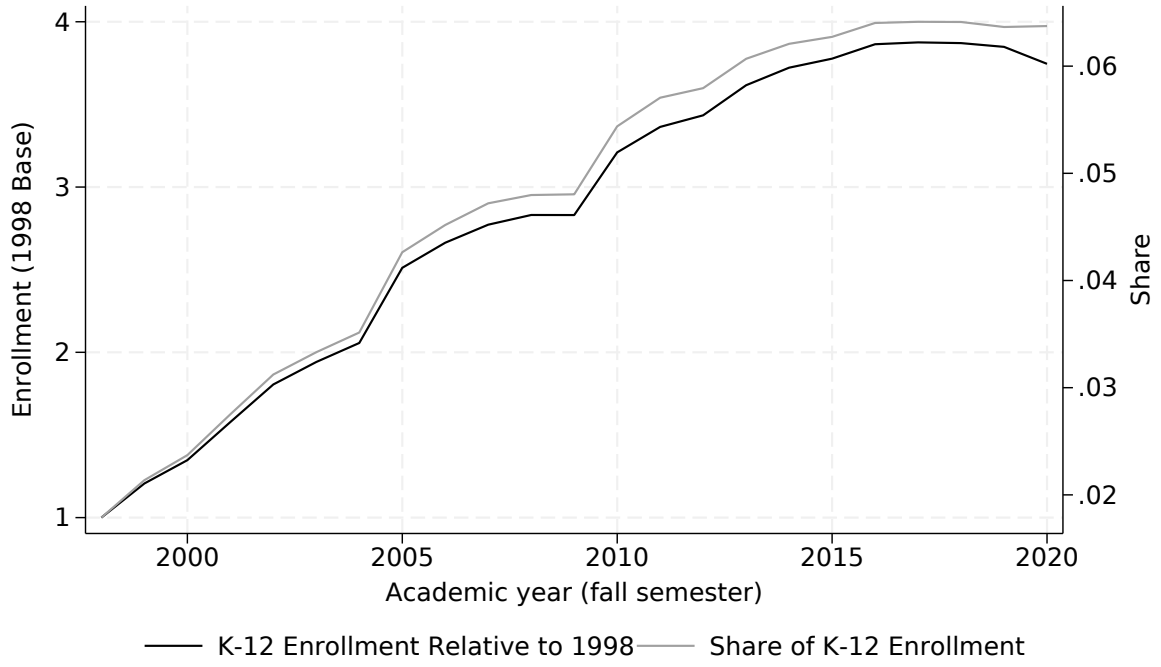
Lincove, Jane Arnold and Jon Valant, "The Effects of Unified School Enrollment Systems on New Orleans Schools: Enrollment, Demographics, and Outcomes after the Transition to OneApp. Technical Report.," *National Center for Research on Education Access and Choice*, 2023.

Neilson, Christopher A, "Targeted Vouchers, Competition Among Schools, and the Academic Achievement of Poor Students," Technical Report 2021.

Ovidi, Marco, "Parents Know Better: Sorting on Match Effects in Primary School," *Review of Economics and Statistics*, 2025, pp. 1–94.

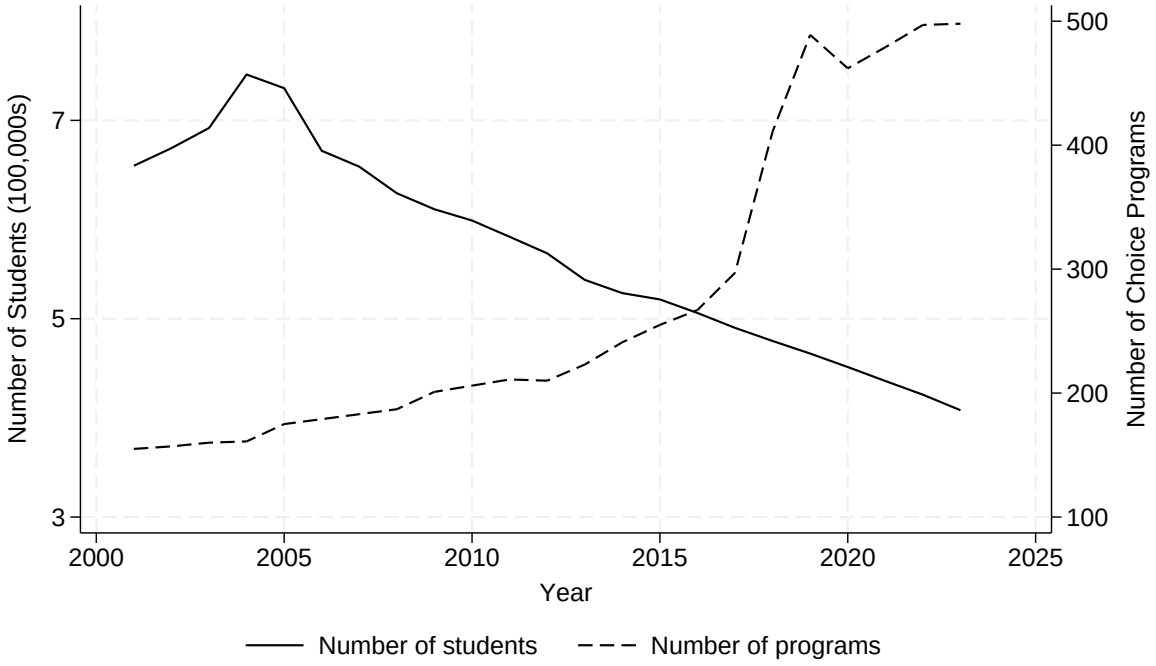
Walters, Christopher R, "The demand for effective charter schools," *Journal of Political Economy*, 2018, *126* (6), 2179–2223.

Figure 1: National Trends in Public School Choice Program Enrollment



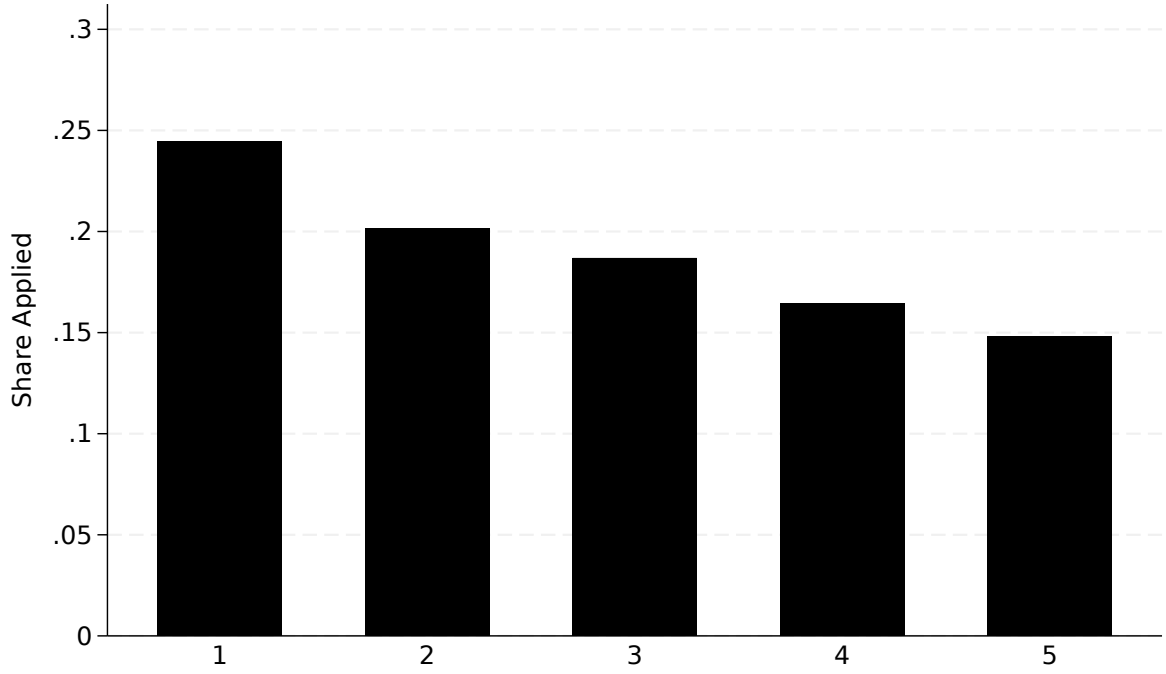
Notes: This figure reports statistics on the number of students enrolled public school choice programs based on annual data covering the years 1998 to 2020 from the National Center for Education Statistics (NCES). We consider choice programs that school districts operate and exclude charter schools. The NCES's Common Core data allows us to identify magnet schools, so our counts will exclude dual-language programs and other schools that use selective admission criteria. The right-side vertical axis reports the share of all public school students who are enrolled in a choice program, and the left-side vertical axis reports enrollment relative to 1998.

Figure 2: Policy Variation in Choice Program Availability



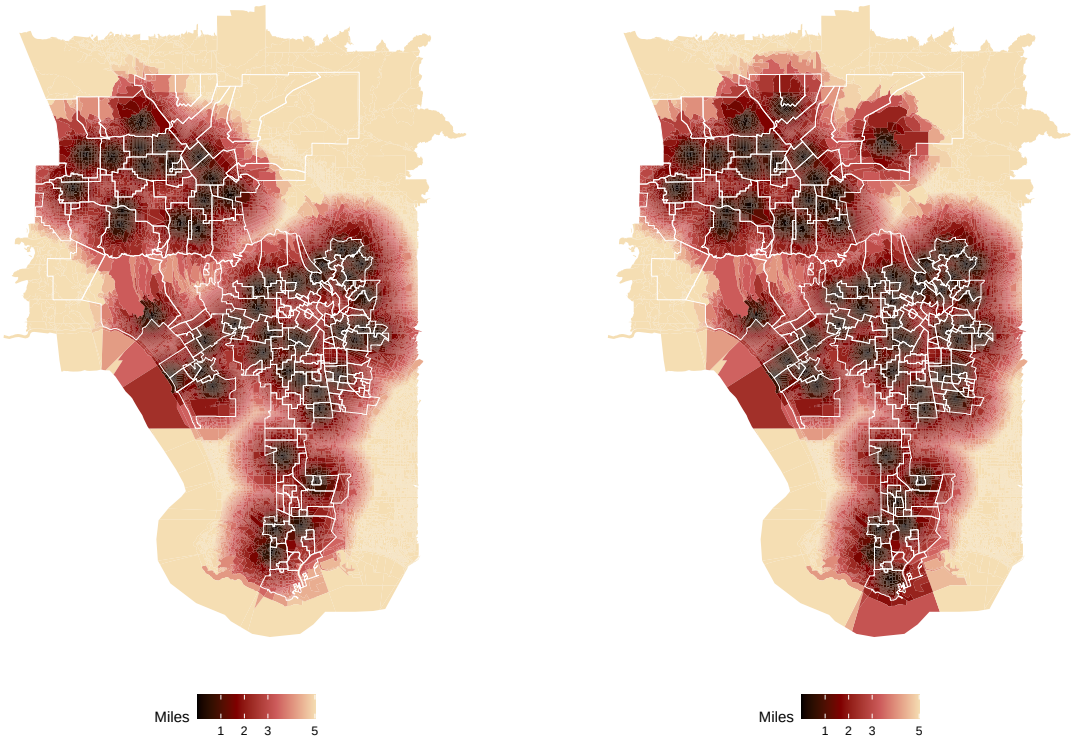
Notes: This figure reports two time series: LAUSD's total K-12 enrollment and the number of choice programs. The left-vertical axis tracks total enrollment and the right-vertical axis tracks the number of choice programs. Choice programs include magnet programs and dual-language immersion programs, as well as other choice offerings in LAUSD. The sample covers all LAUSD enrolled students or available programs between the years 2001 to 2023.

Figure 3: Relative Distance to Oversubscribed School Choice Programs and Application Likelihood



Notes: This figure reports the share of students that apply to choice programs for different relative distance quintiles. Students in Quintile 1 live closest to choice programs in terms of relative distance, while students in Quintile 5 live farther away. Data cover all enrolled fifth-grade students during the 2004 to 2017 academic years.

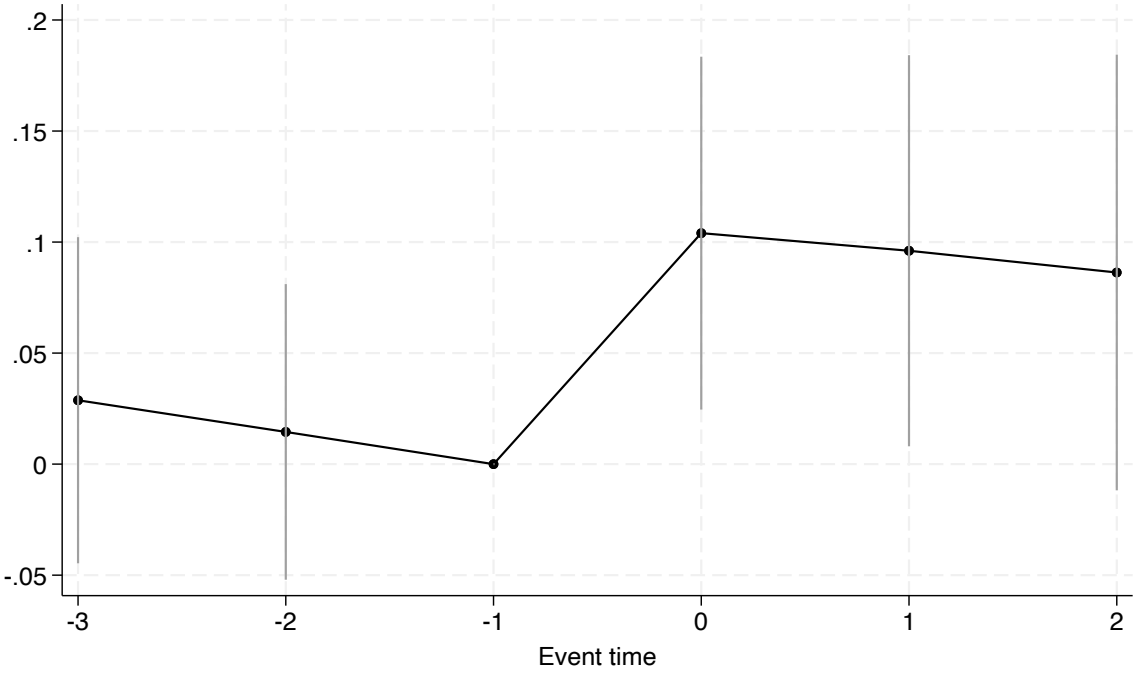
Figure 4: Relative Distance to Middle School Choice Programs Over Time



(a) 2004 (b) 2017

Notes: Panels (a) and (b) are census block level maps of Los Angeles in 2004 and 2017, respectively. We calculate distances between the block centroid and the nearest neighborhood school and the nearest choice program. We define a block's relative distance as the difference between the distance to the neighborhood school and the distance to nearest choice program. Each census block shown is shaded according to its relative distance. The white borders are middle school attendance zone boundaries.

Figure 5: Changes in Relative Distance Predict Applying

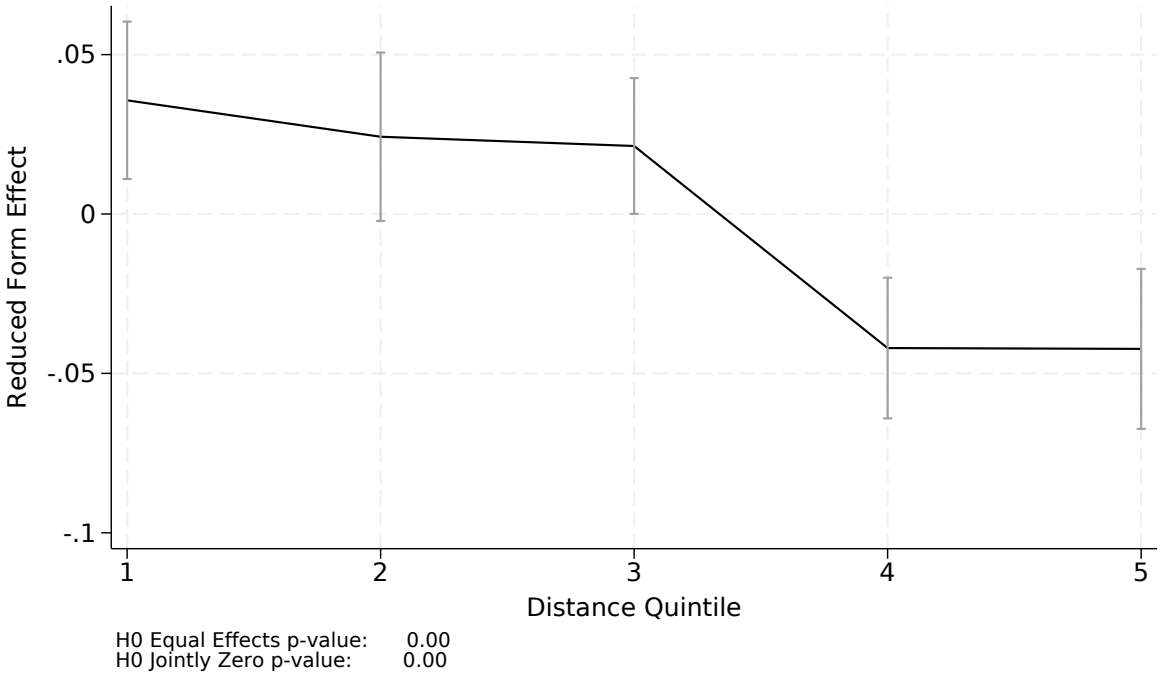


Notes: This figure reports evidence documenting how changes in Census block level relative distance to choice programs influence application behavior. We first construct a stacked dataset by identifying all blocks that experience a change in relative distance in a focal year t and which do not experience any changes in relative distance in the previous two years. After identifying the treated blocks in the focal year, we identify control blocks that are all other blocks that do not experience a change in relative distance in the focal year and also do not experience changes in relative distance in the previous two years. We repeat this procedure for each focal year t covering the years 2004 to 2019. We then estimate the following block-level regression model:

$$Y_i = \alpha_{st} + \alpha_{sb} + \sum_{k \neq -1} \beta_k 1\{Treat_{sb}\} \times 1\{t = k\} \times Shock_{sb} + u_i$$

where α_{st} and α_{sb} are stack-by-event time and stack-by-block fixed effects, $Treat_{sb}$ is an indicator for track b being identified as a treated block in stack s, and $Shock_{sb}$ is a continuous measure capturing the change in relative distance measured in the focal year for block b in stack s. The parameters β_k are event-time difference-in-difference impacts on block-level choice enrollment. We report 95 confidence intervals where standard errors are robust and clustered at the block level.

Figure 6: Achievement: Reduced Form Estimates by Distance Quintile

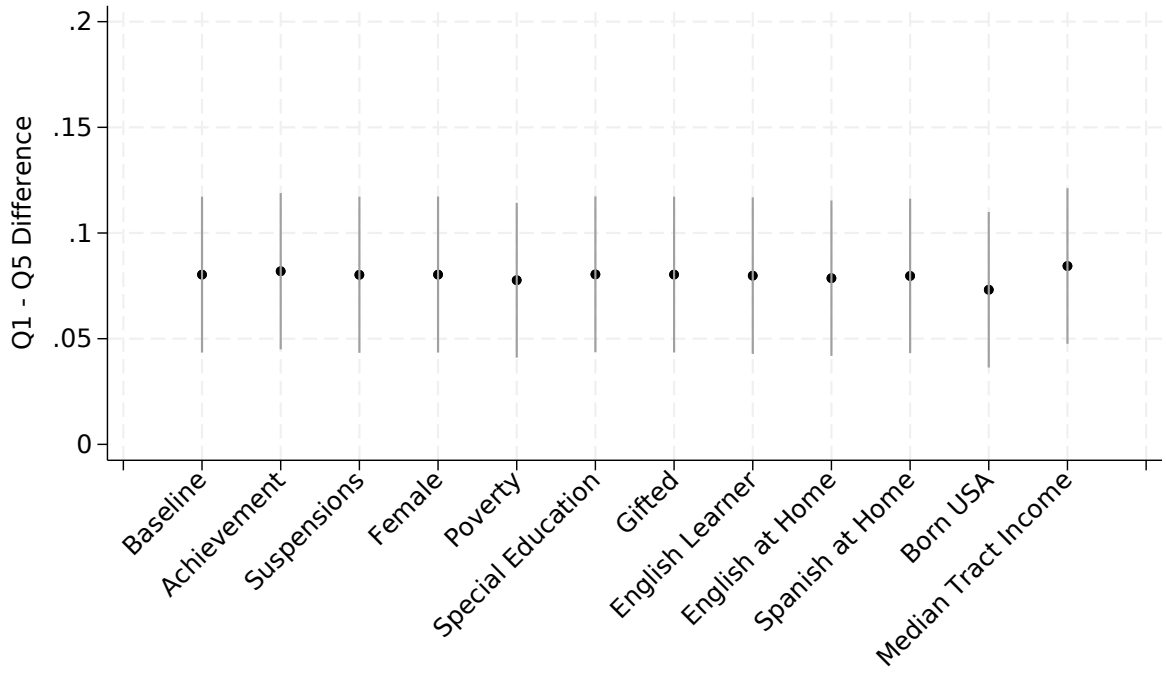


Notes: This figure reports the estimated impacts of receiving an offer to attend a public school choice program. The results are based on individual-level regressions for students who submitted an application to an oversubscribed school choice program. Each school conducts randomized lottery admissions at the program, year, grade, priority points, and race level. Formally, we estimate impacts using the following model:

$$Y_i = \alpha_{\ell(i)} + \beta Z_i + X_i'\gamma + u_i,$$

where $\alpha_{\ell(i)}$ are lottery strata fixed effects, Z_i is an indicator for being offered a seat at the program of application, X_i is a vector of baseline student controls included to increase precision. We estimate this model separately after grouping students based on the quintiles of the distribution of distance to the nearest choice program. The figure reports each of the point estimates of β (along the solid line) and the associated 95-percent confidence interval based on robust standard errors that are clustered at the lottery level. The outcome is the mean of standardized math test scores in the years following an application. Data cover all enrolled fifth grade students during the 2004 to 2017 academic years. During this period, all students can only submit exactly one application to their most preferred school choice program.

Figure 7: Robustness of Distance-based Treatment Effect Heterogeneity

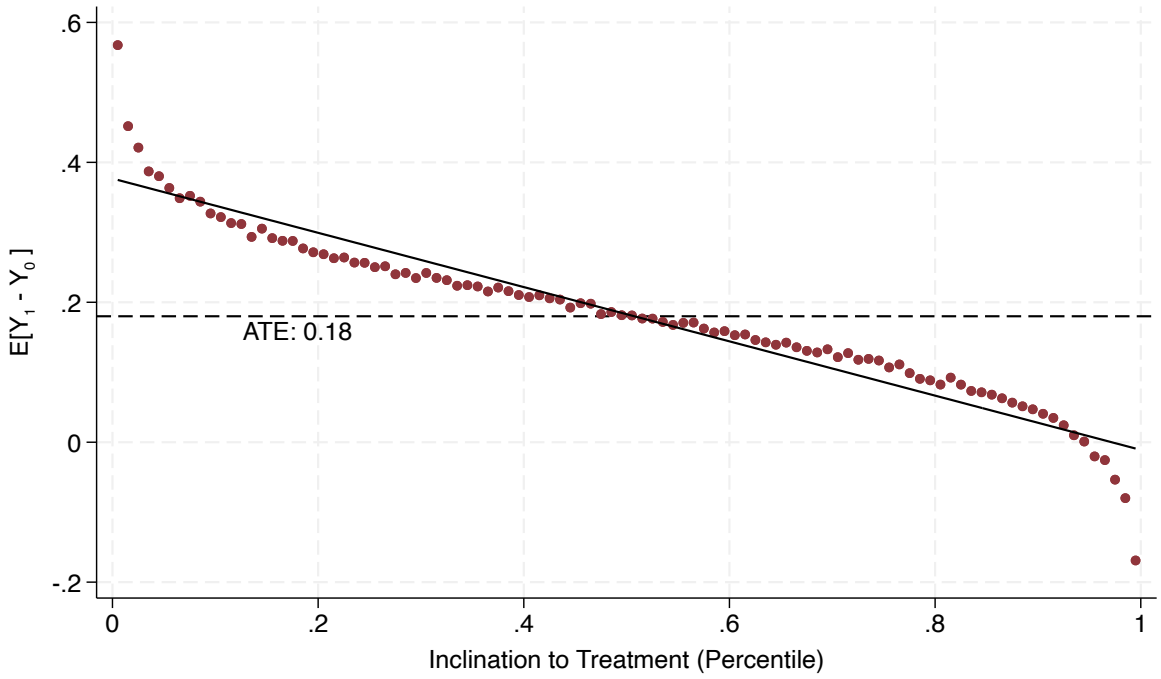


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$$Y_i = \alpha_{\ell(i)} + \beta Z_i + \psi X_i + \pi(X_i \times Z_i) + u_i,$$

where $\alpha_{\ell(i)}$ are lottery strata fixed effects, Z_i is an indicator for being offered a seat at the program of application, X_i is a single baseline student control variable. We estimate this model separately for each X_i listed on the x-axis and a group of students in the same quintile of distance to the nearest oversubscribed program. Data cover all enrolled fifth grade students during the 2004 to 2017 academic years. During this period, all students can only submit exactly one application to their most preferred school choice program. The figure reports the point estimates of β (along the solid line) and the associated 95-percent confidence interval based on robust standard errors that are clustered at the lottery level. The outcome is the mean of standardized math test scores in the years following an application.

Figure 8: Marginal Treatment Effects: Taste-Based Treatment Effect Heterogeneity



Notes: This figure reports the relationship between causal effects and inclination to treatment, a notion of a marginal treatment effect from Walters (2018). The structural model estimates allows us to calculate posterior means of idiosyncratic tastes for choice schools denoted by $\theta_i^* = \theta_i^*(A_i, X_i, D_i, Z_i)$ where A_i is a vector describing student applications to choice programs, X_i is a vector of student attributes, D_i is the relative distance between student i's residence and the school they enroll in, and Z_i is a vector of offers. We then associate θ_i^* with potential outcomes to assess its relationship with achievement levels and gains. We estimate the following empirical outcome model for achievement Y_i via OLS:

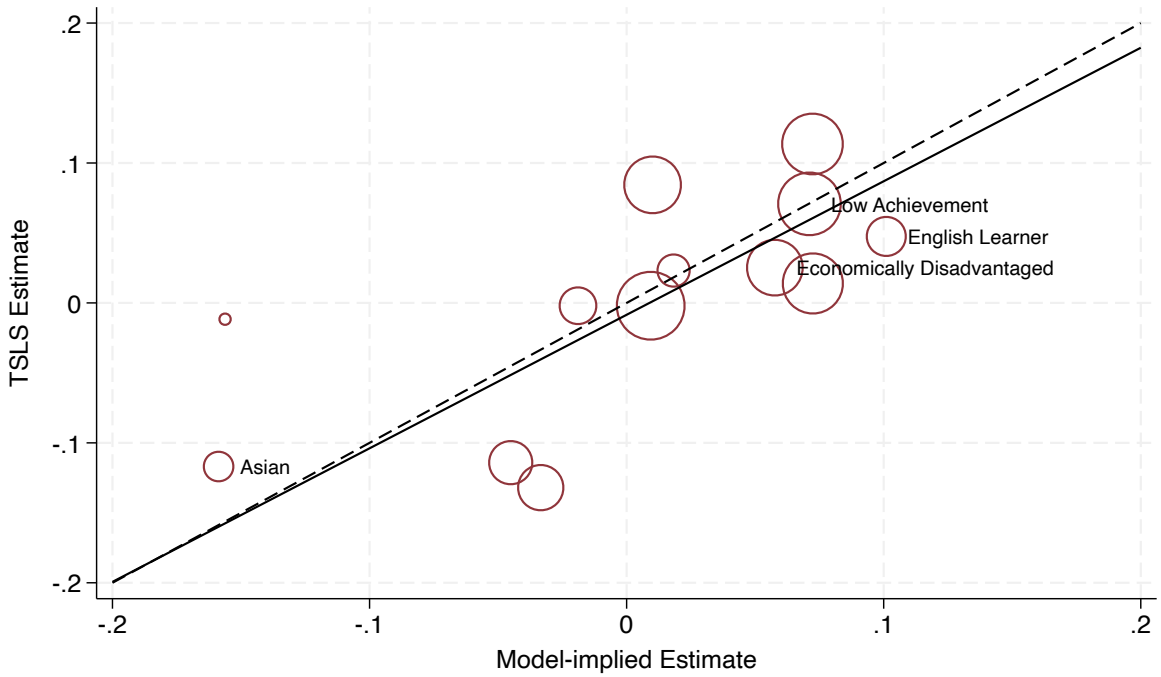
$$Y_i = \underbrace{\alpha_b + \alpha_t + \beta_0 + X_i'\delta_0 + \gamma_0\theta_i^*}_{E[Y_{i0}|X_i,\theta_i^*]} + \underbrace{(X_i \times C_i)'\delta_C + (\theta_i^* \times C_i)'\gamma_C}_{E[Y_{i1}-Y_{i0}|X_i,\theta_i^*]} + e_i,$$

where X_i is a vector of student attributes, α_b are neighborhood fixed effects, α_t are year fixed effects, and u_i is an error term. Variation in offers Z_i and distance D_i identify the selection parameters, where the inclusion of neighborhood and year fixed effects ensures that we leverage policy-induced variation in relative distance. The parametric assumptions on potential outcomes imply that causal effects are $E[Y_{i1} - Y_{i0}|X_i, \theta_i^*] = (X_i \times C_i)'\delta_C + (\theta_i^* \times C_i)'\gamma_C$, indicating there are match effects with respect to observables X_i and tastes θ_i^*. The relationship between percentiles of θ_i^*, denoted by U_i, allows us to define a marginal treatment effect expressed in terms of the relationship between treatment effects and a student's inclination towards treatment as governed by θ_i^*:

$$\Delta(u) \equiv E[Y_{i1} - Y_{i0} \mid U_i = u]$$

We report $\Delta(u)$ in the figure at each percentile of the distribution of U_i. We also report the average treatment effect (ATE) which equals 0.18σ with SE=0.017. Standard errors are robust and clustered at the school level.

Figure 9: Validation Exercise: Comparison of Model-Based and 2SLS Estimated Impacts by Subgroups



Notes: This figure reports the bivariate relationship between subgroup-specific TSLS estimates and our model-based control function (CF) estimates in the lottery sample. Each observation corresponds to a specific subgroup. The dashed line is a 45-degree line, and the solid line is the weighted slope, where the weights are equal to the inverse of the standard error of the TSLS estimate. The slope coefficient equals 0.95 with SE=0.25.

Table 1: LAUSD Summary Statistics by Choice Program Status

	Non-Applicants (1)	Applicants (2)	Estimated Difference (3)
Panel A: Magnet School Application and Attendance			
Applied to a magnet program	0.00	1.00	–
Received a magnet offer	0.00	0.53	–
Enrolled in magnet program	0.05	0.34	–
Panel B: Student Demographics			
Hispanic	0.79	0.54	-0.25***
			(0.02)
Black	0.09	0.13	0.04***
			(0.01)
White	0.07	0.19	0.12***
			(0.01)
Asian	0.03	0.11	0.08***
			(0.01)
Female	0.49	0.51	0.02***
			(0.00)
Poverty	0.75	0.60	-0.14***
			(0.01)
English Learner	0.31	0.10	-0.21***
			(0.01)
Panel C: Standardized Test scores			
ELA	-0.18	0.63	0.81***
			(0.03)
Math	-0.16	0.60	0.77***
			(0.03)
Observations	477,068	116,482	593,550

Notes: Columns (1) and (2) report summary statistics for students who did and did not apply to school choice programs in LAUSD, respectively. Data cover all enrolled fifth-grade students during the 2004 to 2017 academic years. Panel A reports statistics regarding their participation in the school choice process, Panel B reports student characteristics, and Panel C reports standardized test scores.

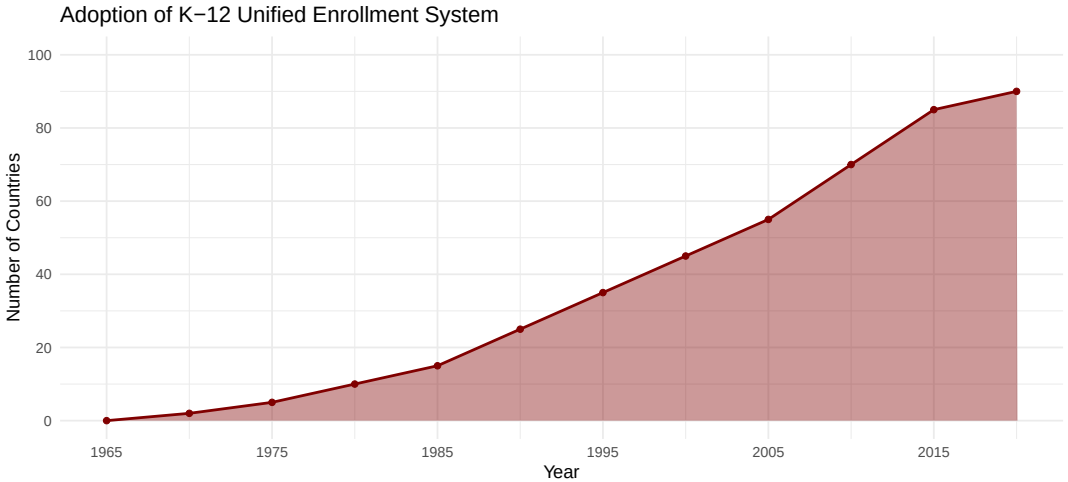
Who Chooses and Who Benefits?
The Limits of Decentralized Choice

Jesse Bruhn (Brown) Christopher Campos (Chicago Booth) Eric Chyn (UT Austin) Antonia Vazquez (UT Austin)

Opportunity Insights Interdisciplinary Seminar

Well-Known Fact: Education Systems Have Widely Adopted Unified Enrollment Systems

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(Source: Neilson 2021)

Less is known about adoption in the United States...

Most school districts offer choice



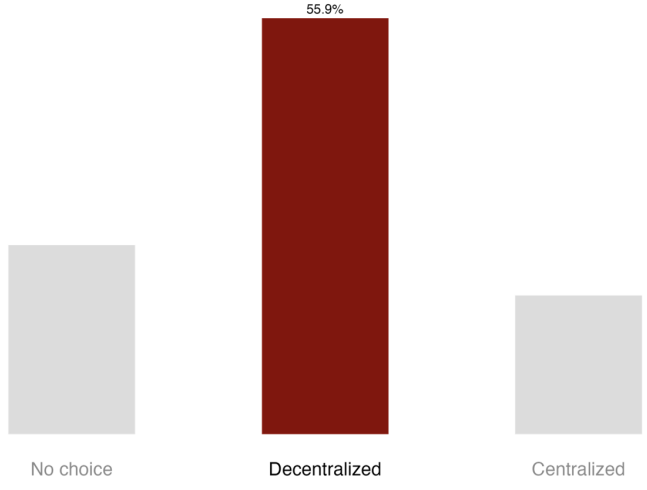
(Source: Bruhn, Campos, Chyn, and Vazquez 2025)

A minority of the school districts that offer choice have fully centralized the process



(Source: Bruhn, Campos, Chyn, and Vazquez 2025)

Lesser known fact: Decentralized systems are the most common



(Source: Bruhn, Campos, Chyn, and Vazquez 2025)

Motivation: Potential implications of decentralized UE systems

- Most existing literature that has studied UE has been agnostic about the selection of students that participate
- Why? Typical choice arguments come to mind
  - → Access: School choice gives students trapped in struggling schools *access* to better schools
  - → Match Quality: Parents can more effectively match students with schools that suit their needs
- But in practice:
  - → Not clear that the parents of students who need it most actually take up these opportunities
  - → Information frictions are large. Who are they largest for?
  - → Do families actually know match quality *before* trying or experiencing the school?
- Three new stylized facts to motivate paper:
  - → Do decentralized UE systems reach the students who need them most?
  - → Do choice programs produce better outcomes for students?
  - → How prevalent are intra-district choice programs?

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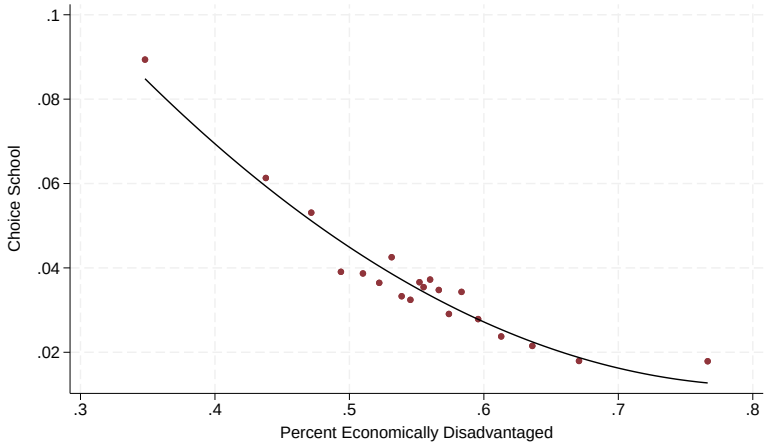
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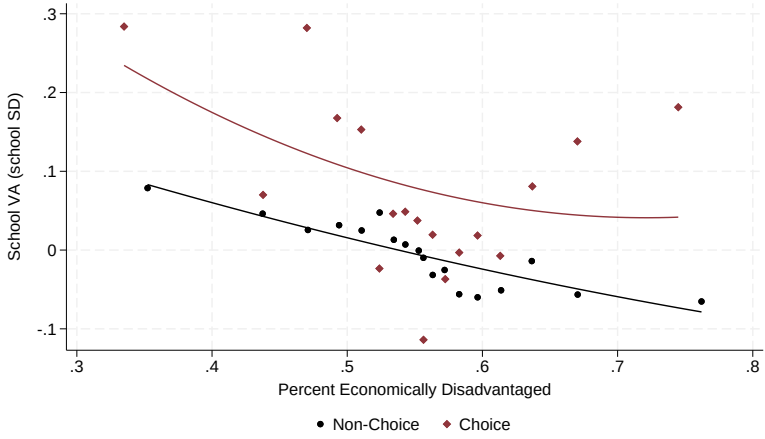
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Choice schools in decentralized districts tend to educate economically advantaged students



(Source: NCES Common Core Data)

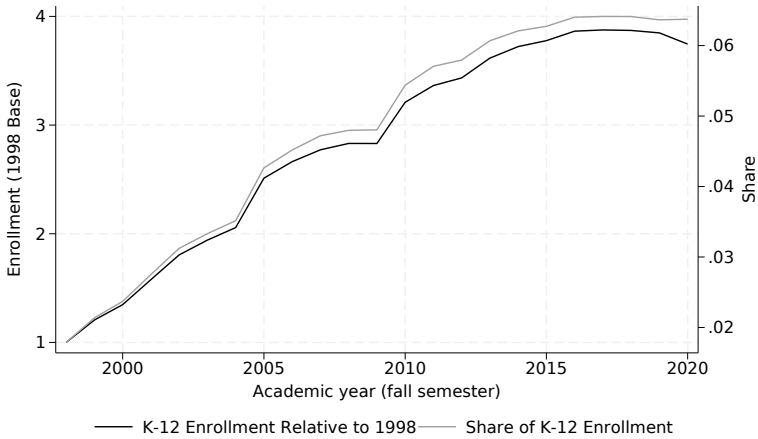
Choice schools in decentralized districts also tend to be higher value-add



(Source: NCES Common Core Data and Stanford Education Data Archive)

A fourfold increase in the number of students educated in district-run choice programs

Definition: Any non-charter choice school that is run by a public school district



Source: NCES Common Core Data

This Paper

Setting:

- Los Angeles Unified School District that operates the largest decentralized UE system in the nation

Three Questions:

1. Who participates in decentralized systems with unified enrollment?
2. What are the potential gains for applicants and non-applicants in decentralized systems?
3. What are the potential impacts of alternative policies?
   - → Targeted information policies aimed at those least likely to participate
   - → Centralization of participation, e.g., New York City

Preview of Results:

1. Economically and academically advantaged students are most likely to participate in decentralized systems
2. Negative-roy selection on potential achievement gains; the least likely to participate stand to gain the most
3. (Preliminary and suggestive): Centralization or targeted information policies have the potential to produce substantial reductions in inequality in educational outcomes

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Contributions

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- Centralized UE systems can elevate student outcomes, reduce educational inequality, and spur competition (Campos and Kearns 2024)
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  - → Decentralized UE is understudied
  - → Opt-in nature has implications for inequality

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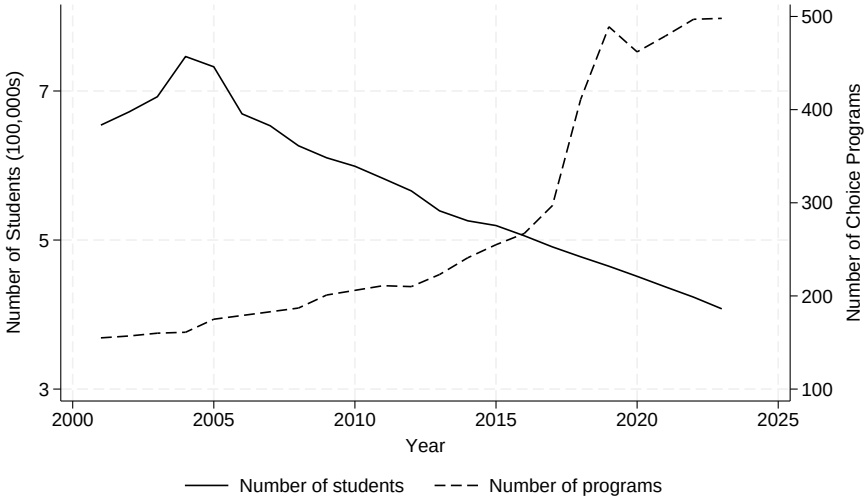
Roadmap

1. Setting and Data: Who participates, and what are they choosing?
2. Lottery Evidence: What are the benefits to participants?
   - → Using two decades of lottery records, document reduced form evidence of achievement impacts
   - → Document sources of treatment effect heterogeneity
3. Model and Treatment Effect Estimates: Who benefits the most?
   - → Model both the decision to apply and enroll to measure idiosyncratic taste heterogeneity governing these decisions
   - → Key question: Is taste heterogeneity—net of distance, application costs, and other observables—associated with causal effects?

LA's Unified Enrollment Choice System

- LA's UE choice system would rank as the 35th largest school district in the country if it were its own district
- In 2024, there were roughly 300 programs students could apply to
- In 2024, roughly 20% of families applied to a choice program
- The typical student lives roughly 0.7 miles away from their neighborhood school and 3.7 miles away from a popular choice program
- The number of choice options has substantially increased in the past decade

In LAUSD, choice program expansion is likely a response to declining enrollment



The Details

The Mechanism

- First-preference-first application system (i.e., the Boston mechanism)
- Between 2000-2013, applicants could rank at most one option

Participation

- Like most large urban school districts, participation is optional
- If a student does not participate, they get defaulted to their neighborhood school

Priorities and Allocation

- Students can gain geographic, sibling, waiting list, and race priority points
- Oversubscribed schools $\Rightarrow$ randomized **lotteries** by priority groups

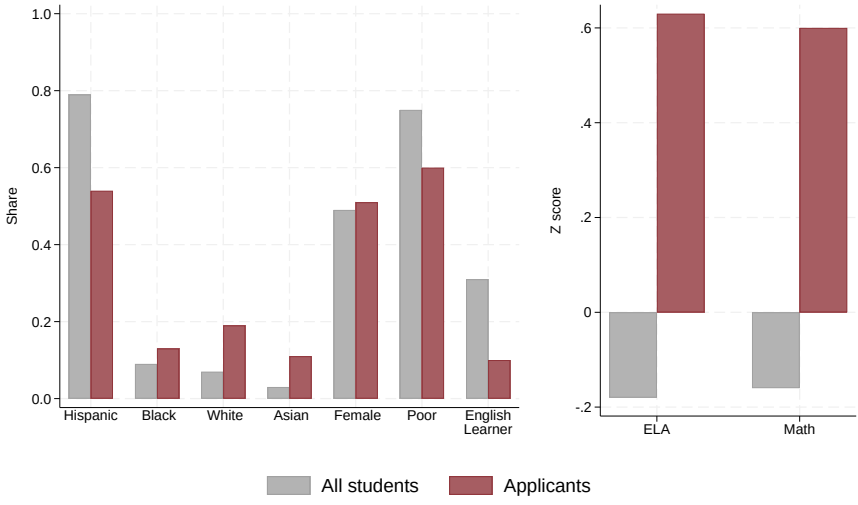
Transportation

- Elementary: Transportation available if the student resides over one mile away from the school
- Secondary: Transportation available if the student resides over three miles away from the school

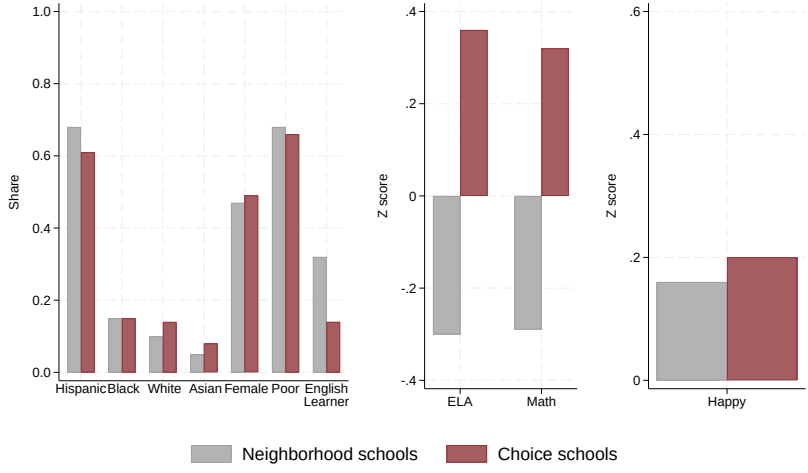
Data

- **Administrative student records (2000-2024)**
  - → Demographics
  - → Addresses
  - → Test scores
  - → Survey-based non-cognitive outcomes (2016-2024)
- **Choice program records (2000-2024)**
  - → Applications
  - → Program capacities
  - → Admission records
  - → Lottery numbers

Who applies to choice schools?



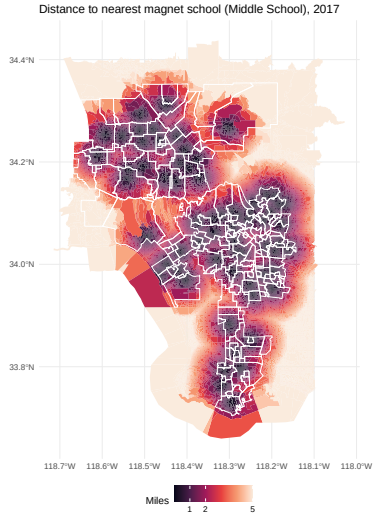
Characteristics of choice schools



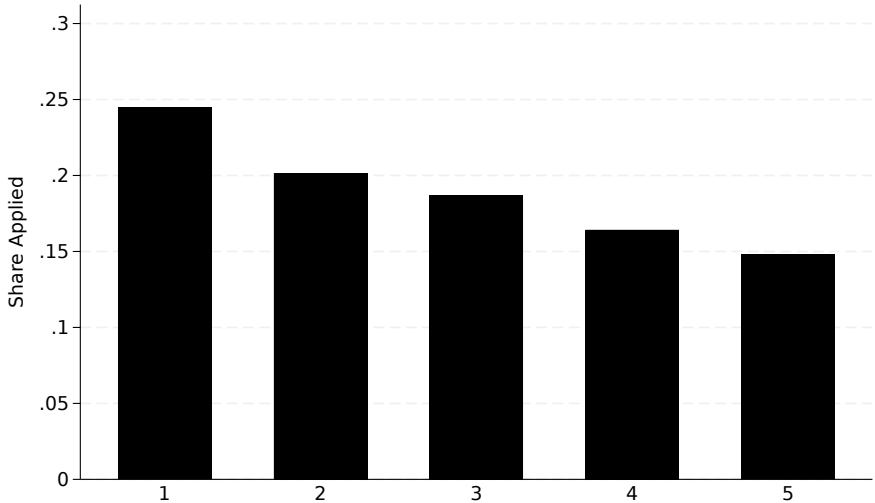
Map of Choice Programs
Differences in Per-pupil Expenditures

Choice Program Availability

Relative distance to nearest choice school



Relative Distance Predicts Applying



Empirical Strategy: Causal Impacts of Admissions to Choice Programs

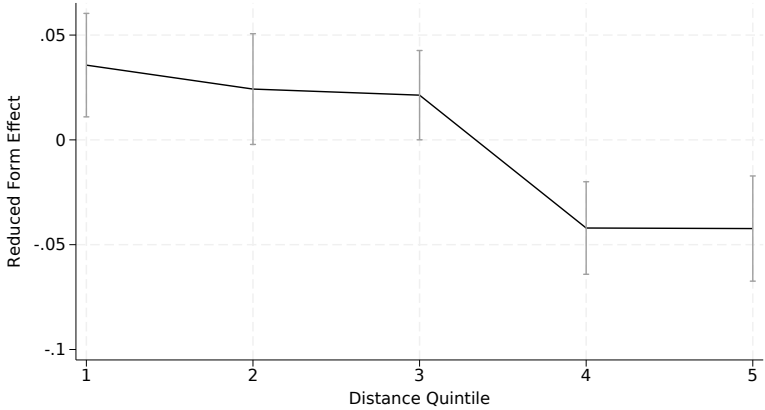
- Oversubscribed programs use priority group lotteries to allocate offers to students
- Estimates causal impacts of receiving an offer using the following model:

$$Y_i = \alpha_{\ell(i)} + \beta Z_i + X_i'\gamma + u_i$$

  - → $\alpha_{\ell(i)}$ are lottery strata dummies (based on program, year, grade, and race)
  - → Z_i: indicator for being offered a seat at your most-preferred magnet program
  - → X_i: vector of baseline student controls
  - → β: intent-to-treat effect of choice enrollment
- Observables are balanced within lotteries ▸ Lottery Balance

Distance strongly predicts treatment effects

Math ITT Effects

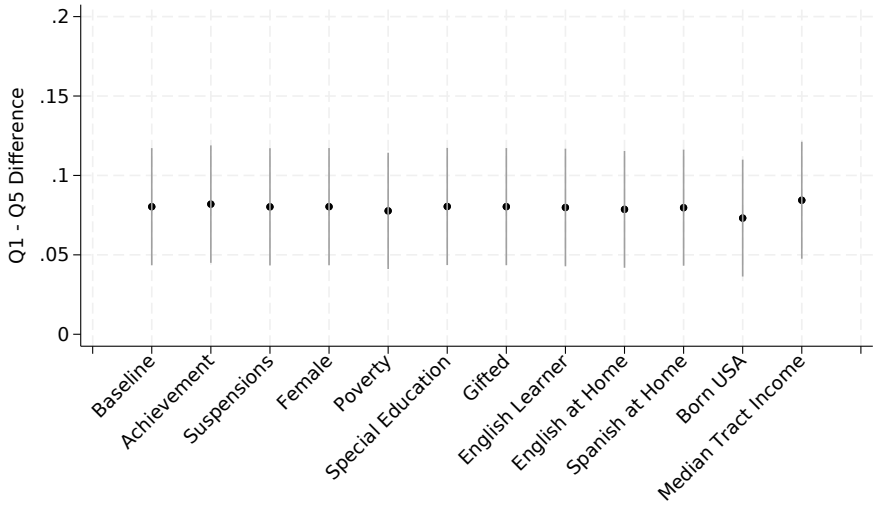


▸ ELA Effects ▸ TSLS Estimates

Distance effects not explained by other observable treatment effect heterogeneity

- Could this pattern be due to treatment effect heterogeneity with other observables correlated with distance (e.g., more advantaged students live closer to choice programs and benefit more)?
- Augment model with interactions between X_i and Z_i and report the distance Q1-Q5 difference from the previous figure

Distance effects not explained by other observable treatment effect heterogeneity



Building towards a better understanding of the treatment effect heterogeneity

What is distance heterogeneity capturing?

- Distance could be capturing how taste heterogeneity relates to causal effects but a host of other explanations loom
- Can we isolate the relationship between preference heterogeneity and causal effects?

Beyond Lottery Effects

- Our approach: Model preferences, application decisions, enrollment decisions, and outcomes to assess the connection between tastes and causal effects
- Identification will require instruments that affect application and enrollment decisions but do not directly influence outcomes
  - → Relative distance to nearest choice program
  - → Offers to choice programs
- Equipped with a model that captures idiosyncratic tastes governing selection into application and enrollment, we can estimate treatment effects for populations not yet reached by the existing system

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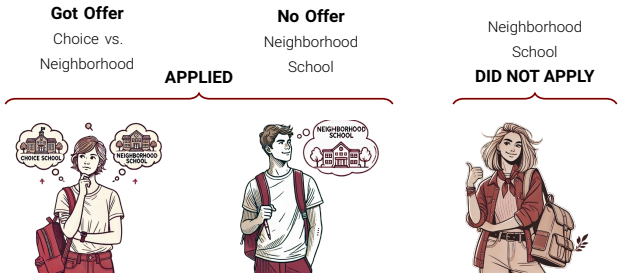
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Model Overview: Application Decision



- Student decides whether to apply to a choice school
- School j utility depends on:
  - → Observed characteristics X_i
  - → Relative distance to program D_{ij}
  - → Idiosyncratic choice school taste θ_i
- Decision to apply depends on:
  - → School j utility, $v_j(X_i, \theta_i, D_{ij})$
  - → Application cost, $c(A_i, X_i, \eta_i)$
  - → Perceived admissions chances, π_j, conditional on applying
- Choice of application induces a lottery; students make decisions based on their expected utility

Model Overview: Enrollment Decision



- If applied and received an offer, student decides whether to enroll in the choice program or remain in the neighborhood school:
  - → School utilities, $v_j(X_i, \theta_i, D_{ij})$
  - → Post-lottery shock, ξ_{ij}
- If no offer (or no application), the student enrolls in the neighborhood school

Model Overview: What is θ?





- Families differ in observables that correlate with their choices
- We want to isolate variation in tastes for choice **within** observationally similar parents, where idiosyncratic preferences (θ) can vary

Model Overview: What is θ?



- Parents with identical X_i and D_i have similar observable preference and cost heterogeneity, so differences in θ can reflect differences in
  - $\rightarrow$ parental motivation
  - $\rightarrow$ access to information
- Identification of $F(\theta)$: Among observationally similar parents, if we observe one applying to a choice program and the other does not, then we infer the applicant has higher θ_i. Variation in these choices across combinations of (X_i, D_i) allows us to learn about the variance of θ_i

Model Overview: Achievement Exams

- After enrollment, students take achievement exams
- Test scores, Y_i, are observed
- Key question: What is the relationship between $E[Y_{i1} - Y_{i0}|\theta_i]$ and θ_i?



▸ Model Details

Intuition for the Empirical Outcome Model

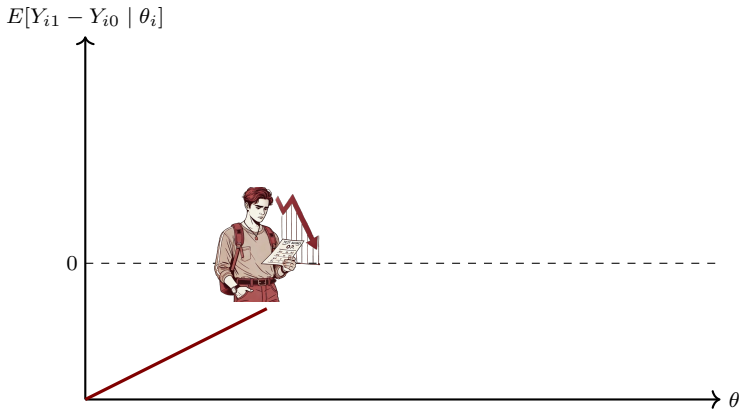
- Equipped with model estimates we can estimate posterior means of θ_i via simulation Details

$$\theta_i^* \equiv \theta^*(A_i, S_i, X_i, D_i, Z_i) = E[\theta_i | A_i, S_i, X_i, D_i, Z_i]$$

- We incorporate θ_i^* into an outcome equation to estimate heterogeneous causal effects
  - → θ_i^* serves as a control function to account for selection
  - → Distance, D_i, and offers, Z_i, provide variation that identifies selection parameters
  - → We can assess the relationship between θ_i^* and $E[Y_{i1} - Y_{i0} \mid X_i, \theta_i^*]$

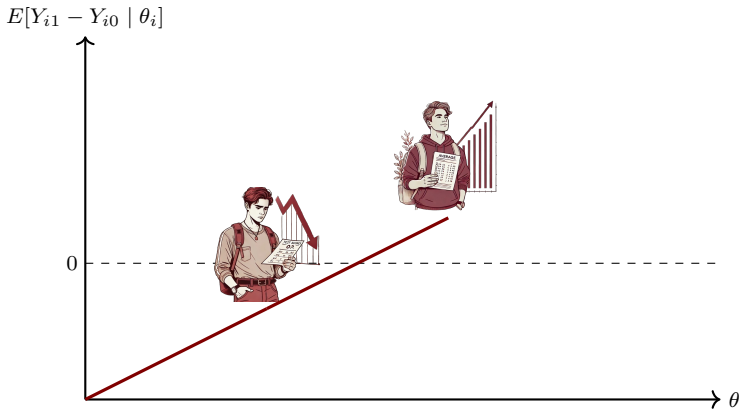
Intuition for the Empirical Outcome Model

Is there a positive association between tastes and test score gains?



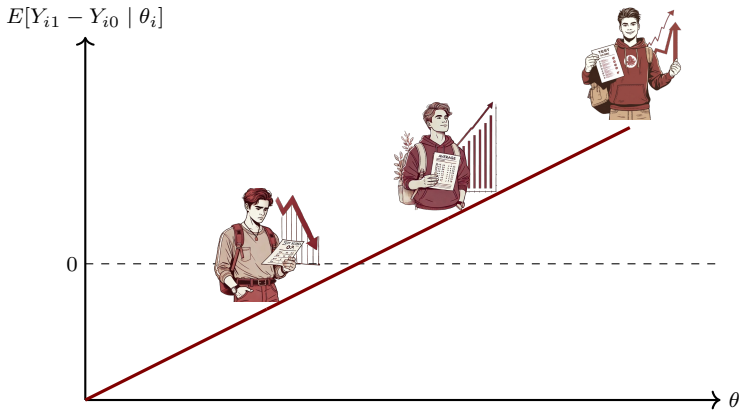
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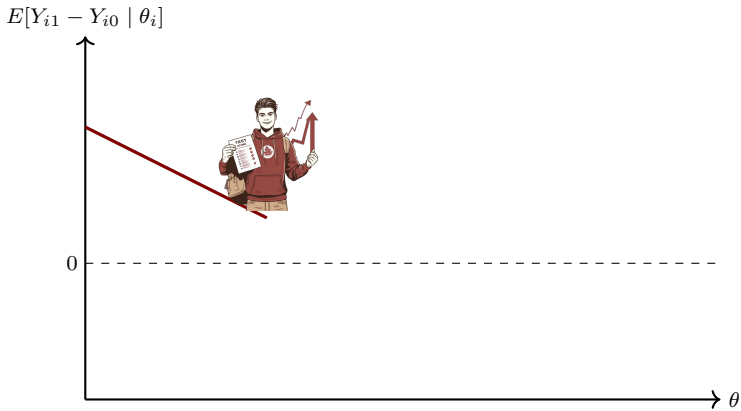
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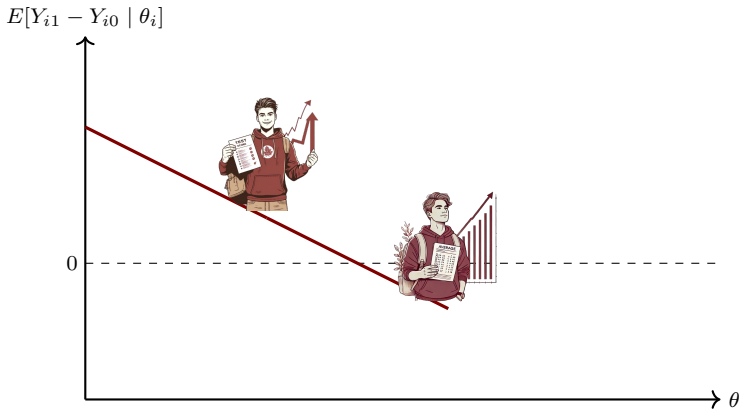
Intuition for the Empirical Outcome Model

Or is the association between tastes and test score gains negative?



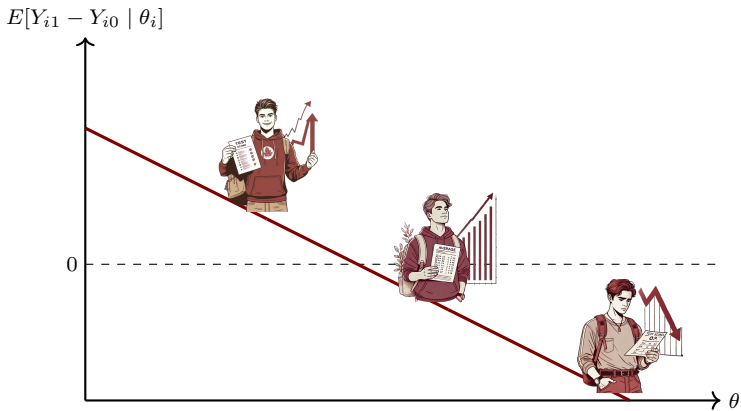
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Intuition for the Empirical Outcome Model

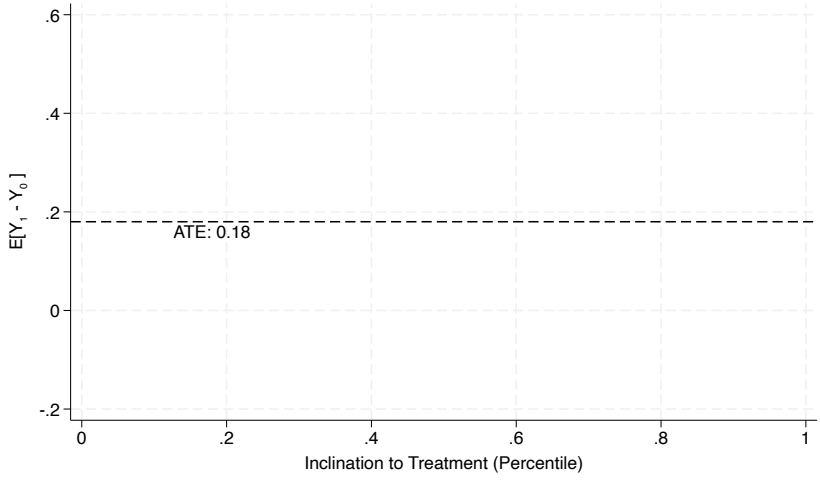
- We order θ_i^* in terms of percentiles, generating a close resemblance with marginal treatment effects
- Key intuition: How do treatment effects vary with idiosyncratic inclination to treatment? Details

  → Relationship between percentiles of θ_i^*, denoted by U_i, is one notion of a marginal treatment effect (Walters 2018):

$$\Delta(u) \equiv E[Y_{i1} - Y_{i0} \mid U_i = u]$$

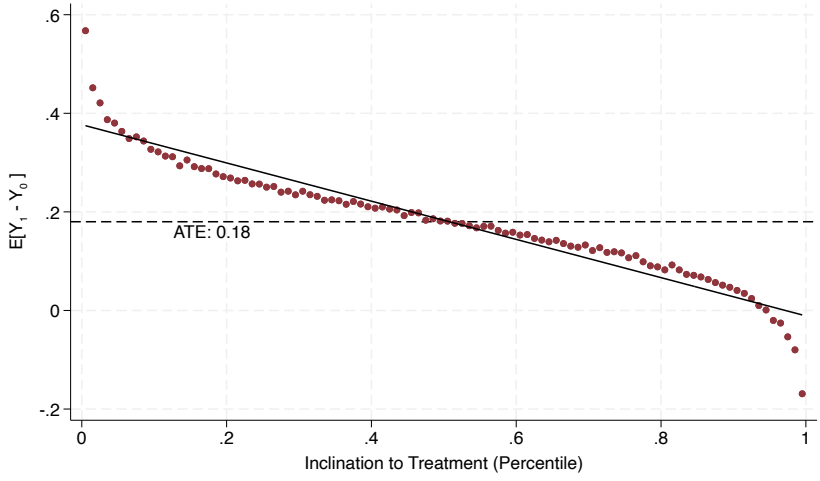
  → $\Delta(u)$ informs about the relationship between causal effects and idiosyncratic "inclination" to treatment

We estimate an average treatment effect of 0.18σ



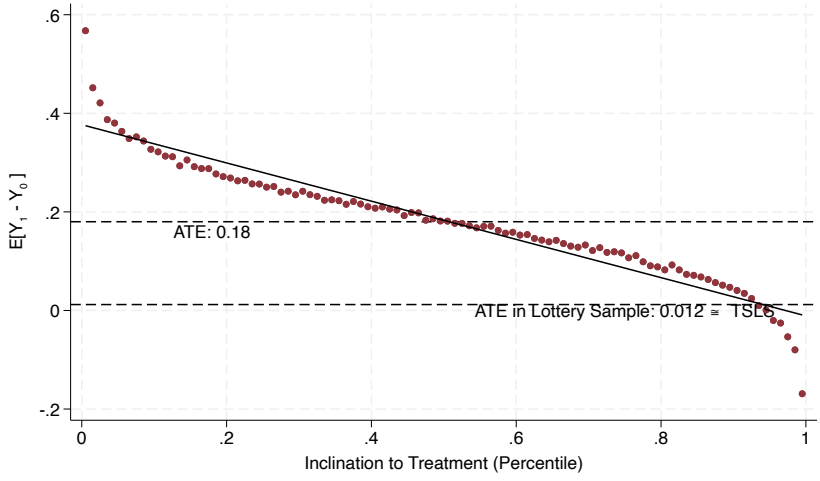
▸ Model Estimates ▸ Distribution of U_i ▸ Observable Heterogeneity ▸ Validation Exercise

Causal effects are highest for those with the lowest inclination to participating (lowest θ)



▸ Model Estimates ▸ Distribution of U_i ▸ Observable Heterogeneity ▸ Validation Exercise

Model ATE in the lottery sample roughly matches TSLS



▸ Model Estimates ▸ Distribution of U_i ▸ Observable Heterogeneity ▸ Validation Exercise

Next Steps

1. Formalize a validation exercise

   → Further scrutinize the internal validity of model-based estimates

   → Kline and Walters 2019: *An estimator derived from a properly specified model of treatment assignment and potential outcomes should come close to matching a nonparametric IV estimate of the same parameter*

   → Current results: Evidence

2. Counterfactual policy analysis

   → Evidence suggests boosting application rates could improve outcomes but capacity constraints and other countervailing forces may attenuate potential gains

   → Two counterfactual policies in our framework:

   - Targeted information campaigns to induce application from those with lowest θ_i
   - Centralization of applications, similar to NYC Public Schools, analogous to eliminating application costs

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Concluding Thoughts

- **New fact:** Decentralized UE is the most common way school districts have organized their school choice offerings
  - → Decentralized UE is understudied
  - → The opt-in design has natural implications for inequality that we study
- **Who chooses:** Opt-in systems tend to segment the public education system based on prior achievement and socioeconomic status, with more advantaged students being more likely to participate
- **Who benefits:** Choice programs produce sizable average achievement effects (0.16σ) but do not reach the students who would benefit the most
- **Takeaways and implications for policy:**
  - → Decentralized UE systems not only segment public education systems, they also exacerbate inequality in educational outcomes
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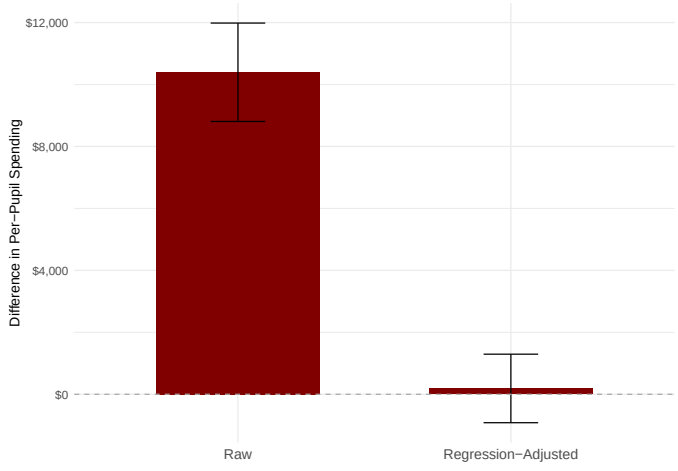
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Thank you!

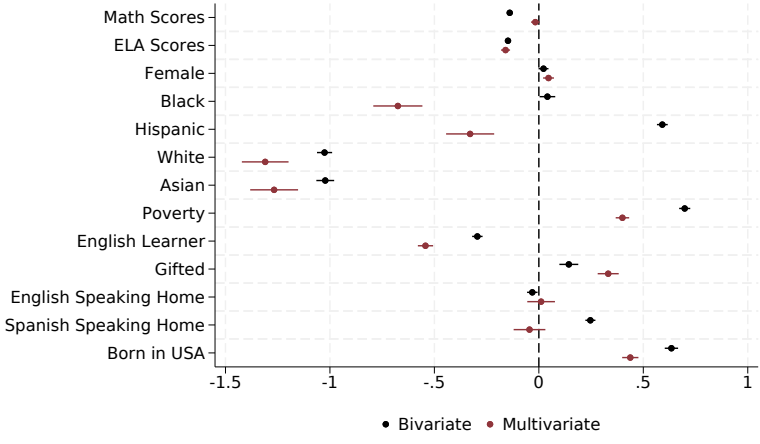
Christopher.Campos@chicagobooth.edu

Choice programs operate with lower per-pupil expenditures



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Distance Correlates



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Balance Table

	Difference	F-Score	P-Value
Female	-0.001	0.036	0.850
	(0.006)		
Special Education	-0.002	2.020	0.155
	(0.002)		
In Poverty	-0.008	2.117	0.146
	(0.005)		
Parent College Grad	0.000	0.000	0.992
	(0.006)		
English Spoken in Home	0.003	0.396	0.529
	(0.005)		
Born in the US	0.004	1.404	0.236
	(0.003)		
Lagged ELA Score	-0.024	6.777	0.009
	(0.009)		
Lagged Math Score	-0.028	9.650	0.002
	(0.009)		
Jointly Zero SUR		0.018	
Jointly Zero RI		0.023	

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Setup

- Students can apply to choice schools $j \in \mathcal{J}$ or default to their neighborhood school
  - → $A_i = (A_{i1}, \cdots, A_{iJ})$ summarizes students application decisions
  - → Students can apply to at most one program: $\sum_{j=}^{J} A_{ij} \leq 1$
  - → $Z_i = (Z_{i1}, \cdots, Z_{iJ})$ summarizes their offers
  - → Students receive at most one offer: $\sum_{j=}^{J} Z_{ij} \leq 1$
- A centralized system outputs offers conditional on applications and students make enrollment decisions
  - → Offers at school j occur with probability π_j
  - → A student with an offer decides between the offered school and their neighborhood school
- Students take exams and have outcomes Y_i

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Preferences

$$V_{ij} = U(Y_{ij}, X_i, D_{ij}, \omega_{ij})$$

- Y_{ij} : potential achievement of student i at school j
- X_i : student demographics
- D_{ij} : distance from student i's residence to school j
- ω_{ij}: residual unobserved preference heterogeneity
- Define utility relative to neighborhood school enrollment

$$V_{ij} - V_{i0} \equiv \nu_j(X_i, D_{ij}, D_{i0}) + \Psi_{ij}$$

$\rightarrow$ Dependence of Y_{ij} on preferences embodied through Ψ_{ij} and X_i

The key unobservables

- The unobserved preference heterogeneity can be decomposed

$$\Psi_{ij} = \psi_{ij} + \xi_{ij}$$

  → ψ_{ij} : unobserved pref. heterogeneity known at application decision

  → ξ_{ij} : post-lottery shock that is EVT1

- ψ_{ij} can be further decomposed

$$\psi_{ij} = \theta_i + \tau_{ij}$$

  → θ_i : unobserved taste for choice programs

  → τ_{ij} : school-specific preference heterogeneity

- θ_i and τ_{ij} are the key unobservables eventually linking preferences to outcomes

Enrollment Decision

- If a student receives an offer from the school they applied to, their choice set is $\mathcal{O}(Z_i) = \{j \mid Z_{ij} = 1\} \cup \{0\}$
- Student i with an offer at j chooses school S_i such that

$$S_i = \begin{cases} j & \text{if } V_{ij} - V_{i0} > 0 \\ 0 & \text{otherwise} \end{cases}$$

- Before the post-lottery logit shock to preferences, students' expected utility is

$$w(Z_i|X_i, D_i, \theta, \tau_i) = \log\left(1 + \sum_{j=1}^{J} Z_{ij} \times \exp\left(v_j(X_i, D_{ij}, D_{i0}) + \theta_i + \tau_j\right)\right)$$

→ Students take this expected utility into account when deciding whether to apply or not

Application Decision

- Because students can apply to at most one school, the centralized assignment mechanism operates as if separate lotteries are run with assignment probability π_{ij}

  → Offer probabilities vary by student race

- The probability mass function of offers, conditional on applying is

$$f(Z_i|A_i) = \prod_{j=1}^{J} \{A_{ij}[\pi_j Z_{ij} + (1-\pi_j)(1-Z_{ij})] + (1-A_{ij})(1-Z_{ij})\}$$

- The optimal application decision for students is therefore

$$A_i = \arg\max_{a \in \mathcal{J}} \sum_{z \in \mathcal{J}} [f(z|a) w(z|X_i, D_i, \psi_i)] - c(a, X_i, \eta_i)$$

  where $c(a, X_i, \eta_i)$ is an application cost

Solving the model

1. Enrollment Decisions

   → Student receive an offer vector with a single offer $Z_i = (Z_{i1}, \cdots, Z_{iJ})$ and face offer set $O(Z_i) = \{0\} \cup \{j \mid Z_{ij} = 1\}$

   → Student chooses school

$$S_i = \arg \max_{j \in O(Z_i)} V_{ij} - V_{i0}$$

2. Students Apply to Schools

3. Student i's likelihood contribution is $\mathcal{L}$ depends on:

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Solving the model

1. Enrollment Decisions
2. Students Apply to Schools

   → To form applications, students consider potential utility from different application/offer combinations

$$w(Z_i|X_i, D_i, \psi_i) = E[\max_{j \in O(Z_i)} V_{ij} - V_{i0}|X_i, D_i, \psi_i]$$

   → Expected utility weighs $w(Z_i|A_i, X_i, D_i, \psi_i)$ with offer probability mass function $f(Z_i|A_i)$

   → Students face application costs $c(A_i, X_i, \eta_i)$

   → Students choose an application that maximizes their utility

$$A_i = \arg\max_a \sum_z f(z|a)w(z|X_i, D_i, \psi_i) - c(a, X_i, \eta_i)$$

3. Student i's likelihood contribution is $\mathcal{L}$ depends on:

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Solving the model

1. Enrollment Decisions
2. Students Apply to Schools
3. Student i's likelihood contribution is $\mathcal{L}$ depends on:
   - $\rightarrow$ $P(S_i)$: Probability of enrolling in school S_i conditional on offers
   - $\rightarrow$ $P(A_i)$: Probability of submitting application A_i
   - $\rightarrow$ $P(Z_i|A_i)$: Probability mass function of offers, conditional on application
   - $\rightarrow$ Estimate via simulated maximum likelihood

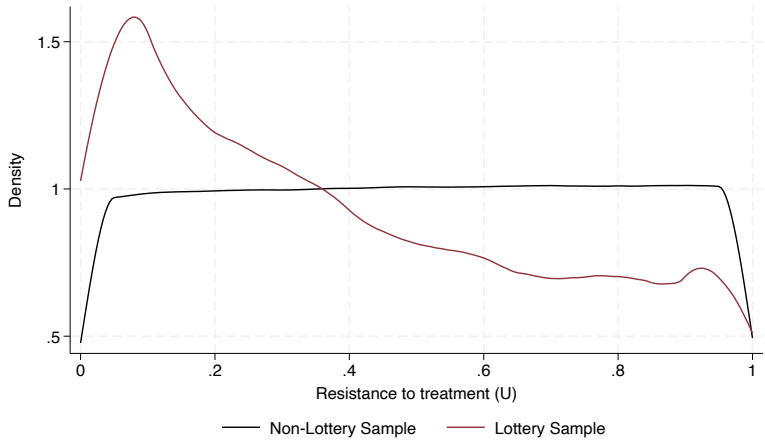
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Model Estimates

	Choice School Preference	Distance Disutility	Log Application Costs
Baseline Utility	12.616	-1.870	4.726
	(0.023)	(0.081)	(0.006)
Female	-10.295	0.887	2.097
	(0.012)	(0.040)	(0.037)
Black	-0.732	0.372	4.795
	(0.010)	(0.032)	(0.714)
Hispanic	-5.924	0.801	0.087
	(0.014)	(0.046)	(0.357)
Poverty	2.143	-0.292	-0.188
	(0.012)	(0.041)	(0.159)
LEP	-6.202	0.441	0.905
	(0.009)	(0.034)	(0.242)
English at home	-0.341	-0.046	0.031
	(0.014)	(0.045)	(0.324)
Reading Scores	4.784	-0.296	0.026
	(0.029)	(0.104)	(0.382)
Math Scores	-0.075	-0.080	-0.278
	(0.029)	(0.108)	(0.265)
Distance Squared		0.031	
		(0.669)	

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Distribution of U_i by Lottery Status



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Calculating Posterior Means, θ_i^*

Want to calculate

$$\theta_i^* \equiv E[\theta_i|A_i, Z_i, S_i] = \int \theta_i \cdot p(\theta_i|A_i, Z_i, S_i)\, d(\theta_i)$$

By Bayes' Rule, we know

$$p(\theta_i|A_i, Z_i, S_i) = \frac{p(A_i, Z_i, S_i|\theta_i) \cdot p(\theta_i)}{p(A_i, Z_i, S_i)}$$

We approximate using weighted simulation draws (r)

$$E[\theta_i|A_i, Z_i, S_i] \approx \sum_r w_{ir} \cdot \theta_{ir}$$

where weights are proportional to the posterior density

$$w_{ir} \propto p(A_i, Z_i, S_i|\theta_{ir}, \tau_{irj}) \cdot p(\theta_{ir}, \tau_{irj})$$

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Empirical Model

We estimate the following model via OLS:

$$Y_i = \underbrace{\beta_0 + X_i'\delta_0 + \gamma_0\theta_i^*}_{E[Y_{i0}|X_i,\theta_i^*]} + \underbrace{(X_i \times C_i)'\delta_C + (\theta_i^* \times C_i)'\gamma_C}_{E[Y_{i1}-Y_{i0}|X_i,\theta_i^*]} + u_i$$

- C_i is an indicator for enrolling in a choice school
- θ_i^* is the posterior mean of θ_i Details
  - → Serves as a control function to account for selection
  - → We can assess the relationship between θ_i^* and $E[Y_{i1} - Y_{i0} \mid X_i, \theta_i^*]$
- Translating θ_i^* into utility costs and ordering in terms of percentiles generates a close resemblance with marginal treatment effects. How do treatment effects vary with unobserved resistance to treatment? Details
  - → Relationship between percentiles of $-\theta_i^*$, denoted by U_i, is one notion of a marginal treatment effect (Walters 2018):

$$\Delta(u) \equiv E[Y_{i1} - Y_{i0} \mid U_i = u]$$

  - → $\Delta(u)$ informs about the relationship between causal effects and idiosyncratic "resistance" to treatment

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Relationship between preferences and causal effects

Define the utility cost index

$$P_i = -\theta_i$$

- Index captures utility cost for choice programs, net of other observables and distance
- θ_i enters both application and enrollment stages so informative about frictions into applying
- Individuals with higher $P(\theta_i)$ face higher "costs" of applying and enrolling
- Let $F_P(\cdot)$ represent the CDF of the index and $U_i = F_P(P_i)$ denote student i's percentile
- Define mean potential outcomes conditional on $U_i = u$ as

$$m_0(u) = E[Y_{i0} \mid U_i = u] \qquad m_1(u) = E[Y_{i1} \mid U_i = u]$$

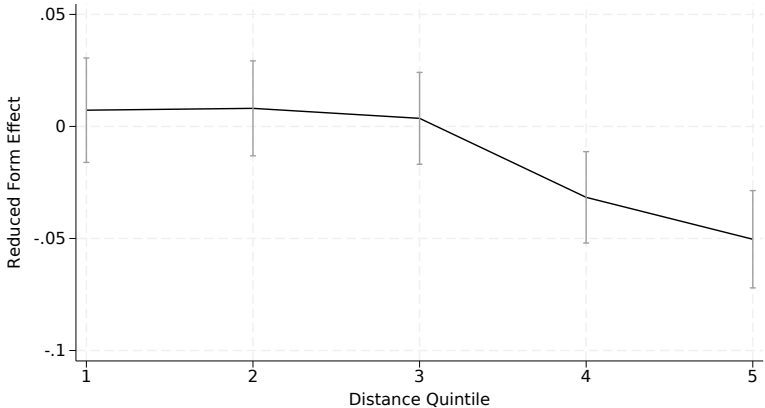
- Define the implied marginal treatment effect as

$$\Delta(u) = m_1(u) - m_0(u)$$

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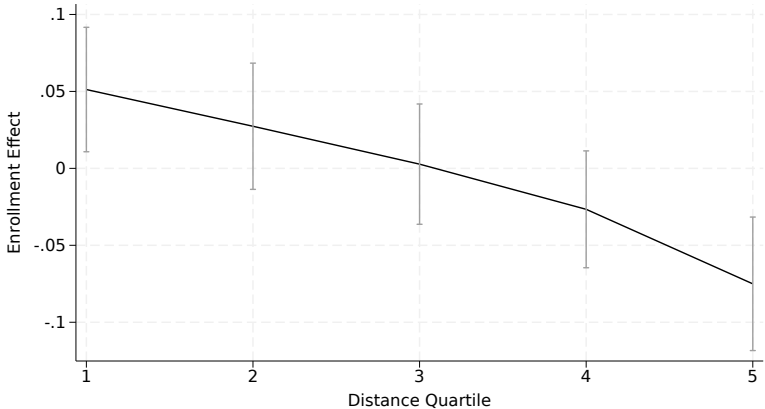
Distance strongly predicts treatment effects

ELA ITT Effects



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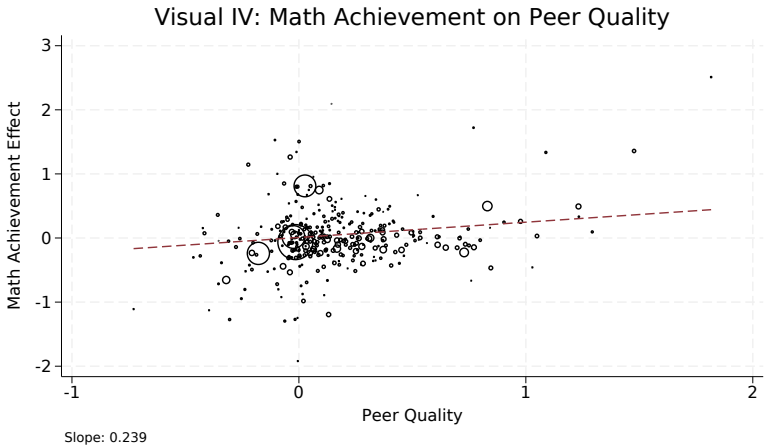
TSLS Estimates



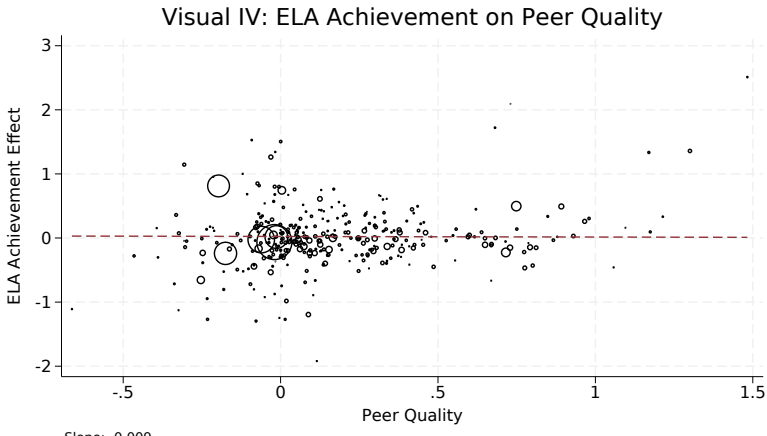
H0 Equal Effects p-value: 0.00
H0 Jointly Zero p-value: 0.00

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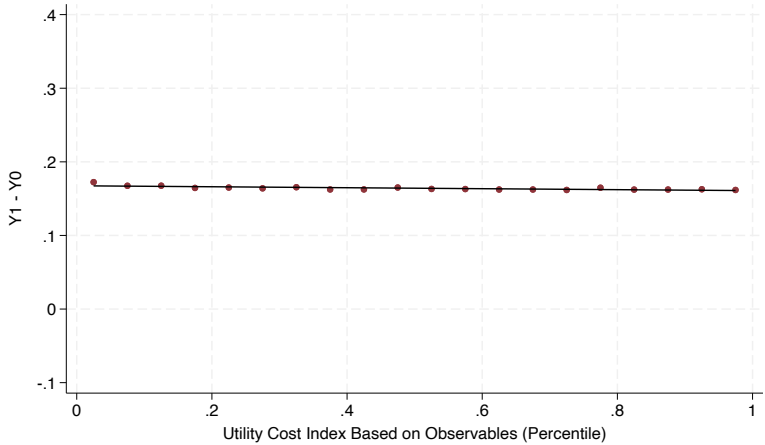
Math Peer Effects



ELA Peer Effects

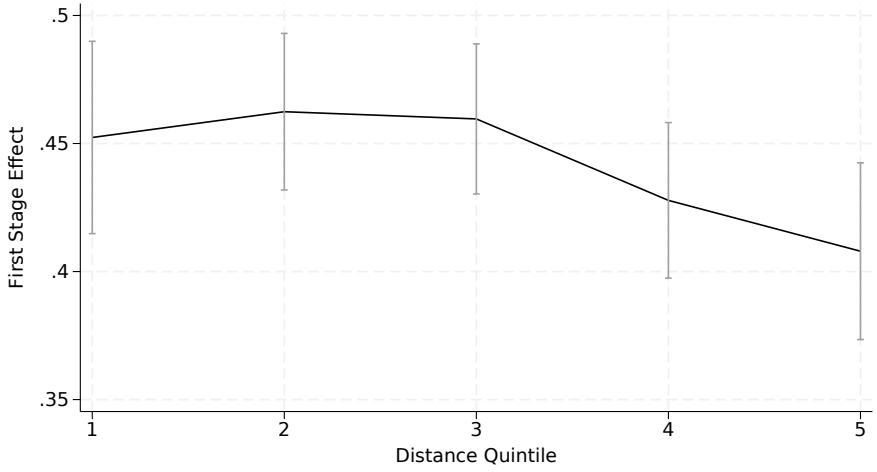


Observable preference heterogeneity does not explain the pattern

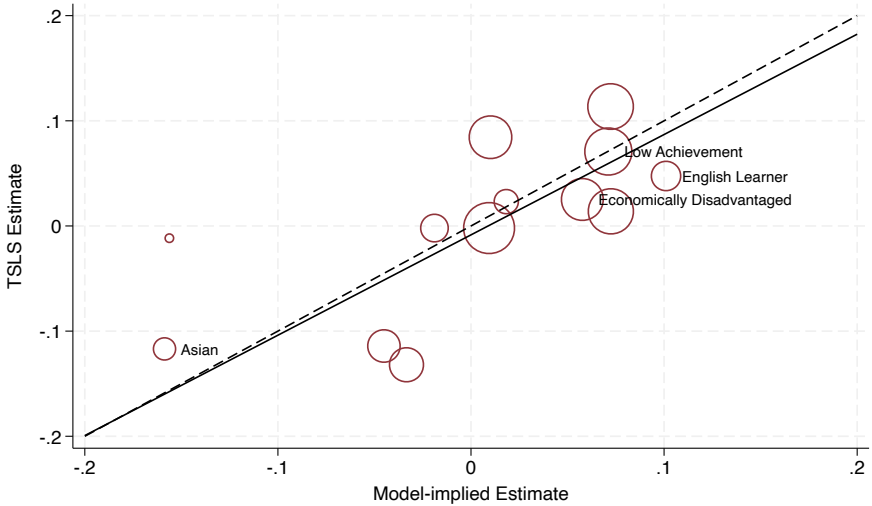


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Motivation: Offer affect enrollment and take up varies with distance



Covariate-specific estimates are forecast unbiased



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