Who Chooses and Who Benefits?
The Design of Public School Choice Systems

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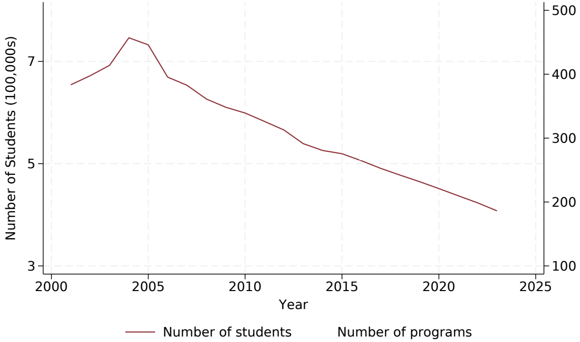
NBER Fall Education Meeting

December 2025

Well-Known Fact: There has been pronounced enrollment decline in urban US school districts



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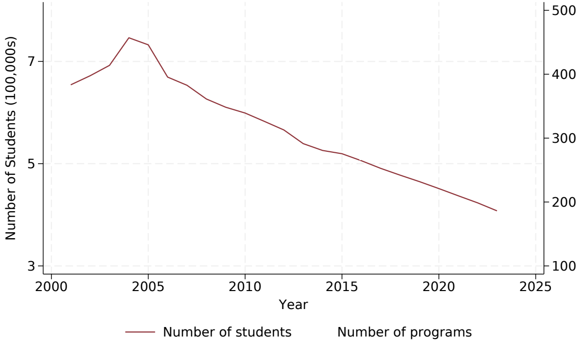
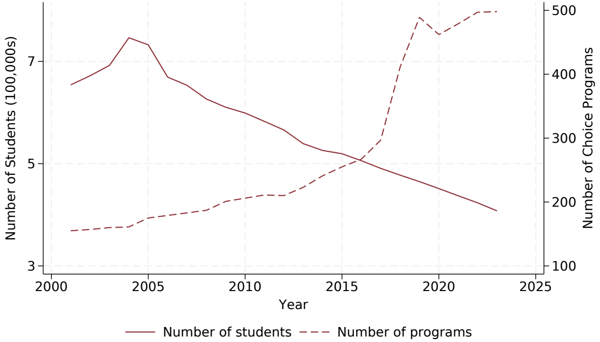


- In LA, roughly 50% drop in enrollment from the peak in 2004

Lesser-Known Fact: School districts are responding by expanding public school choice



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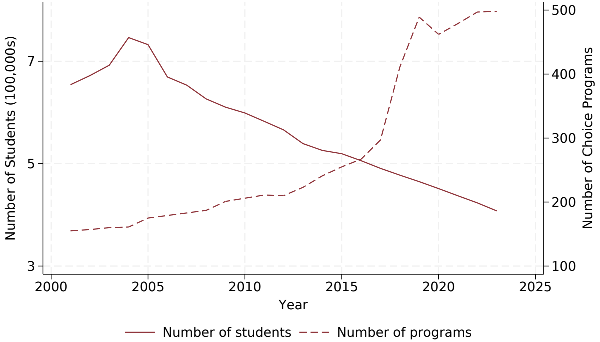

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- Patterns are not unique to Los Angeles

Evidence

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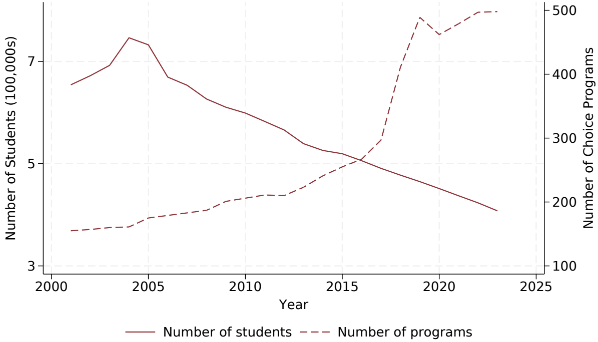
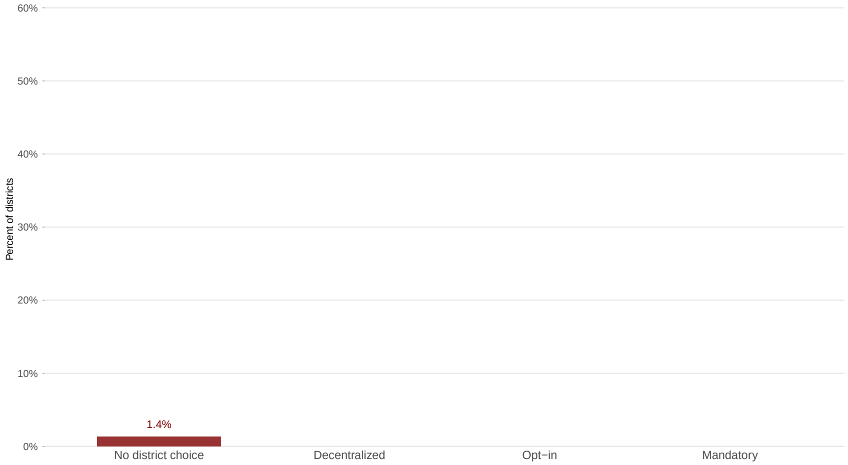


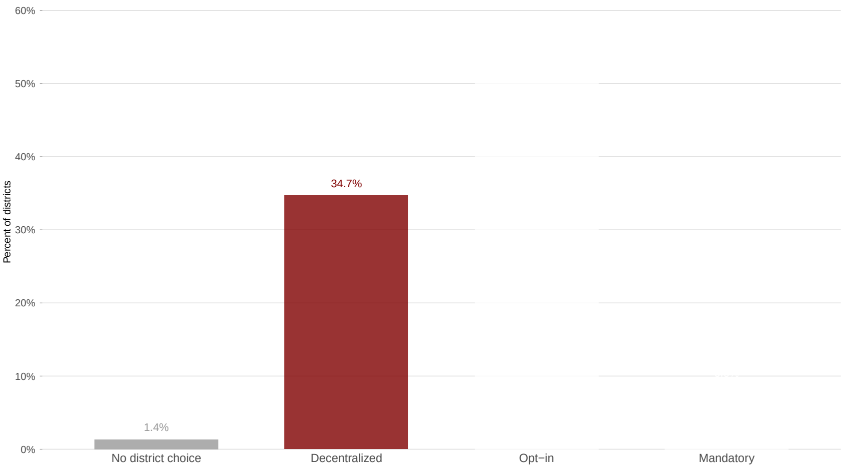
- In LA, roughly 50% drop in enrollment from the peak in 2004
- Districts have responded by expanding public school choice offerings
- Patterns are not unique to Los Angeles ▸ Evidence
- **Motivating question:** How have school districts organized public education markets as they expand public school choice?

We survey the 150 largest school districts (27% of public enrollment nationwide)...

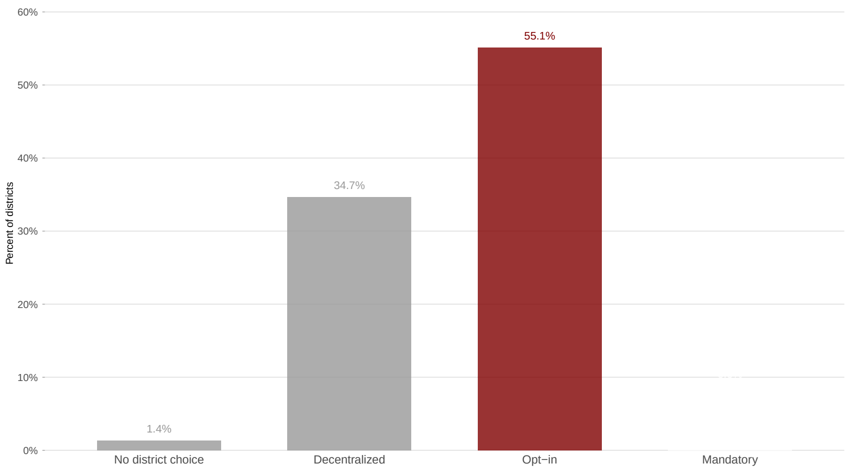
Nearly all offer some kind of intra-district choice



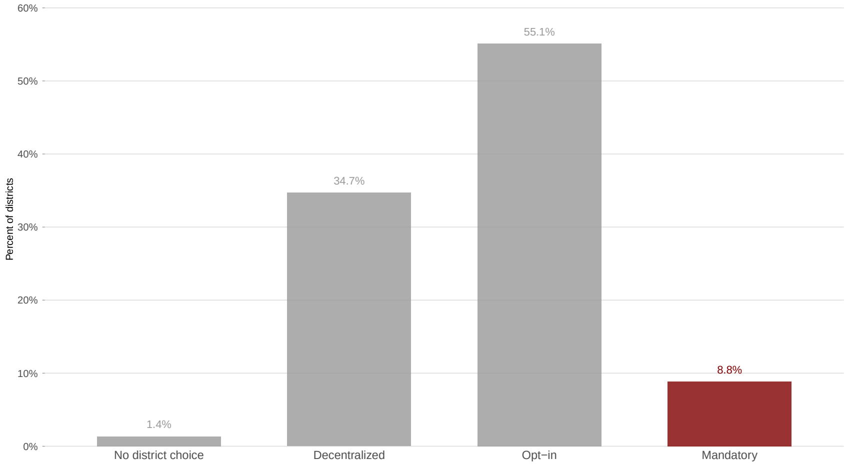
One third are decentralized i.e., have not adopted a centralized assignment system



A majority of districts with centralized clearinghouses have an “opt-in” design



De facto mandatory systems—commonly studied in the literature—are rare



List of Mandatory Districts

This Paper: Study the largest opt-in system in the US

Two primary questions:

1. What are the implications of LAUSD's opt-in choice system for aggregate achievement and inequality?

2. How do alternative market designs or policy interventions change who benefits from public school choice?

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   - → **Who** opts in to LAUSD's voluntary choice system?
   - → **The What:** Are LAUSD's choice options vertically differentiated, high-return programs?
   - → **The How:** How do application costs, travel, and preferences shape participation and who benefits?
2. How do alternative market designs or policy interventions change who benefits from public school choice?
   - → Holding constant the participation architecture, how far can polices that expand access go?
   - → What are the effects of decentralized markets and de facto participation mandates (e.g., NYC-style deferred acceptance)?

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What we do:

- Descriptive characterization of who participates and how policy shapes access
- Use oversubscribed admission lotteries to estimate achievement effects and heterogeneity
- To study system-level effects, we use a structural model of application, and enrollment to extrapolate the quasi-experimental variation
- Use the estimated model to simulate counterfactual system design and policy intervention effects

Preview of Results

1. **The Who:** Participants are more advantaged
   - → Baseline achievement $\approx 0.8\sigma$ higher than non-applicants and they are less likely to be low-income or EL
   - → Recent expansions of the choice sector are effective in drawing in more students

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   - $\rightarrow$ Students least likely to opt in have treatment effects about 0.30σ larger than those most likely to enroll

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   - → Many (45%) high quality seats go unfilled
   - → Students least likely to opt in have treatment effects about 0.30σ larger than those most likely to enroll
4. **Policy / System design:** System design—not school effectiveness alone—shapes who benefits and to what extent
   - → Mandatory participation with deferred acceptance raises district-level achievement by $\approx 0.016\text{–}0.019\sigma$
   - → Participation architecture—a first-mile problem—is a key determinant of who benefits from public school choice

Contributions

1. Benefits of Centralized Assignment Systems

- Large literature in empirical market design has shown that Centralized Assignment Systems (CAS) can improve welfare and affect other market-level outcomes
  (Abdulkadiroglu, Agarwal, and Pathak 2017; Oosterbeek et al. 2021; Kutscher et al. 2023; Avery et al. 2025; many others)
- Evidence on how such systems affect student outcomes is more rare but perhaps more relevant for policymakers
  (Campos and Kearns 2024; Agarwal and Somaini 2025)
- This paper: Most school districts offer opt-in systems, a deviation from the textbook example we tend to think of
  - → Focus on understudied opt-in system
  - → Quantify the implications of opt-in systems on *outcomes*
  - → Quantify the potential effects of alternative system-level designs

Contributions

2. Improving the performance of existing systems

- A large literature assessing the effects of enhancing the quality of information
  (Ainsworth et al. 2023; Andrabi et al. 2017; Arteaga et al. 2022; Campos 2024; Corcoran et al. 2018; Corradini 2023; Corradini and Idoux 2025))

- Debate about the impacts of strategy-proof mechanisms
  (Kapor et al. 2020, Calsamiglia et al. 2020; Terrier et al. 2025; many others)

- Outside options distort market outcomes applicable to textbook market design
  (Karnani et al. 2023; Akbarpour et al. 2022; Vrioni 2023; many others)

- This paper:

  → Study the effects of design details on *outcomes*

  → Existing body of work has focused on frictions, conditional on participation, we show that the *first-mile* problem of opting in is a first order concern

Contributions

3. Sorting in school choice

- A large body of work has shown that school choice policies intensify sorting and stratification (Urquiola 2005; Hsieh and Urquiola 2006; Rothstein 2006; Munteanu 2024; many others)
- Machado and Szerman 2021 show that CAS change the composition of students in in-demand programs
- Preferences and travel costs strongly affect sorting patterns (Idoux 2023; Laverde 2024) but policies that target these margins can affect them (Bergman 2018; Setren 2024)
- This paper:

  → Emphasize that system design, and importantly, the participation rule is a first-order determinant of student sorting and subsequently reshapes academic outcomes

Contributions

4. Effectiveness of public school choice programs

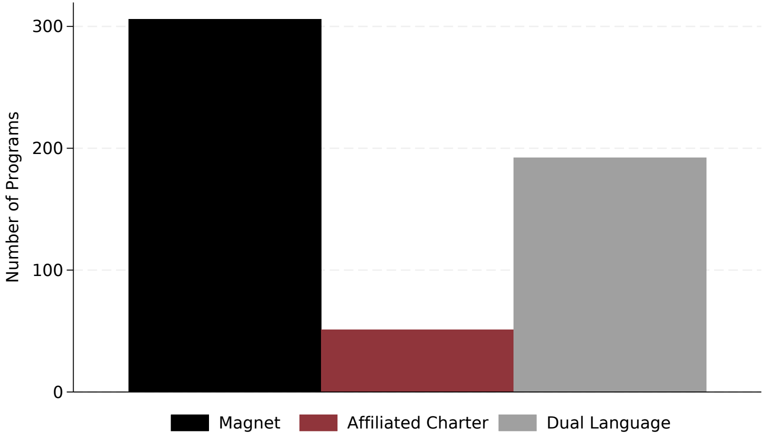
- Intra-district school choice
  (Cullen, Jacob, and Levitt 2006; Bifulco, Cobb, and Bell 2010; Angrist et al. 2024; Deming et al. 2014; Hastings, Kane, and Staiger 2009; many others)
- Charter school effectiveness
  (Abdulkadiroglu et al. 2011; Angrist, Pathak, and Walters 2013; Hoxby and Murarka 2009; Hoxby and Rockoff 2005; Chabrier, Cohodes, and Oreopoulos 2016; Angrist et al. 2016; Gleason et al. 2012; Dobbie and Fryer 2015; Chingos and West 2015; Baude et al. 2020; Setren, Cohodes, and Walters 2021; Monarrez, Kisida, and Chingos 2022; Imberman and Johnson forthcoming; many others)
- Supply side responses to school competition
  (Neilson 2013; Figlio and Hart 2014, 2023; Gilraine, Petronijevic, and Singleton 2021; Karbownik, Figlio, and Hart; Carruthers 2012; Chakrabarti and Roy 2016; Weiner and Dougherty 2016; Betts and Hill 2010; Campos and Kearns 2024; Crema 2024; many others)
- This paper:
  - → We conduct a large-scale program evaluation in a large school district across two decades
  - → Focus on questions about how to best organize public school choice education markets
  - → School districts seem to be responding to competition by creating vertically differentiated options

Setting and Data

The Largest Opt-in System in the US

- 35th largest school district in the country if it were its own district
- In 2024, there were roughly 500 programs/schools students could apply to
- Participation rates have increased
  - → In 2000, roughly 10% of families participated
  - → In 2024, roughly 25% of families participated
- Between 2000-2013, applicants could rank at most one option but in more recent years an immediate acceptance mechanism used to allocate students to schools
- If a student does not participate, they get defaulted to their neighborhood school
- Type of choice offerings have evolved over the past twenty years

School Choice Offerings in Los Angeles

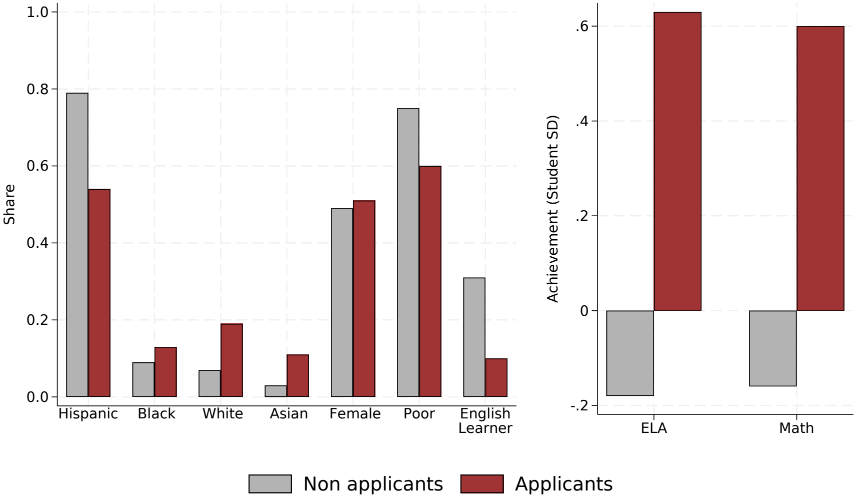


Data

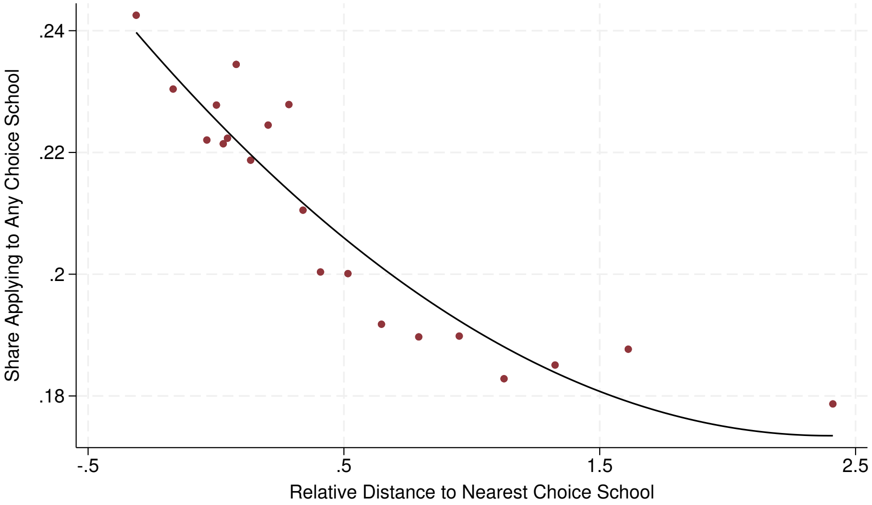
- Administrative student records (2000-2017)
  - → Demographics, addresses, and test scores
- Choice program records (2004-2017)
  - → Applications, program capacities, admission records
- We use these data to define three samples:
  - → Baseline sample (2004-2017) - all fifth grade students
  - → Lottery sample (2004-2017) - Restricts the baseline sample to students who apply to oversubscribed choice middle schools
  - → Structural sample (2004-2013) - Restricts the baseline sample to students with addresses, who enroll in LAUSD middle schools, and for whom we observe at least one test score outcome for

Who Chooses?

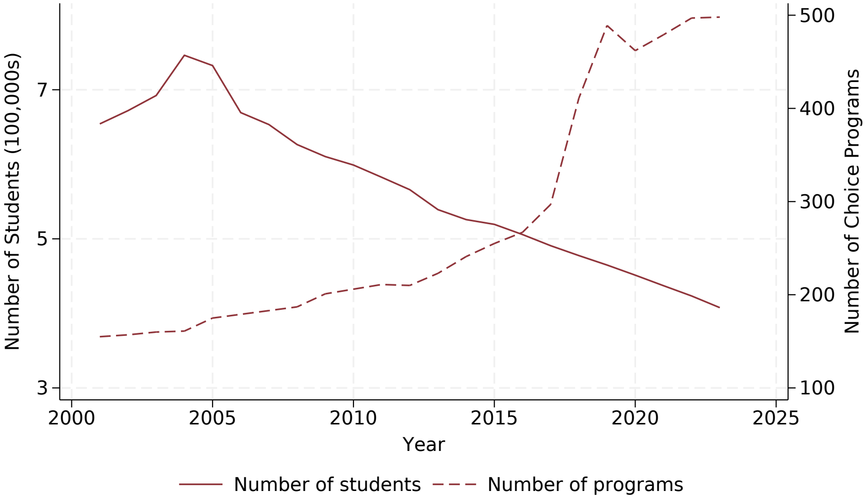
Applicants are positively selected on baseline achievement



Distance Predicts Participation



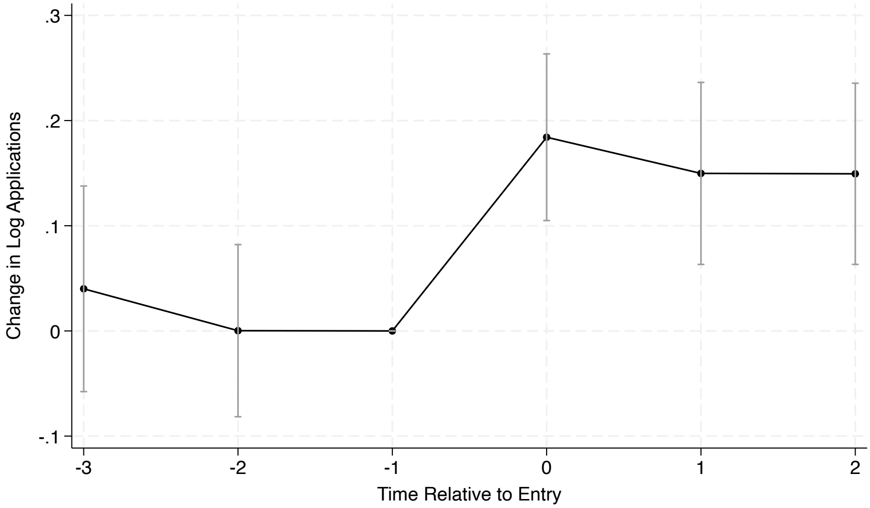
There has been substantial policy-induced variation in access



Does entry increase participation from more local students?

- We consider how neighborhood-level participation evolves around entry
- We create stacked data where each stack correspond to an academic year
- Define treatment and control as:
  - → "Treated" neighborhoods are those that experience a reduction in distance to nearest choice program
  - → "Control" neighborhoods are those that did not experience a reduction in distance to their nearest choice program
  - → Both groups restricted to not having any changes in distance in the prior three years

Entry induces more applications



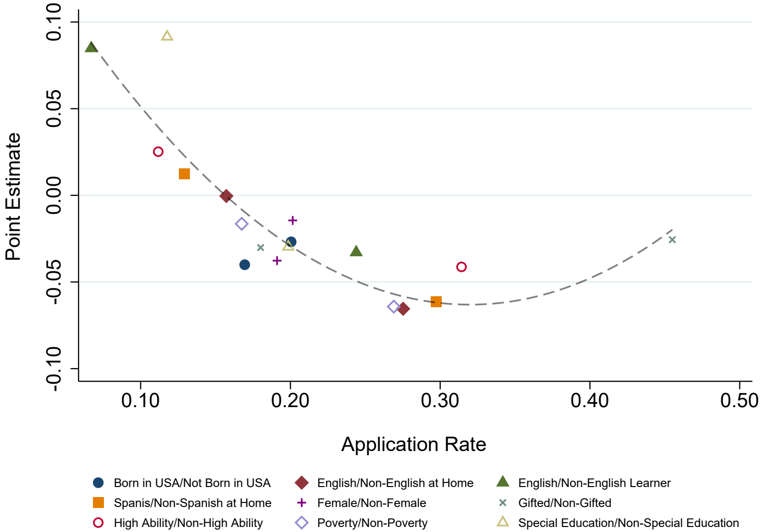
Reduced Form Evidence

Reduced Form Exercises

- **Key Question: Does demand predict treatment effect heterogeneity?**
- Three reduced form exercises to assess that
  1. Lottery Effects Against Application Rates
  2. Lottery Effect Heterogeneity by Preference Index (will skip for today)
  3. Lottery Effect Heterogeneity by Distance

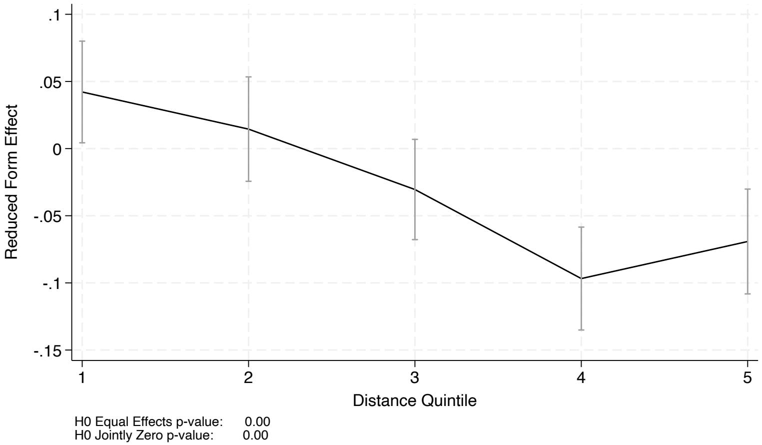
▶ Lottery Details

Lottery Effects and Application Rates by Group



Distance strongly predicts treatment effects

Winning an offer produces more positive impacts on achievement for students traveling shorter distances



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

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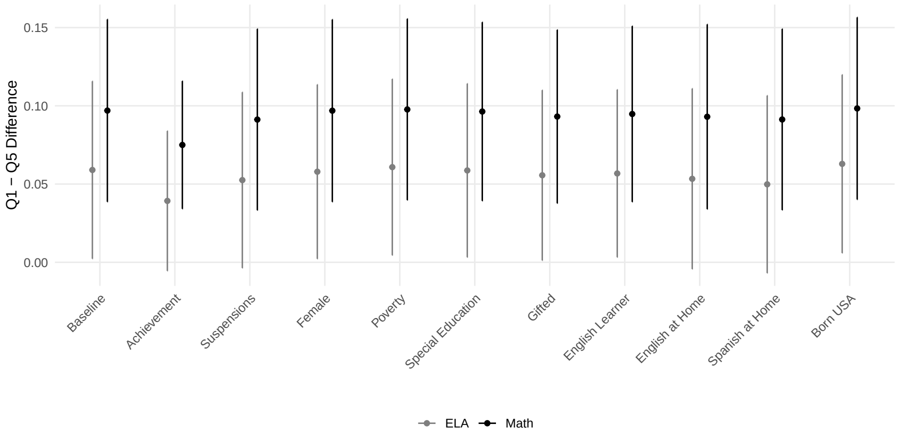


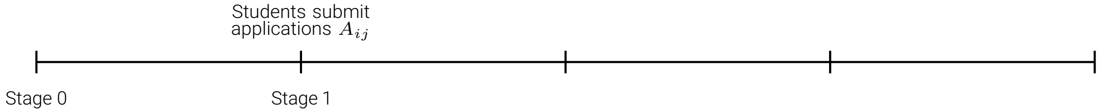
▸ Preference Index Exercise
▸ Group-Specific Roy Patterns

Next steps

- Evidence suggests that latent tastes are negatively correlated with effects, in the lottery sample
- To move towards system-level effects, we need to characterize effects for the entire population of students
- Our approach: Model preferences, application decisions, enrollment decisions, and outcomes
  - → The demand model allows us to quantify and contrast distinct frictions to participation
    - Travel costs
    - Application costs
  - → The generalized outcome model allows us to
    - Assess if choice schools are vertically differentiated for the average student
    - Characterize treatment effects for the entire population of students
- Combined, we can quantify the aggregate effects of different design choices

Beyond Lottery Effects

Model Overview: Timeline



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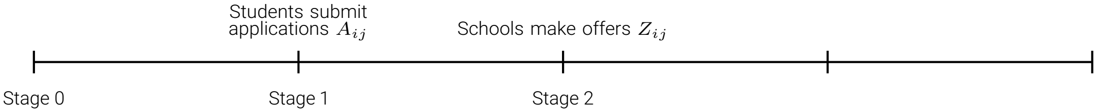

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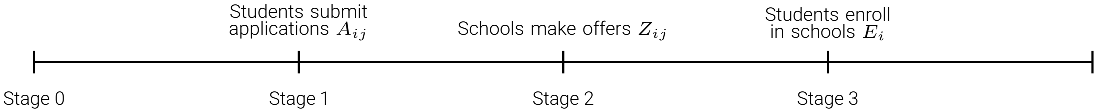

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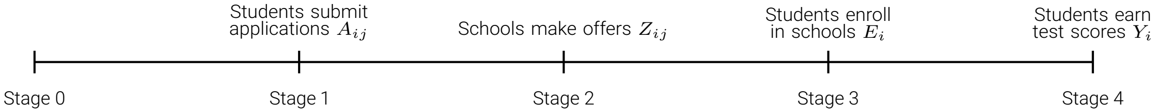

Model Overview: Application Decision

- Decision to apply depends on:
  - → School $j \in \mathcal{J}$ utility, $U_{ij}(X_i, \theta_i, D_{ij})$
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  - → School popularity δ_j
  - → Student observables X_i
  - → Relative distance to programs vector D_{ij}
  - → Idiosyncratic choice school taste $\theta_i \sim F(\theta)$
  - → Unobserved preference heterogeneity $\epsilon_{ij} \sim EVT1$

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- With uncertain admissions, students choose A_i that maximizes their expected utility net of application costs

Model Overview: Enrollment Decision

APPLIED

Got Offer
Choice vs. Neighborhood

No Offer
Neighborhood School

DID NOT APPLY

Neighborhood School

- If applied and received an offer, student has offer set O_i. The decision whether to enroll in the choice program or remain in the neighborhood school depends on:
  - → School utilities, $v_j(X_i, \theta_i, D_{ij})$

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  - → School utilities, $v_j(X_i, \theta_i, D_{ij})$
  - → Logistic post-lottery shock, ξ_{ij}

Model Overview: More on θ

- $\theta_i \sim F(\theta)$ governs idiosyncratic preference heterogeneity for choice schools
- We assume $F(\theta)$ is a finite mixture of normals with K types, with means $(\mu_1, \cdots, \mu_K)$ and corresponding standard deviations $(\sigma_1, \cdots, \sigma_K)$
  - → Intuition: Some families may love choice schools and some may strongly dislike them, corresponding to different types
- Importantly, θ_i affects *both* application and enrollment stages
  - → Characterizing this latent preference heterogeneity is useful for accounting for selection in the outcome model
- What drives differences in θ_i? Parents with identical X_i and D_i have similar observable preference and application cost heterogeneity, so differences in θ_i can reflect differences in
  - → parental motivation
  - → access to information

Model Overview: Achievement Exams

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

Model Details

Potential Outcomes

We assume the following restrictions on mean potential outcomes (Y_{ij}):

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We model selection in the following way:

$$h_j(\tau_i) = \sum_{k \neq 1} \gamma_k T_{ik} + \sum_{k \neq 1} \gamma_{ck} T_{ik} \times \mathbf{1}\{j > 0\}$$

- T_{ik} are indicators for belonging to type $k \in \{1, \ldots, K\}$
- γ_k allow for k-specific differences in achievement levels
- γ_{ck} allow for k-specific differences in achievement gains at choice schools ($j > 0$)

Empirical Outcome Model

- Equipped with model estimates, we can estimate the posterior individual-specific type probabilities ▶ Details

$$p^*_{ik} = E[T_{ik} \mid X_i, D_i, A_i, Z_i, E_i]$$

- p^*_{ik} serves two roles:
  - → p^*_{ik} serves as a control function to account for selection
  - → We allow for flexible heterogeneity by group membership

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$$Y_i = \underbrace{X_i'\gamma_x + \sum_{k \neq 1} \gamma_k p^*_{ik}}_{\text{Ability}}$$

Empirical Outcome Model

- Equipped with model estimates, we can estimate the posterior individual-specific type probabilities Details

$$p^*_{ik} = E[T_{ik} \mid X_i, D_i, A_i, Z_i, E_i]$$

- p^*_{ik} serves two roles:
  - → p^*_{ik} serves as a control function to account for selection
  - → We allow for flexible heterogeneity by group membership

- For expositional purposes, let C_i be an indicator for choice school attendance and let $E[X_i] = 0$. Our empirical outcome model is:

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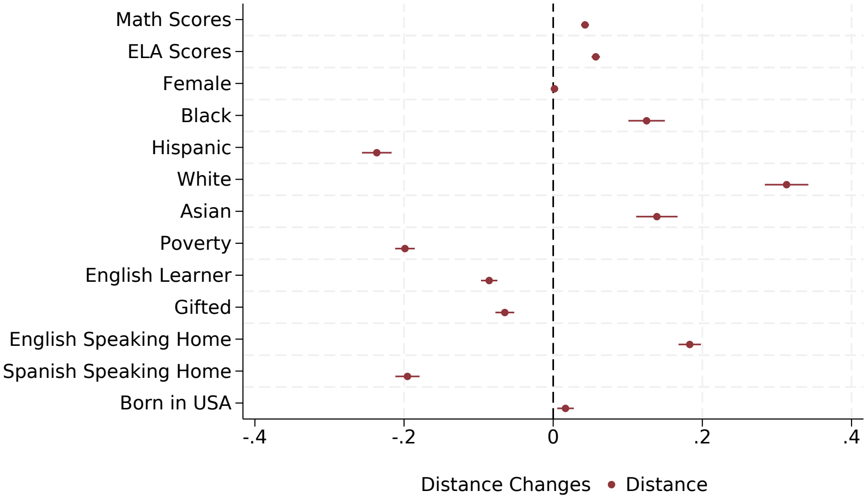
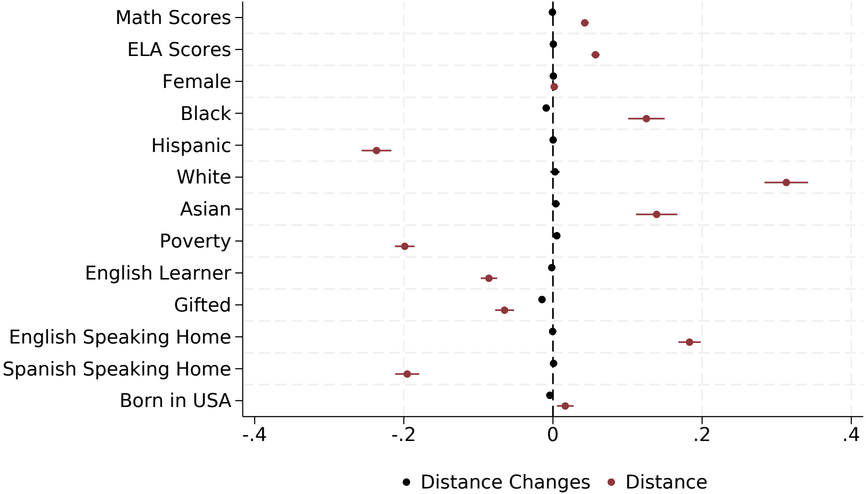
Distance Balance

Distance is not balanced



Distance Balance

Changes in distance are balanced



Results

Summary of Demand Estimates

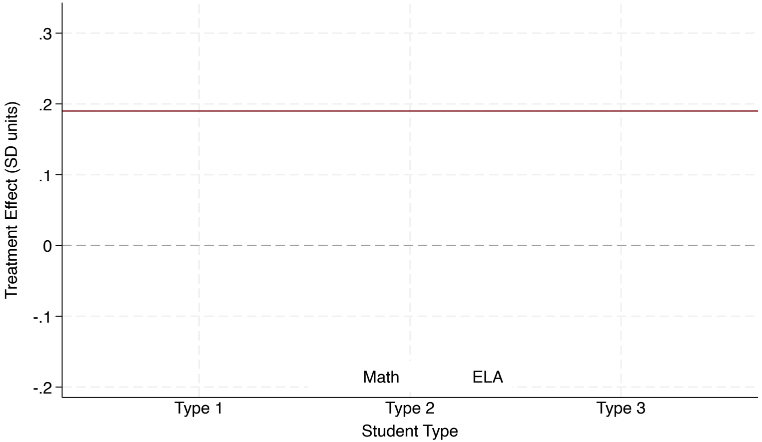
- **Model Fit:** The model produces forecast unbiased school-by-group application and enrollment rates in a holdout sample ▸ Evidence

- **Type Heterogeneity:** The data suggest a model with $K = 3$ types ▸ Evidence

$$\mu = \begin{pmatrix} -0.88 \\ -0.43 \\ 2.75 \end{pmatrix}, \qquad \sigma = \begin{pmatrix} 0.19 \\ 0.13 \\ 0.54 \end{pmatrix}, \qquad p = \begin{pmatrix} 0.44 \\ 0.49 \\ 0.07 \end{pmatrix}$$

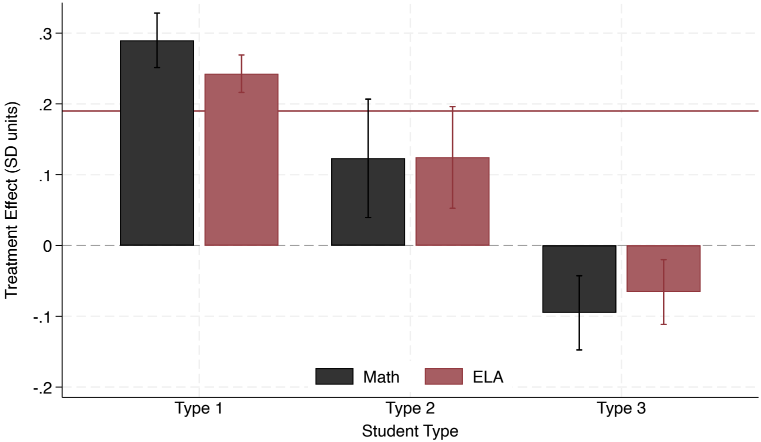
- **Dominant Friction:** Application costs are substantially higher than travel costs ▸ Evidence

Choice schools are effective for the average student



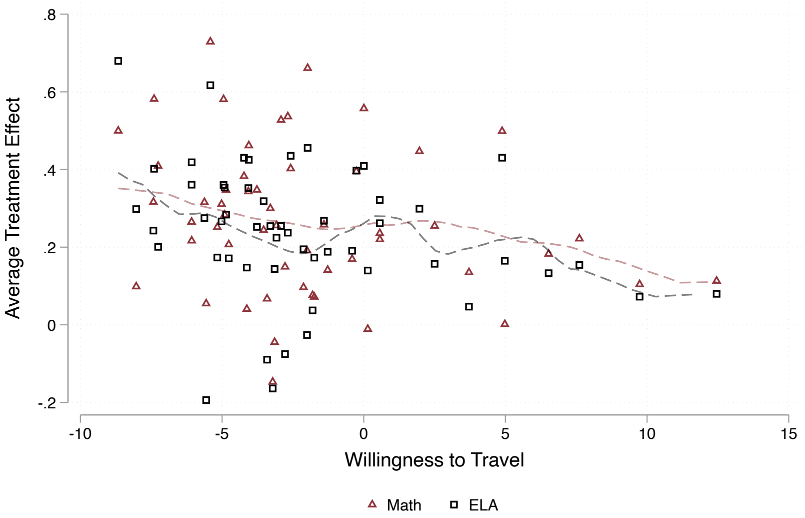
Validation Exercise

Evidence of negative selection on gains



▸ Validation Exercise

Negative association between school popularity and causal effects



System Design

Counterfactual policies of interest

- **Policies that expand access**
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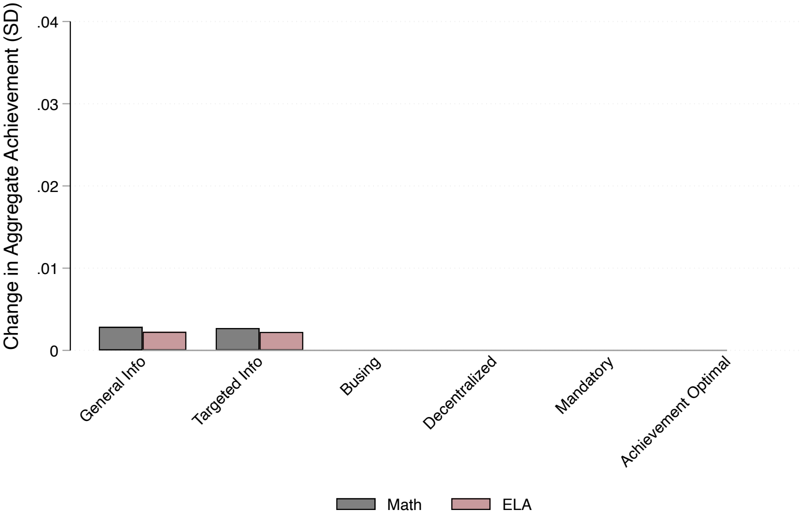
- **What we do:**
  - → Fixed across policies: menu of programs, capacities, school effectiveness
  - → Varying across policies: application costs, travel costs, participation rule, assignment mechanism

▸ Peer Effects

Changes in District-level Average Achievement



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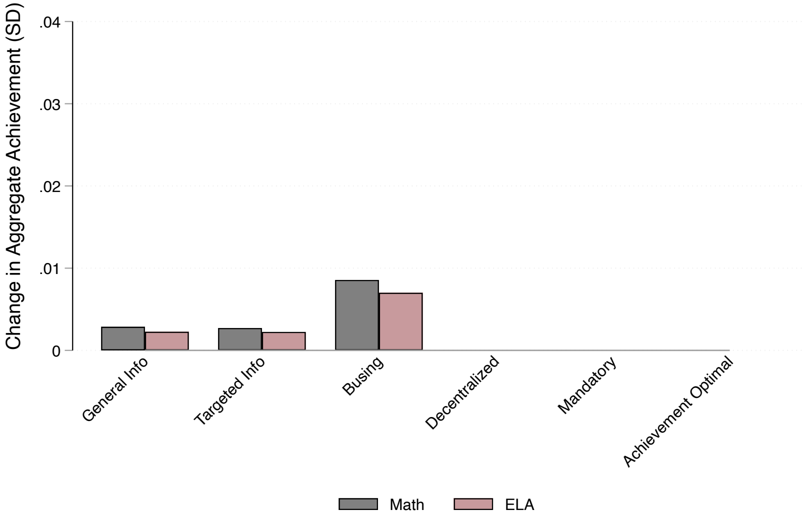

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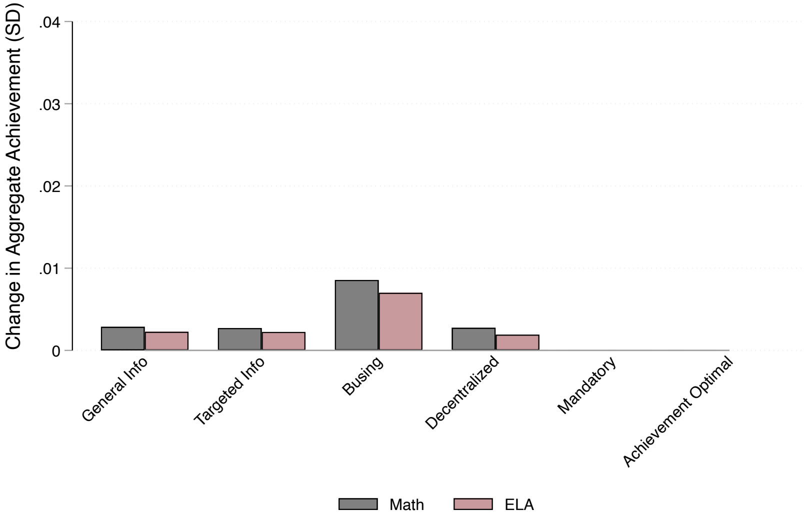

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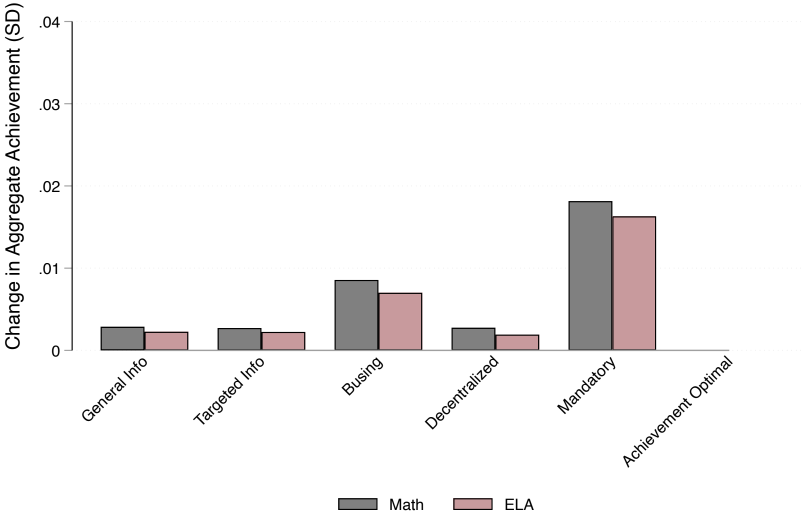

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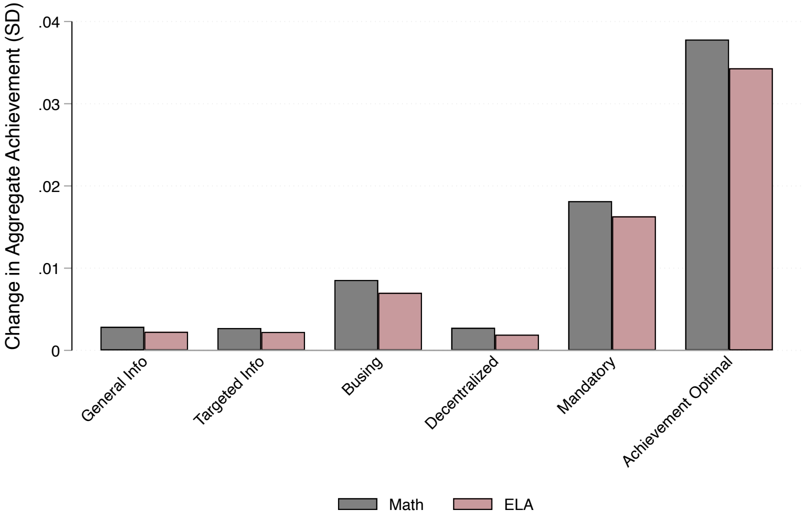
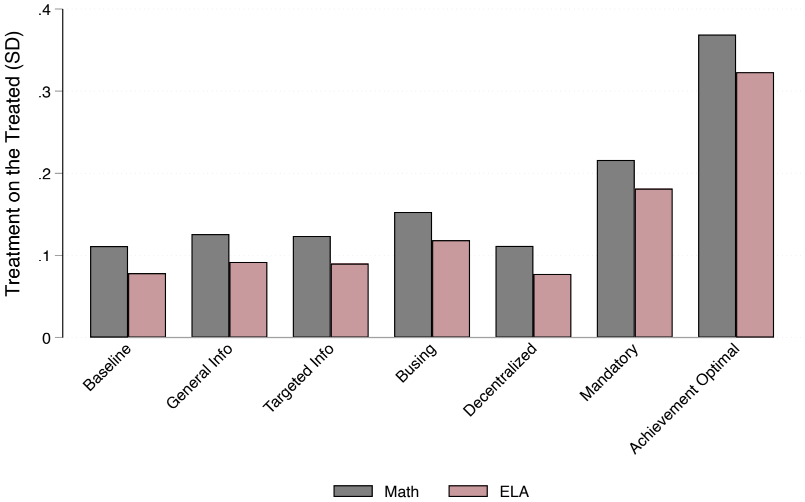
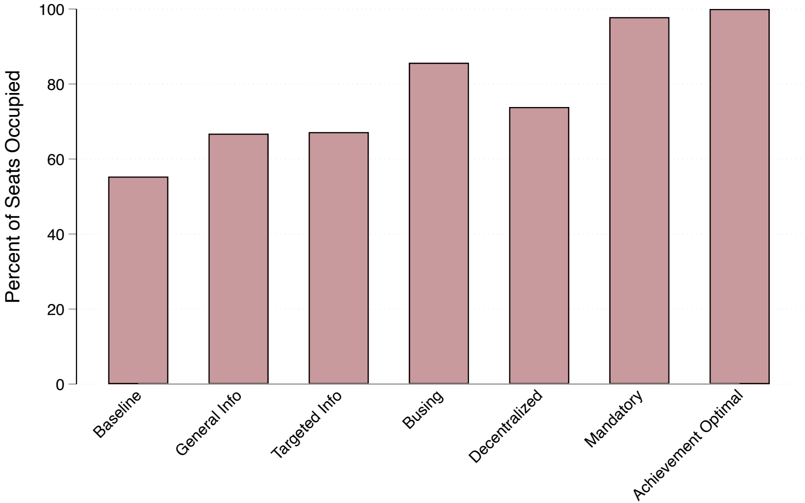


System Design Affects the TOT



Many seats are unfilled with opt-in design



Concluding Thoughts

Conclusion

- **New fact:** Opt-in is the most common way school districts have organized their school choice offerings

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Conclusion

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- **Who:** Opt-in systems tend to segment the public education system based on achievement
- **What:** The average student has a sizable treatment effect ($\approx 0.19\sigma$)
- **How:** Negative selection on gains interacts with opt-in design to produce an allocative inefficiency in achievement
- **Takeaways and implications for policy:**
  - $\rightarrow$ Opt-in designs have several limitations
  - $\rightarrow$ System design—not school effectiveness alone—shapes who benefits from public school choice and to what extent
  - $\rightarrow$ If opt-in is the political constraint, the task is to design systems that deliver gains despite it

Thank You!

Christopher.Campos@chicagobooth.edu

List of Mandatory Districts

State	District	Rank	Enrollment
New York	New York City Public Schools	1	845,509
Texas	Houston ISD	10	184,109
Florida	Lee	27	100,064
Kentucky	Jefferson County	29	94,793
Colorado	Denver	34	88,258
Maryland	Baltimore City Public Schools	45	75,811
Colorado	Jefferson County School District No. R-1	47	74,251
Texas	Austin ISD	49	72,830
Wisconsin	Milwaukee School District	55	66,864
California	Long Beach Unified	60	63,966
Texas	Garland ISD	80	51,659
California	San Francisco Unified	94	48,736
Massachusetts	Boston	109	45,742

Go Back

Examples of Mandatory Language

Long Beach Unified

Who MUST complete an Online High School Choice application?

ALL current 8th grade families MUST complete the High School Choice Application online via ParentVUE. This includes:

- Current 8th grade students attending a LBUSD middle or K-8 school
- Private school students, and New / Returning to LBUSD students that would like to attend a LBUSD high school beginning in the 9th grade. Students must renew enrollment into LBUSD prior to completing the School of Choice application.

NOTE: Students that do not complete a high school choice application are NOT guaranteed placement at their school of residence.

Current high school students seeking a school transfer, please contact the Secondary Schools Office at (562) 997-8115.

Go Back

Examples of Mandatory Language

Garland ISD

When are the Choice periods for the 2026-27 school year?

- **Grades 1-12:** Dec. 1-Jan. 12
- **Prekindergarten and Kindergarten:** April 1-May 1

Who needs to participate?

Students new to GISD, transitioning to a new school level, wanting to change campuses or interested in applying for a magnet program.

Go Back

Examples of Mandatory Language

Baltimore

My child is a 8th grader. Do I have to choose a school for 9th grade?

Yes, you do! All 8th graders have to make choices about 9th grade and high school. There is no automatic admission to 9th grade. You have to apply to get in. Baltimore high schools no longer have “zones,” and they don’t have “feeder” schools.

If you don’t make choices, you will get a school assignment many weeks after other families know where their child will be in 9th grade. And if you don’t like the assignment, you will have to enter a lottery for places in the schools that are not yet filled. So your choices are more limited.

There are two big deadlines in school choice: (1) for the school choice application provided by City Schools, which covers most of the school system’s schools and (2) for some charter schools that don’t participate in the joint choice application.

Go Back

Examples of Mandatory Language

Jefferson County, Colorado

Who Should Use EnrollJeffco?

All families with students kindergarten through 12th grade use **EnrollJeffco** in December (starting Dec. 6 this year) to indicate where their student will be attending school for the following school year. Families use EnrollJeffco whether their student is re-enrolling at the same school, changing schools or just starting in Jeffco.

Go Back

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 for students traveling differing distances with the following model:

$$Y_i = \alpha_{\ell(i)} + \sum_{q=1}^{5} \beta_q \left(Z_i \times \mathbf{1}(Q_i = q)\right) + \sum_{q \neq 1}^{5} \kappa_q \mathbf{1}(Q_i = q) + u_i$$

  → $\alpha_{\ell(i)}$ 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

  → $\mathbf{1}(Q_i = q)$: indicator for belonging to distance quintile q

  → β: effect of receiving an offer

- Observables are balanced within lotteries ▸ Lottery Balance

▸ Go Back

Preference index strongly predicts treatment effects

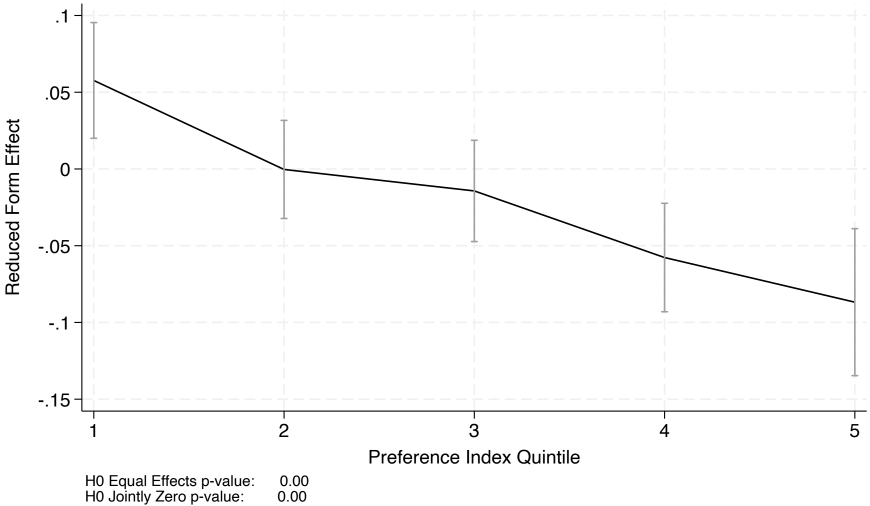
- For each school s, construct an individual-level covariate measuring difference of student i from the typical applicant to school s:

$$P_i = \|X_i - \bar{X}_s\|$$

- P_i is a proxy for idiosyncratic preference heterogeneity

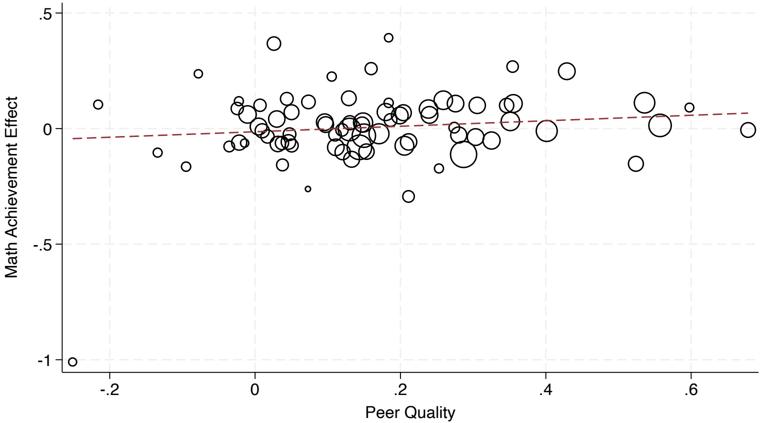
Go Back

Preference index strongly predicts treatment effects



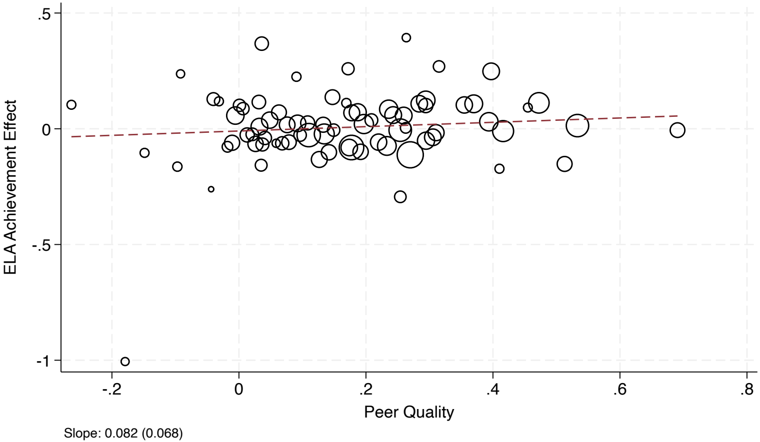
Go Back

Peer Effects for Math



Slope: 0.089 (0.072)

Peer Effects for ELA



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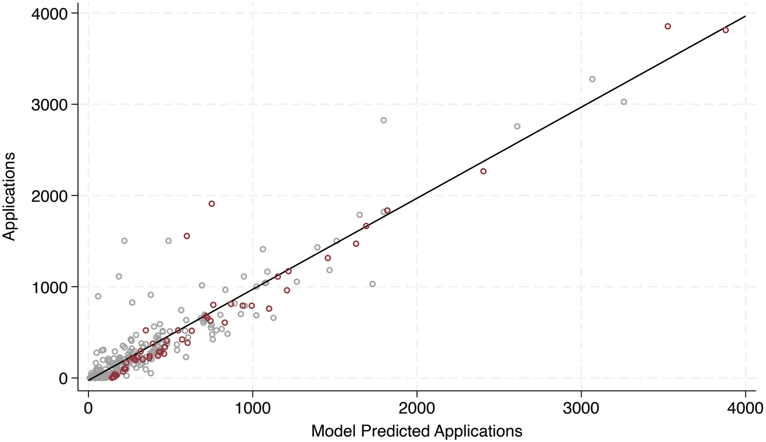
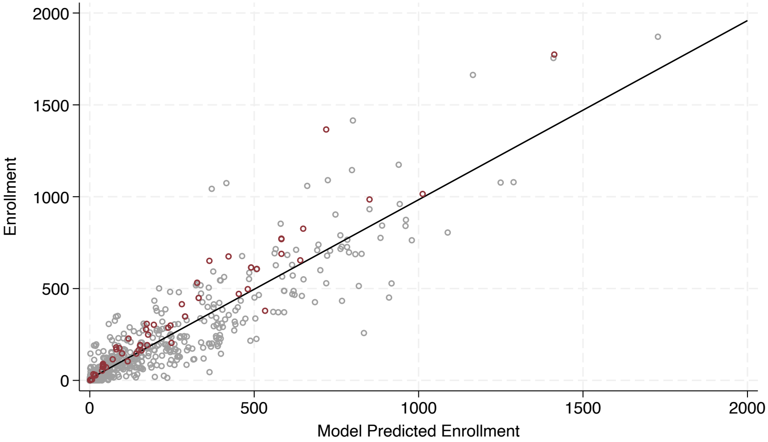
Model Accuracy: Applications

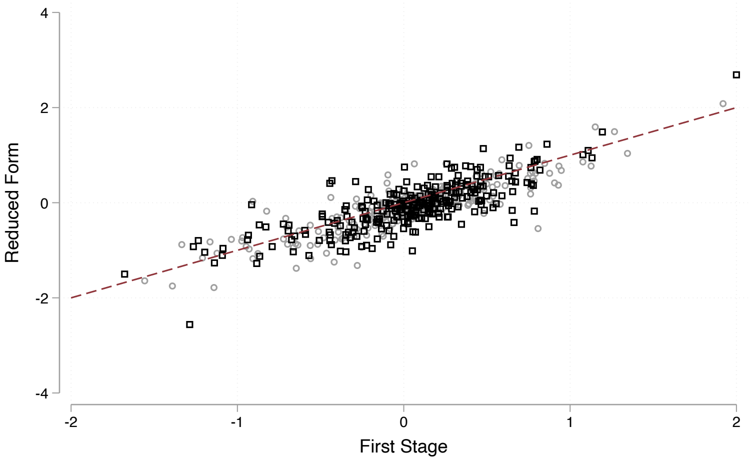


Model Accuracy: Enrollment



Go Back

Model Validation



Slope = 0.927 (0.044)

Go Back