Search and Biased Beliefs in Education Markets

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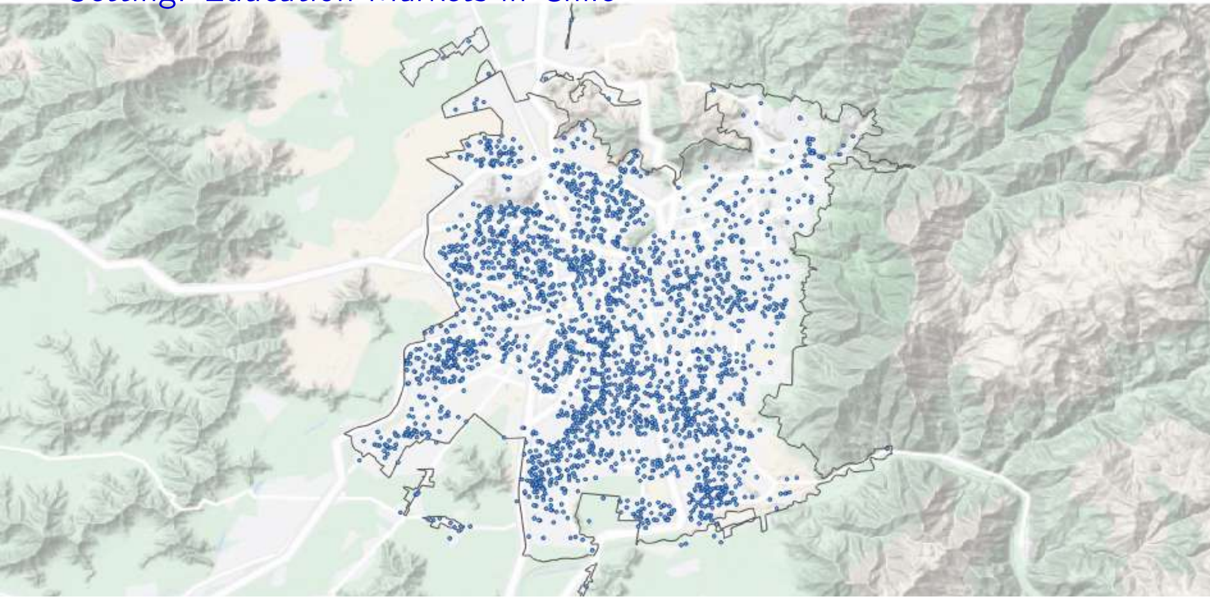
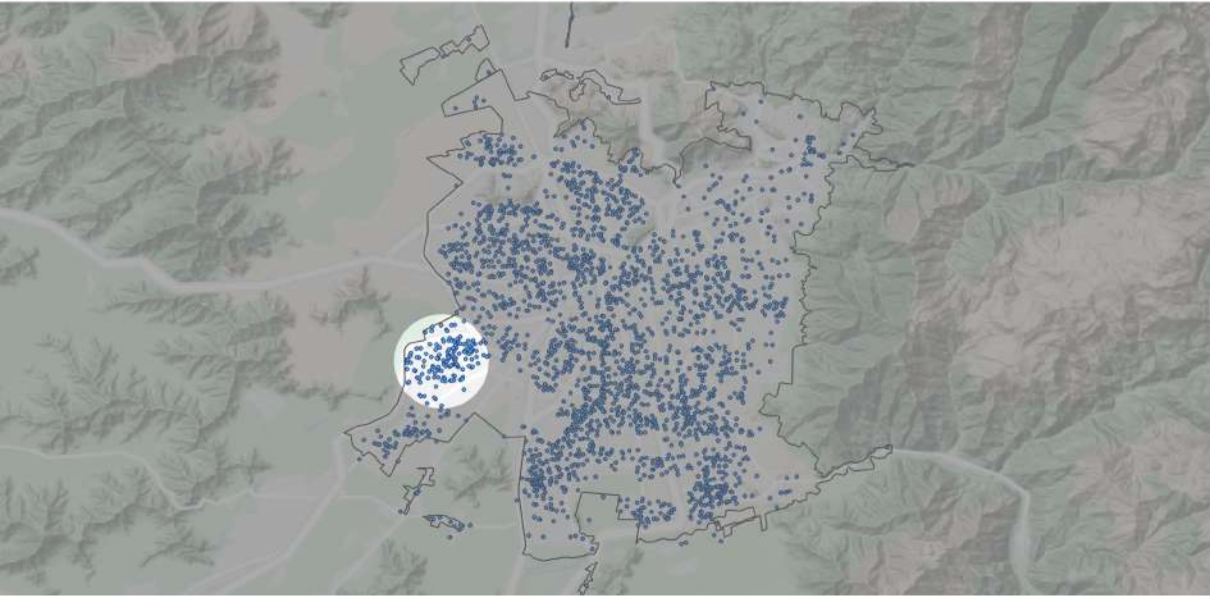
$\implies$ **Research Question**: How do families' limited awareness of options, misperceptions and inaccurate beliefs about characteristics interact with preferences and search costs to distort their information-acquisition efforts, choices, and outcomes in a complex, high-stakes decision?

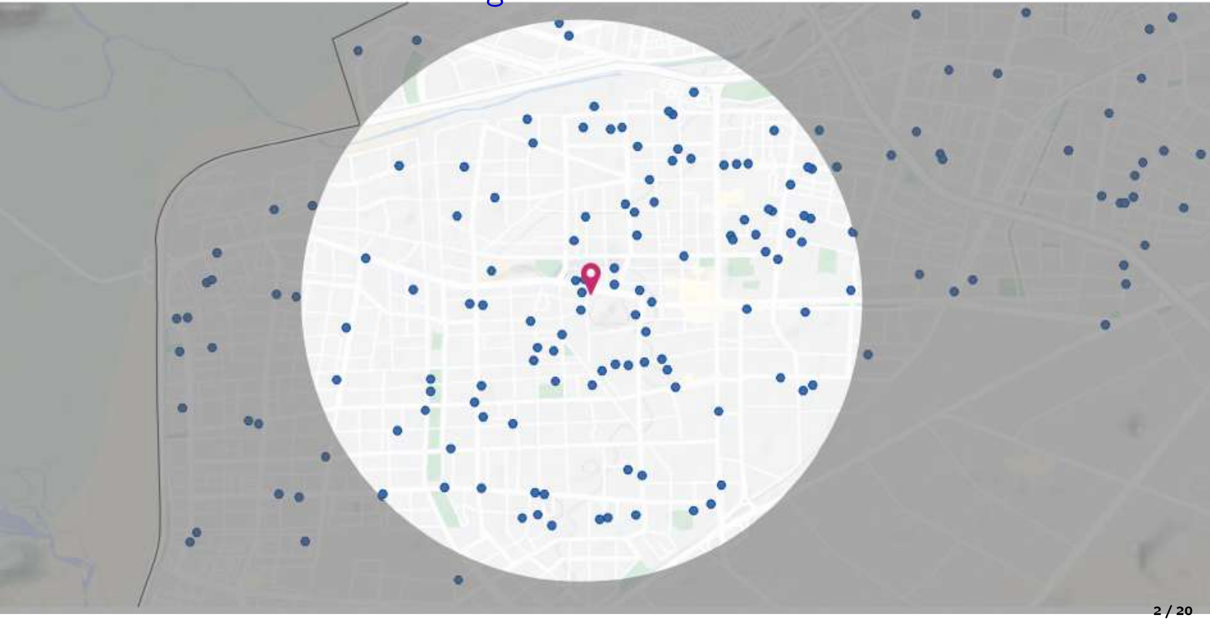
Setting: Education Markets in Chile



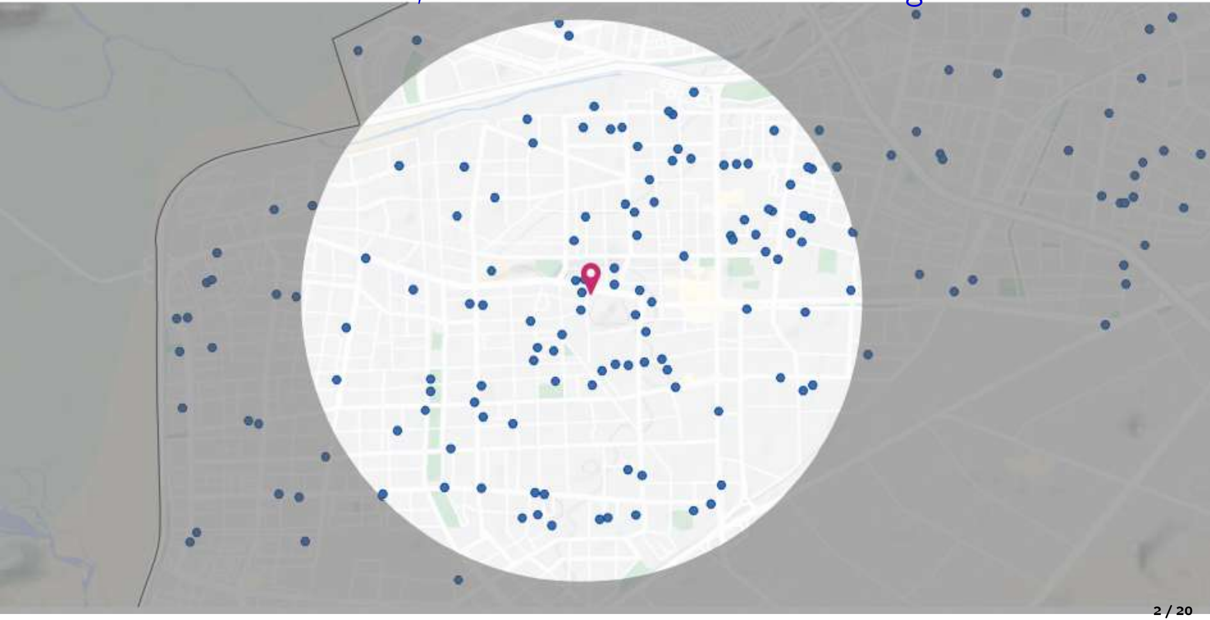
Zoom into a 2km Radius Area



Almost 100 Schools Offering K



Placement is uncertain; must submit ranked list to assignment mech.



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2. Novel search data and surveys:
   - Set up "school explorer" platform w/ personalized information, track search activity
   - 3 survey waves; measure beliefs, perceptions, awareness, preferences pre/post
   - Link survey and clicks to admin applications and enrollment

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3. RCTs:
    1. "Search Aid" via explorer: dist'n of school characteristics + salience of good schools
    2. "Feedback" using app data: info about "known" schools, targeting misperceptions

Today's Talk

- Many frictions exist. But the most important are:
  1. imperfectly-revealing search technology
  2. misperceptions about observables of known schools
  - Fix (1) -> welfare gains + $\approx$ 50% more search
  - Fix (1) + (2) -> more welfare; quality gains $\approx$ full info; close SES school quality gap.

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- Rest of talk:
  1. example
  2. data + descriptives
  3. experiments
  4. model
  5. results

Motivating Example

- Household knows outside option (sure payoff 0), one "inside" school.
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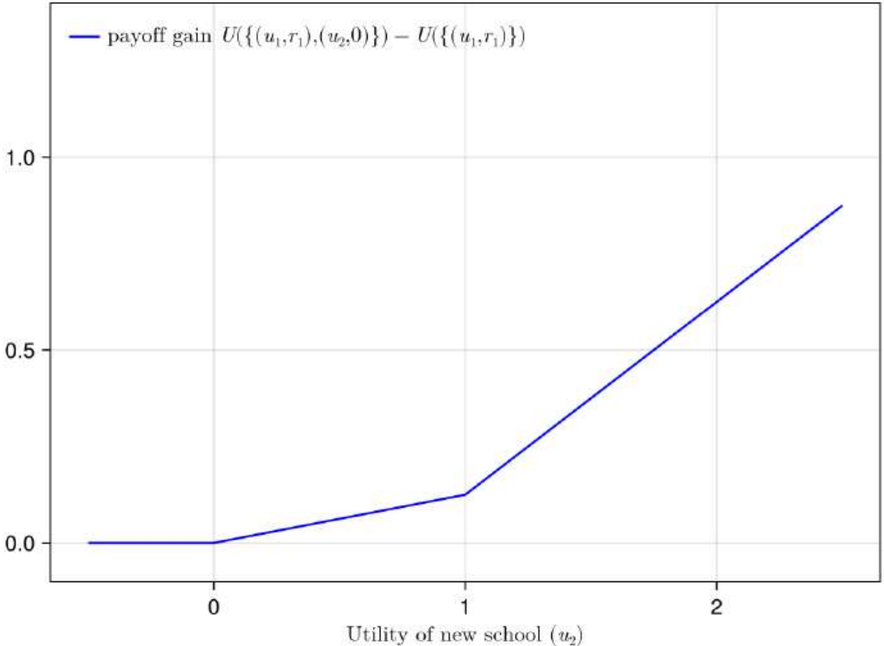
- Expected payoff of optimal app: $\begin{cases} (1 - r_j)u_j + r_j(1 - r_k)u_k & \text{if } u_j > u_k > 0 \\ (1 - r_1)u_1 & \text{if } u_2 < 0 \text{ or don't search.} \end{cases}$


payoff gain $U(\{(u_1,r_1),(u_2,0)\}) - U(\{(u_1,r_1)\})$
1.0
0.5
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0
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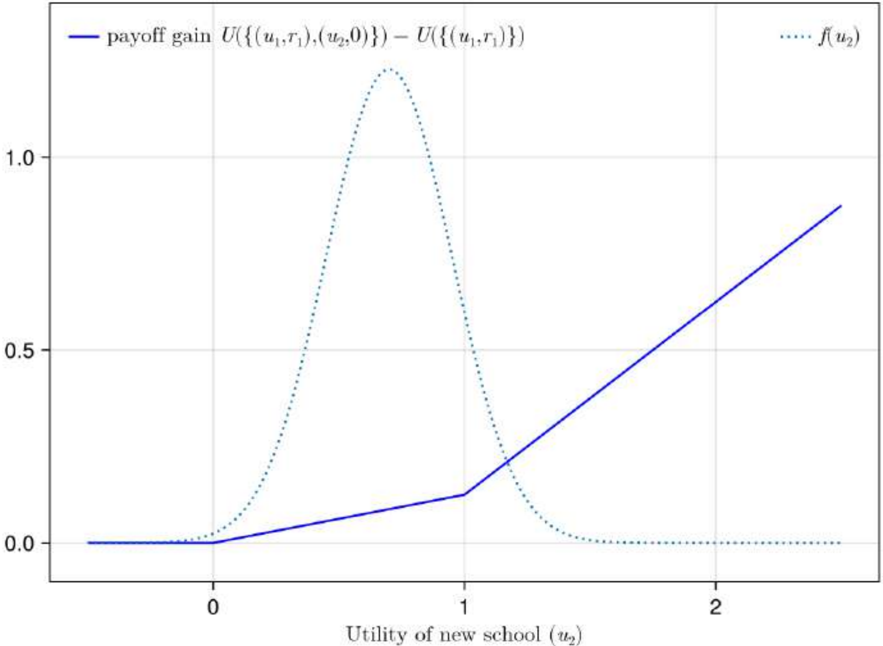
Utility of new school (u_2)



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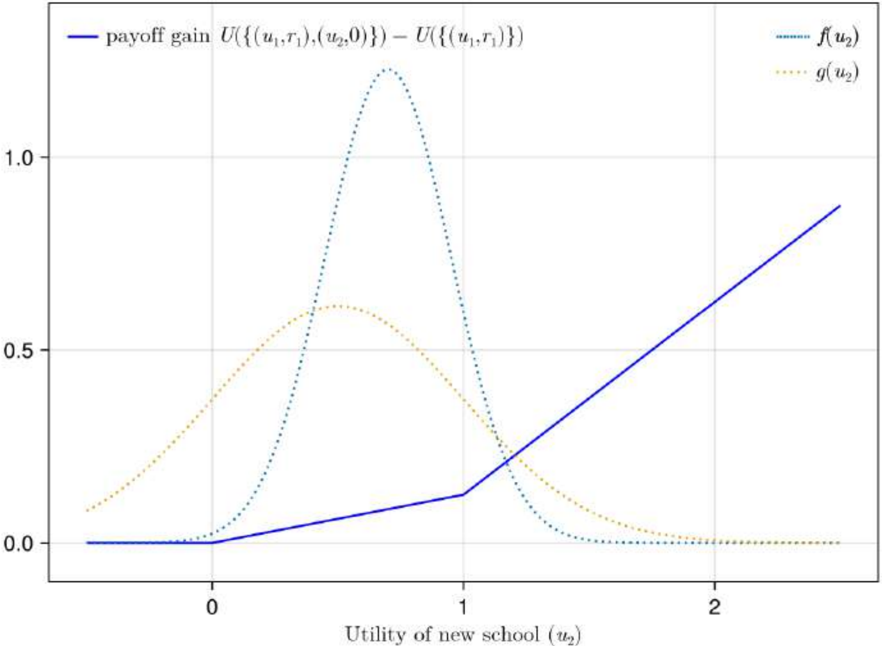

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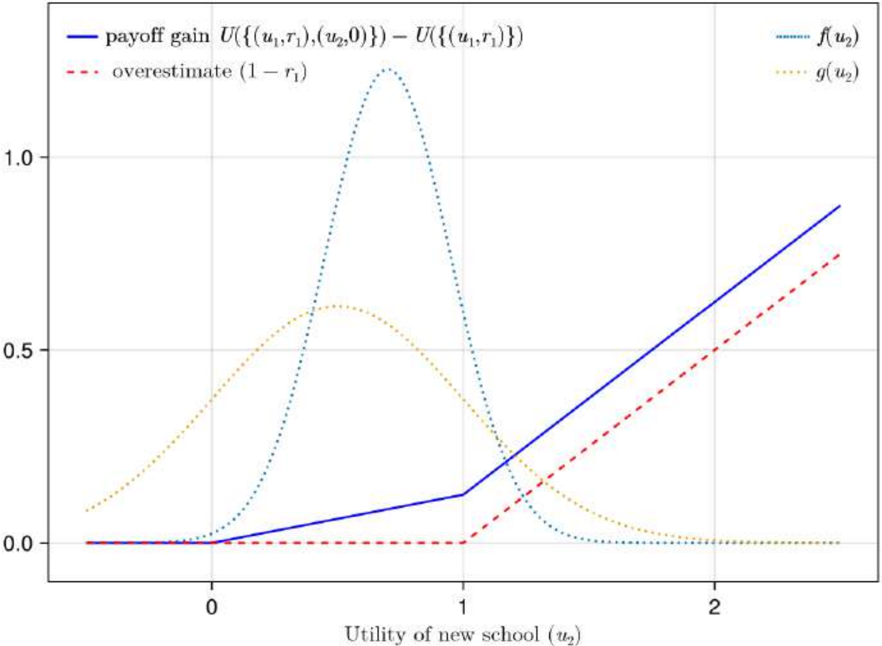

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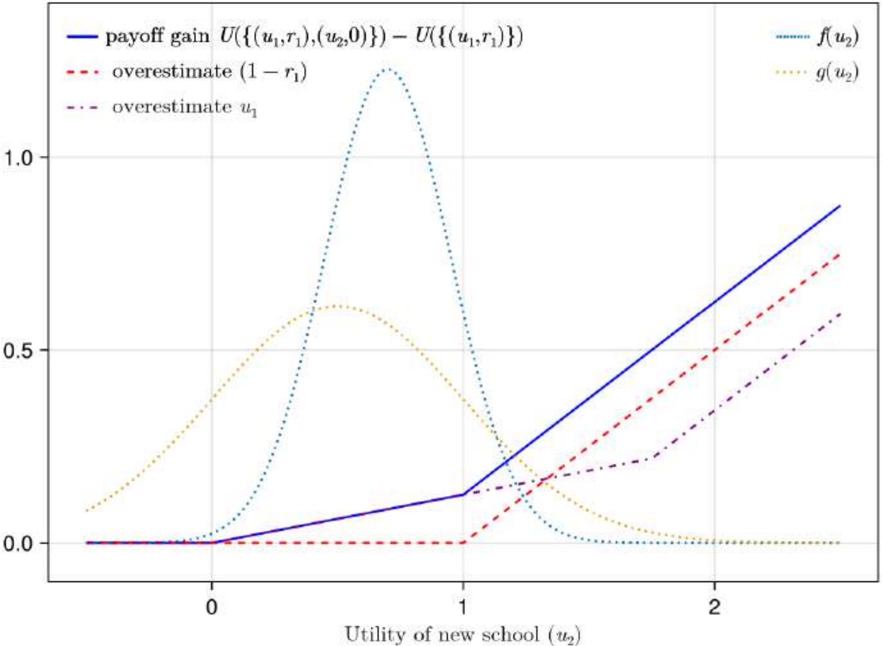

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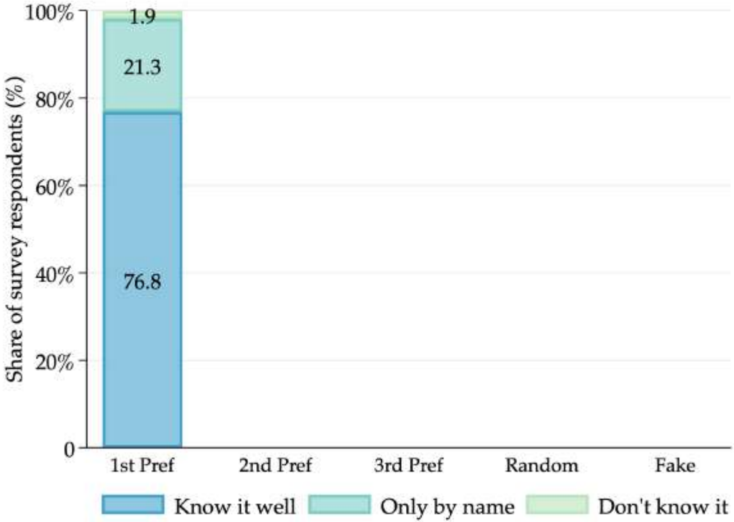
Data + Experiments Outline

- Surveys measure awareness, perceptions (known schools), beliefs (unknown schools)
  1. Baseline: also has subj. ROL, perceived returns to search
  2. Midline: gives repeated perception measures
  3. Endline: awareness and perceptions only
- Sample: recruited from preschools; restrict to first-time preK / K / 1st applicants
  - In study if and only if complete baseline survey
- Timing:
  - 1 Baseline survey. Search RCT. Explorer made available. Almost all on-platform search.
  - 2 Feedback RCT: uses submitted apps, 1 week before deadline.
  - 2-3 Midline survey occurs slightly before/after (timing varied).
  - 3 Final apps due; endline survey post-deadline.
- Admin data: demographics and repeated measures of rank-order lists:
  - Three snapshots: baseline (survey), "just before feedback" and final (admin).

Descriptive Analysis

- **Awareness:**
  - Families don't know all the schools at baseline **[TODAY]**
  - Closer/higher quality schools more likely to be known ▸ Figure
- **Perceptions of known schools' characteristics:**
  - Key vertical characteristic: official gov't quality index $\in \{1, \ldots, 4\}$.
  - Households overestimate quality of schools they like, especially 1st choice **[TODAY]**
  - Households also mispredict price (too high), admissions chances (compression) ▸ Figure
- **Beliefs about unknown schools:**
  - Households overestimate quality and price of unknown schools ▸ Figure
- **Preferences:**
  - ROL explained by subjective perceptions of quality and price, not truth ▸ Figure

Families don't know all schools at baseline



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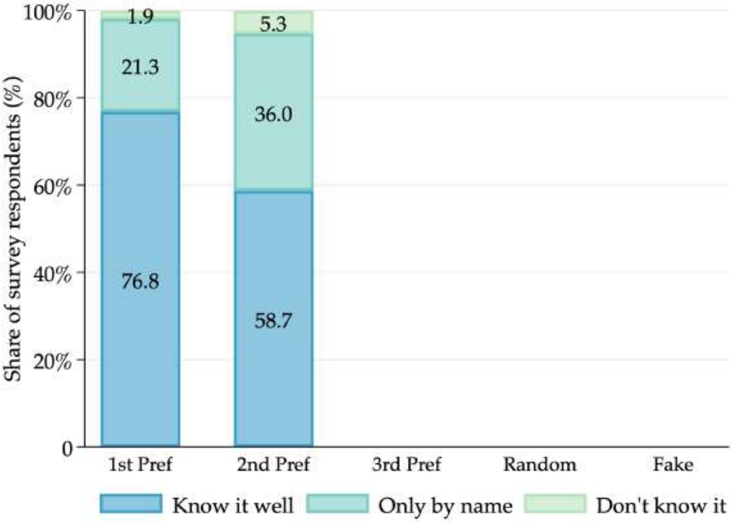

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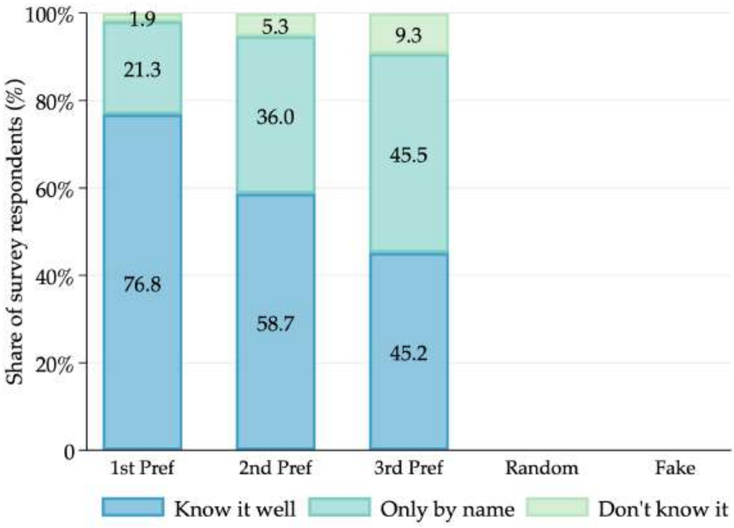

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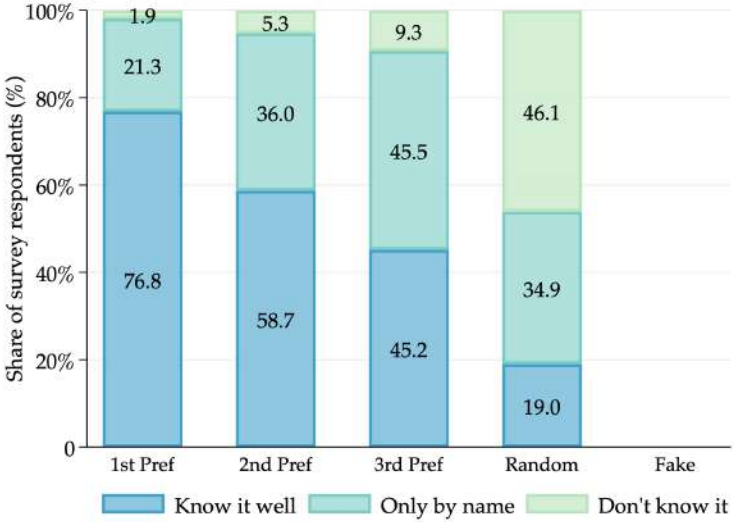

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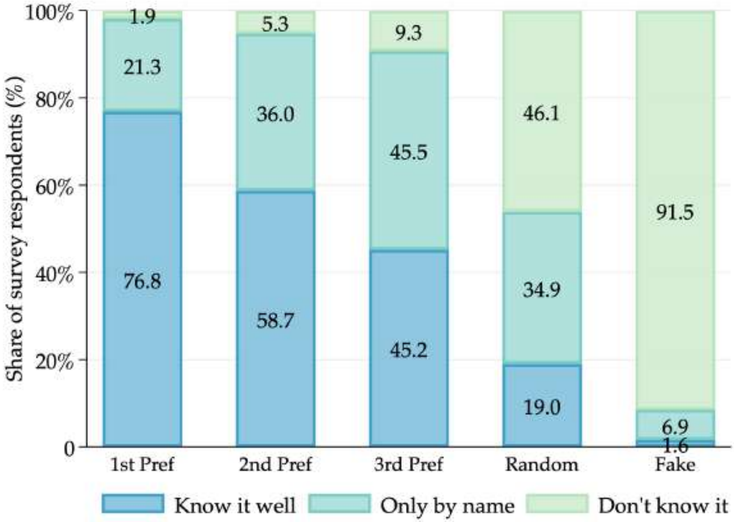
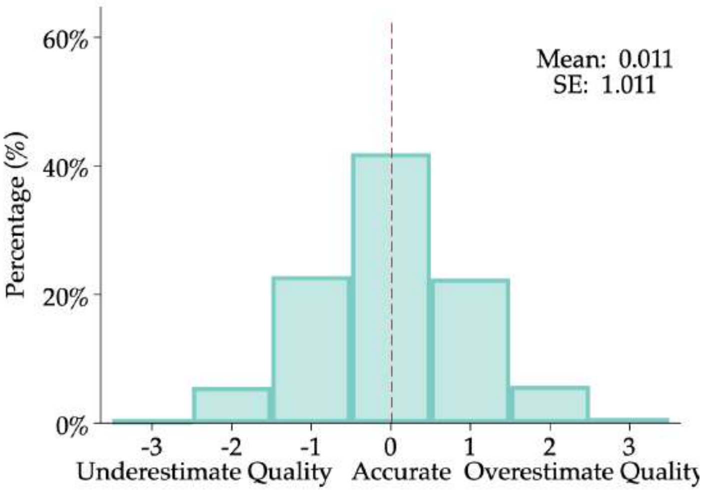


Families overestimate quality of known, liked schools

Winner's curse?



Random not-in-app

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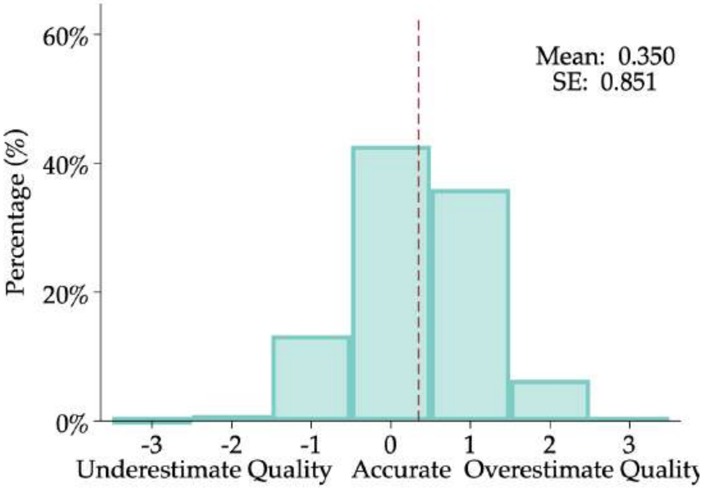

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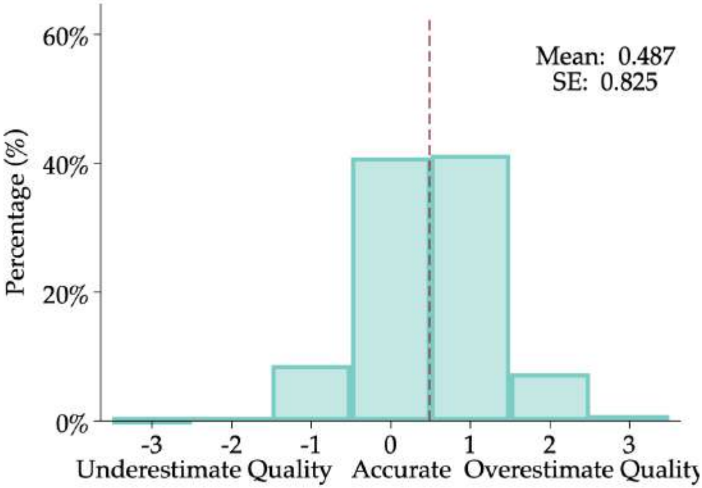
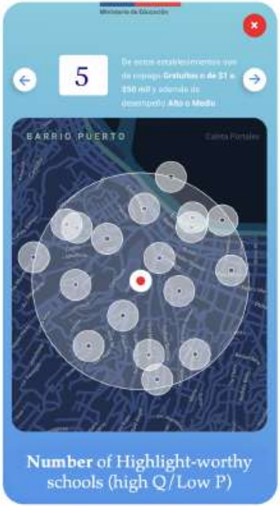


1st Preference

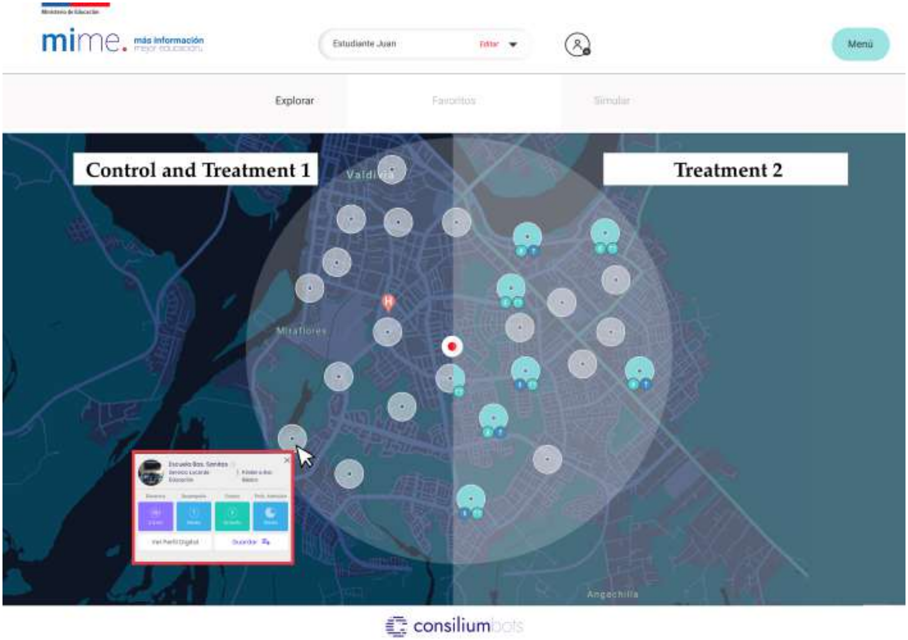
Search Experiment:

Treatment 1 and 2



Treatment 1

Treatment 2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Treatment 2
Valdivia
Miraflores
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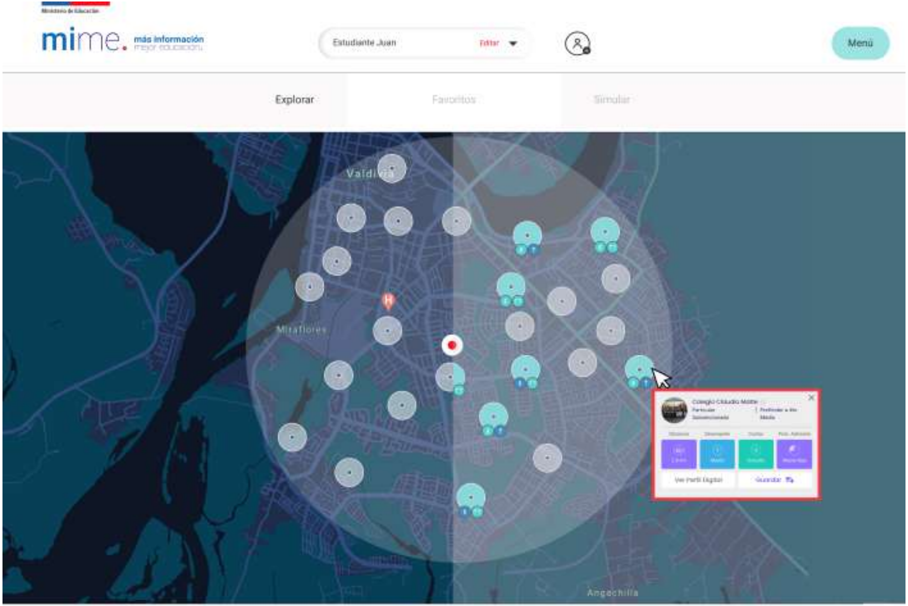

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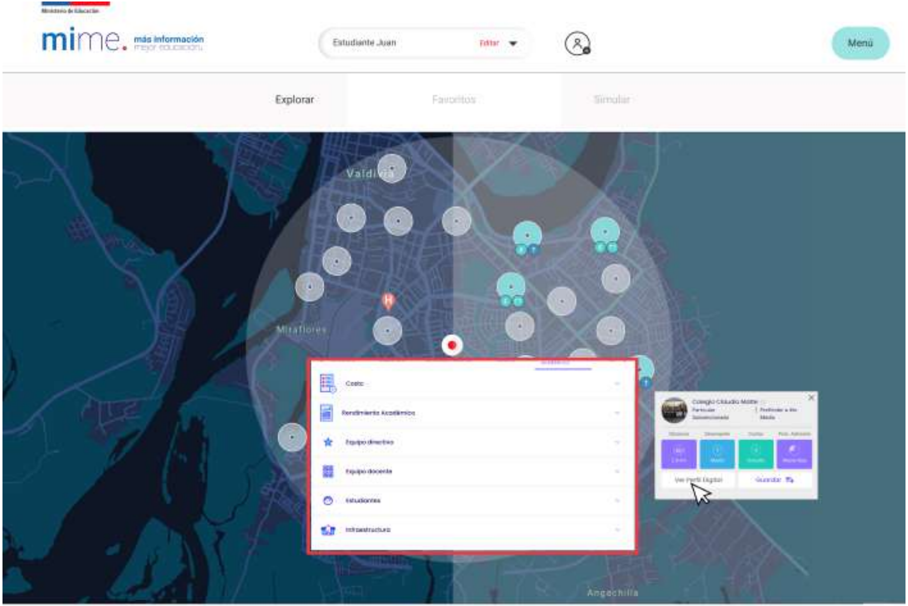

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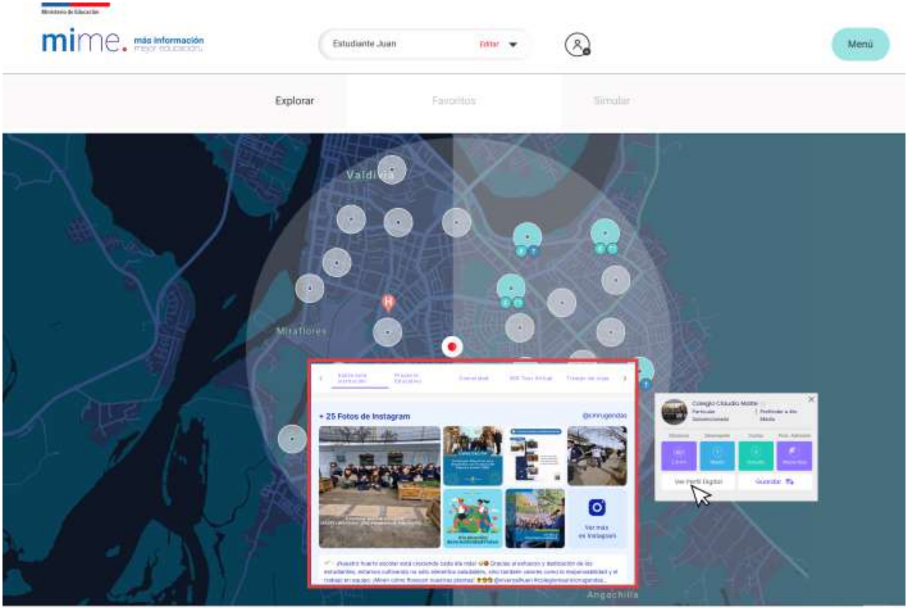
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+ 25 Fotos de Instagram
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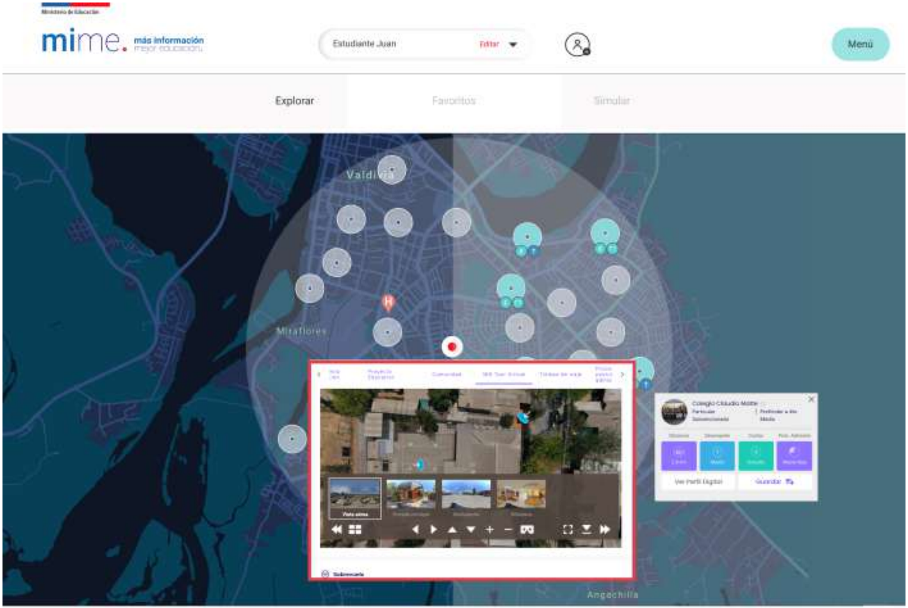

consiliumbots

Experimental Results in Paper

Search Interventions: ▸ Table

- T1: Inform $X's$ distr. → Effects on beliefs (L/H), knowledge (H), search (H)
  → No effects on application outcomes
- T2: Inform $X's$ distr. → Effects on beliefs (L/H), knowledge (H), applications (H)
  + search tech. → No effects on "number of searches"

Feedback Intervention: ▸ Table

- T: Inform $X's$ + recs → Effects on perceptions (Q for H/L, P for L)
  → Effects on applications (L) and assignment (L)

Search intervention effects concentrated among H (high-SES), Feedback intervention among L (low-SES)

Model Overview

- Will present (and estimate) model in two steps:

1. Preferences, awareness, perceptions of known schools' characteristics:
    - Suffices for demand under counterfactuals with given info assignment (e.g. full info)
2. Admissions chances, beliefs about unknowns, search costs and technology:
    - Needed for endogenous info acquisition, e.g. change in info before search decisions

Step 1 Details

- Information:

$$\pi^*_{ijt} = z_{ij}\alpha^z + w_{ijt}\alpha^w + w^{rc}_{ijt}\alpha^{rc}_i + \eta_j + \nu_{ijt} \tag{1}$$

$$\pi_{ijt} = 1(\pi^*_{ijt} > 0) + 1(\pi^*_{ijt} > 1). \tag{2}$$

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$$\hat{x}^{(1)}_{ij} \sim \Gamma(\cdot|x_j), \quad \hat{x}^{(2)}_{ij} = (x_j \text{ w.p. } p^h, \text{ otherwise } \hat{x}^{(1)}_{ij}) \tag{5}$$

- π^*_{ijt}: index for awareness (can't apply if $\pi^*_{ijt} < 0$), perceptions (more accurate if $\pi^*_{ijt} > 1$.)
  - Excluded info shifters w: treatment indicators, search (pin clicks, profile views)

Step 1 Details

- Information:

$$\pi^*_{ijt} = z_{ij}\alpha^z + w_{ijt}\alpha^w + w^{rc}_{ijt}\alpha^{rc}_i + \eta_j + \nu_{ijt} \tag{1}$$

$$\pi_{ijt} = 1(\pi^*_{ijt} > 0) + 1(\pi^*_{ijt} > 1). \tag{2}$$

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  - Off-platform learning: shocks $\nu_{ij} \sim N(0, \Sigma^\nu)$, time indicators $w^{rc}_{ijt} \sim N(\mu^{rc,\pi}, \Sigma^{rc,\pi})$.

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- $\hat{u}^{\pi_{ijt}}_{ij}$: subj. expected payoff of j given i's info at time t.
  - True price and quality category $x \in \{1, \ldots, 4\}^2$. Subj. perceptions: $\hat{x}$.

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    - Mean utility and "discoverability" (δ, η): correlated RE; means depend on (true) x.

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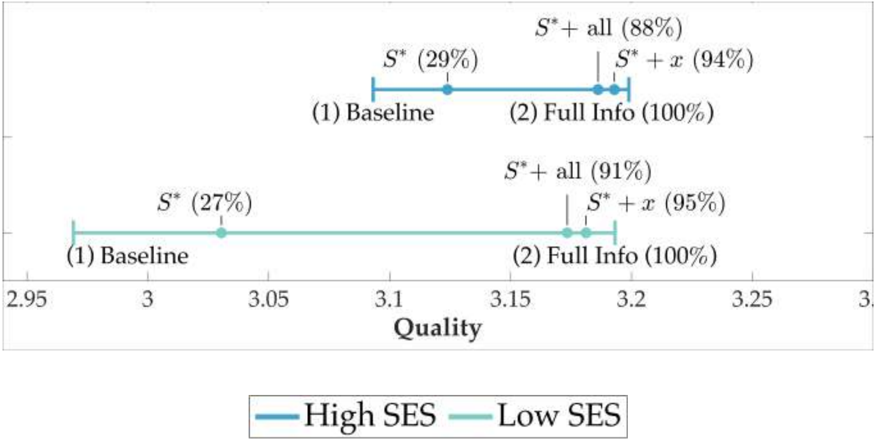
- Estimation: MLE/SMLE.

Counterfactuals Overview

1. **Gains from full information + decomposition:**
   - Base simulation: remove treatments
   - Full information: full information about all schools + we correct all misperceptions
   - Better search (S^*): improves and simplifies the search technology
   - Better search (S^*) + correct biases, misperceptions, and imperfect information
2. **Search Activity and Search Costs:**
   - Does individual level search change with counterfactuals?
   - Gradual Reduction in Search Costs
3. **Misspecified models:**
   - Estimate the model dropping data on $\hat{x}$ and ignoring misperceptions
   - Effects on countrerfactual analysis

Gains of Full Information + Decomposition



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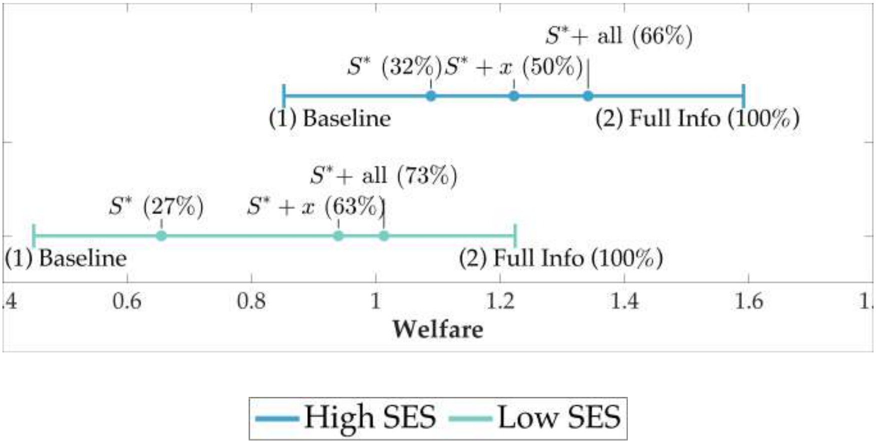

Other Results in Paper:

- Improving search technology induces 47% more search.
- $S^* \to S^* + X$: zero avg. effect on search, but large absolute changes; some search more, others less.
- Gradual reduction in search costs: need to almost eliminate to beat better info.
- Misspecified models: assume $\hat{x} = x$, get *wrong sign* of quality impacts of info provision.

Conclusions

- **Results:** Households' inaccurate perceptions distort search and applications
  - Households value quality — but respond to perception, not truth.
  - Systematically overestimate quality of initial most-preferred "known" school.
- **Counterfactuals:** Perfect takeup of info intervention would close quality SES gap
  - Differences between groups: perceptions of x's, not admissions optimism or prefs.
  - But in practice, high-education households respond more to our search intervention.
- **Methods:** Crucial to model biases/imperfect awareness of "known" options.
- **Agenda:** This paper takes schools' quality, peers as given. Input for eqbm analysis.