Biased Beliefs and Search in Education Markets

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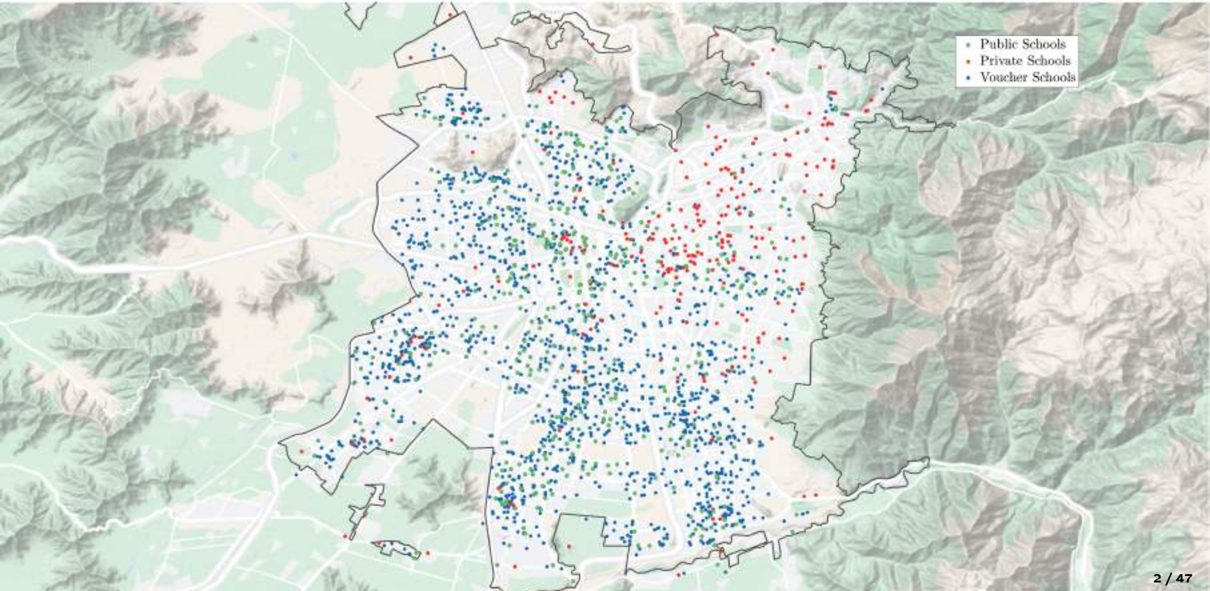
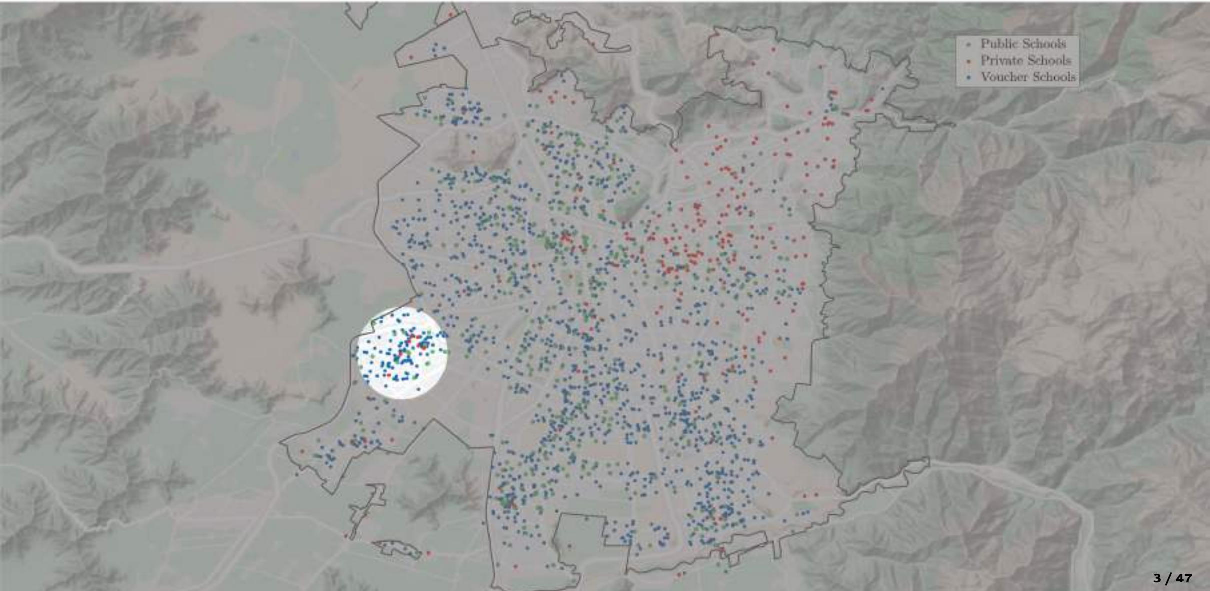
October 2023

Urban Education Markets in Chile (Santiago, Kindergarden Level)



Zoom into a 2km Radius Area



Almost 100 Schools Offering K Among Which Families Can Choose

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- When discovering and evaluating schools is costly, effort depend on beliefs about returns:
- We ask: **how do families' (inaccurate) beliefs/info interact with search costs to affect families' search, applications, and school assignments?**

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  6. Set up and estimate model of search and demand + simulate counterfactuals.

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- Significant cost of status-quo beliefs relative to perfect info: <u>levels</u> and <u>inequality</u>.
  - Low-SES households would gain .2 quality points ($\approx 1/4$ sd of quality measure).

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  - Caveat: larger welfare gains for full info than "info about x's".

Literature

- We are looking at "consumer search" and demand in a high stakes setting.
  - De Los Santos et al (2012; 2017) Dinerstein et al (2018); Hodgson Lewis (2022); Moraga-Gonzales et al (2022); ...
  - Health plan choice: Handel and Kolstad (2015), ...
- Providing information about "X's" of schools can affect applications:
  - Hastings Weinstein (2008); Mizala Urquiola (2013); Corcoran et al (2017, 2022); Andrabi Das Khwaja (2017); Allende Gallego Neilson (2019); Bergman Chan Kapor (2020)
- Giving info about admissions chances can affect apps and assignments.
  - Hoxby Turner (2013, 2015); Gurantz et al (2021); Ajayi Friedman Lucas (2022)
  - Search $\rightarrow$ admissions beliefs relevant, even under SPDA. (AKNZ 2022)
- This paper's contributions:
  - Novel data on search and beliefs + information experiments:
    $\Longrightarrow$ **provide direct evidence that inaccurate beliefs distort search decisions**
  - Estimate demand w/ limited consideration (extending consideration-set approach (Goeree (2008)) to allow inaccurate perceptions of "known" options), imperfect info, rich prefs:
    $\Longrightarrow$ **quantify welfare and school-quality impacts of addressing misperceptions + search costs**

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- Setting and interventions
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- $\hat{u}_{ijt}$: payoff from j given info π_{ijt}; depends on real characteristics and on subjective beliefs

Distance	z_{ij}	
Observable quality/price index $\in \{1, \ldots, 4\}^2$	x_{ij}	$\hat{x}_{ij}(\pi_{ijt})$
Unobserved match value	ε_{ij}	$\hat{\varepsilon}_{ij}(\pi_{ijt})$
Rejection probability	r_{ij}	$\hat{r}_{ij}(\pi_{ijt})$
Mean Utility and Discoverability	δ_j, η_j	
Treatments, search activity: excluded from $\hat{u}$	w_{ijt}	

Model: Information (π), Preferences ($\hat{u}$)

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- π plays two roles:
  - $\pi_{ijt} < 0 \rightarrow$ student doesn't know j at all.
  - $\pi_{ijt} > 1 \rightarrow$ more accurately perceive observables (x_{ij}), match value (ε_{ij}).

Model: timing

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Time is discrete: $t = 0, 1, \ldots, T$.

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$t = T$ — i submits truthful ranking (by $\hat{u}_{ijT}$) over $\{j \in J_i : \min\{\hat{u}_{ijT}, \pi_{ijT}\} > 0\}$.

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* From previous slides: awareness (π) shifters w_{ijt} include indicator for having inspected j at $s \leq t$

Model: What affects expected value of search?

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   - Beliefs about the distribution of match quality: Optimism/pessimism

     $$\varepsilon_{ij} \sim N(\hat{\mu}, \hat{\sigma}^2), \text{ where the truth is } N(0, \sigma^2_{\varepsilon})$$

Outline

- Model
- Setting and interventions
- Data and descriptive analysis
- Estimation and counterfactuals

Chilean School Choice Process

- Chile uses a student-proposing deferred acceptance procedure for centralized assignment
- Single nationwide online platform
  - Pre-K to 12th grade
  - Public and Voucher schools ⇒ approximately 90% of total enrollment
  - Applicants concentrate on entry levels: Pre-K (23.50%), Kindergarten (7.89%), 1st grade (13.62%) and 9th grade (25%)
- Students allocated based on quotas and priorities.
- In 2021, 3,088,505 (85.17%) students enrolled in public and voucher schools ⇒ Of these, 461,223 (14.93%) participated in the regular round

Interventions

1. Personalized Search
   - **Universe:** Households w/ children entering the regular education system for the first time.
     - 3,948 participants, recruited from preschools.
   - **Treatments:**
     1. Control: Access to explorer
     2. Treatment 1: Access to explorer + Distribution
     3. Treatment 2: Access to explorer + Distribution + Report Card + Highlight schools with $p = 0, \text{quality} \in \{3, 4\}$.

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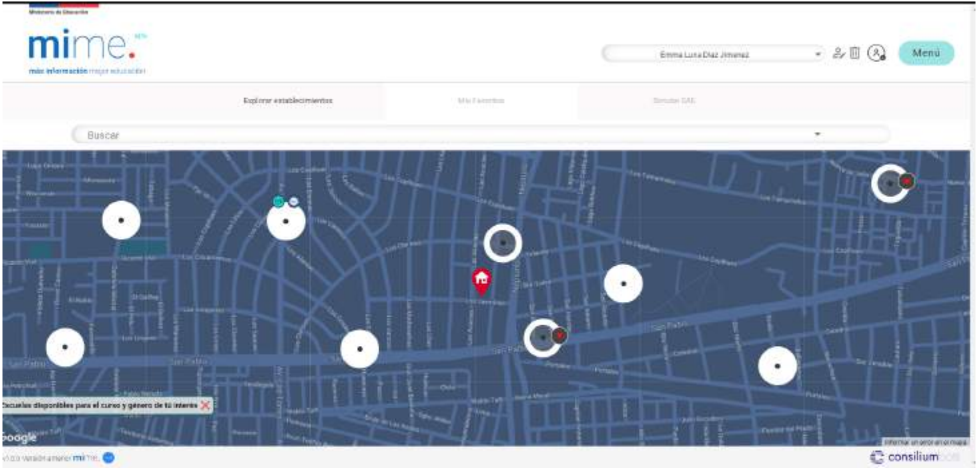
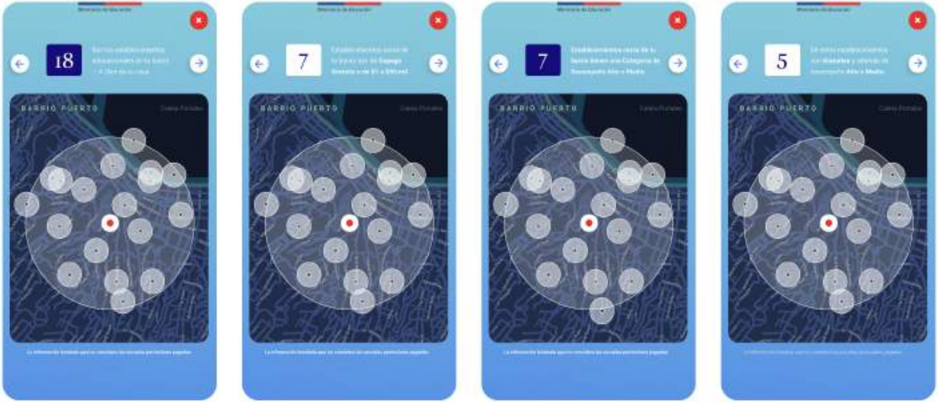
2. Personalized Feedback
   - **Universe:** Households with a valid SAE application one week before the end of main application period. Restrict to urban markets, grades {Pre-K, K, 1, 9}.
     - 162k participants, 45k of which have > 0 risk of non-assignment.
     - This paper: we restrict to intersection with search sample.
   - **Treatments:**
     1. Personalized feedback about schools in portfolio; risk warning; list of recommendations; access to explorer.
     2. Pure control (Whatsapp message)

Treatments: School Explorer



Treatments: Treatment 1



Distribution of Total Schools

Distribution of Free + Low Price Schools

Distribution of Good Schools

Distribution of Free + Good Schools

Treatments: Treatment 2

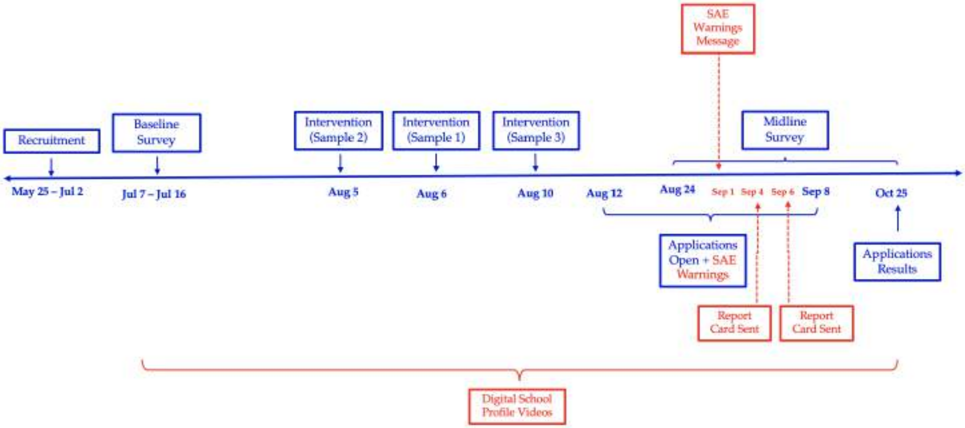
Distribution of Total Schools

Distribution of Free + Low Price Schools

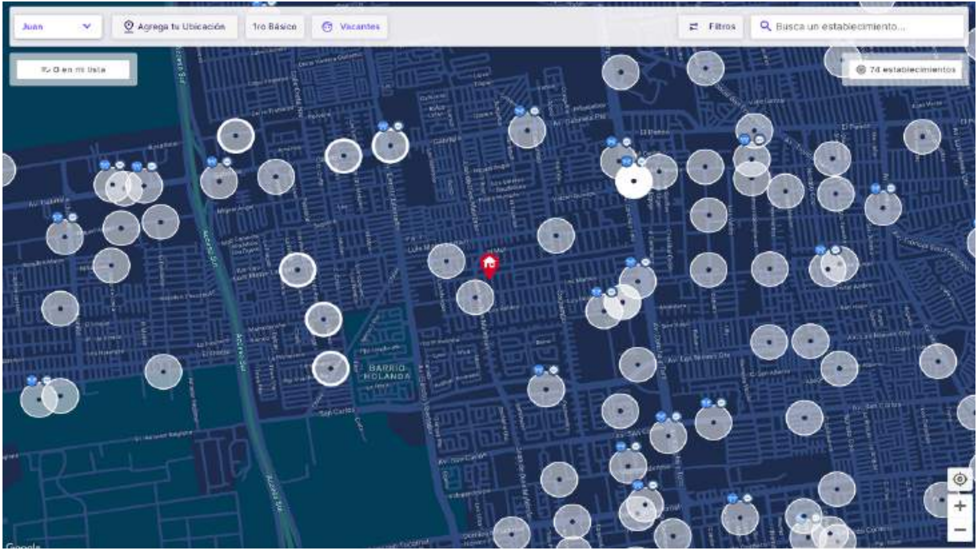
Distribution of Good Schools

Distribution of Free + Good Schools

Timing Intervention 2021



Search History



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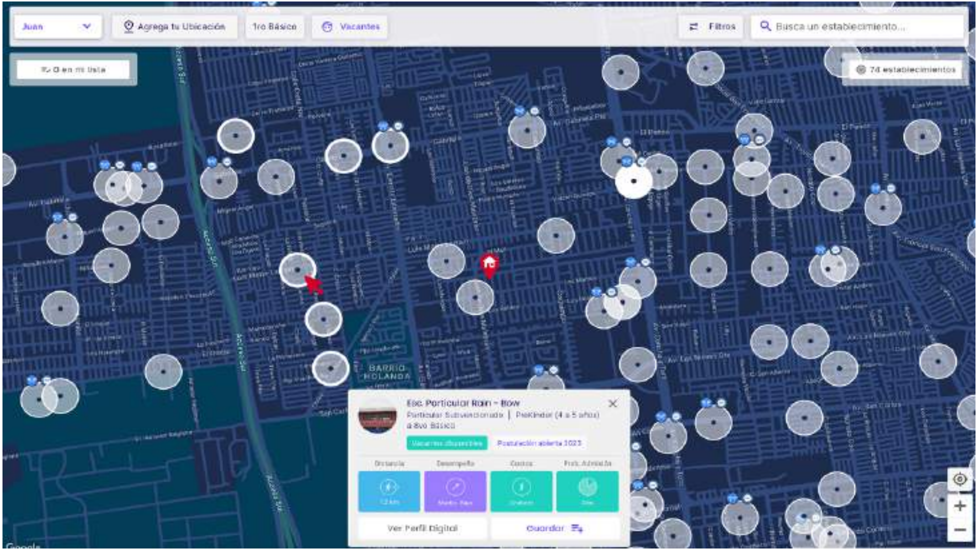

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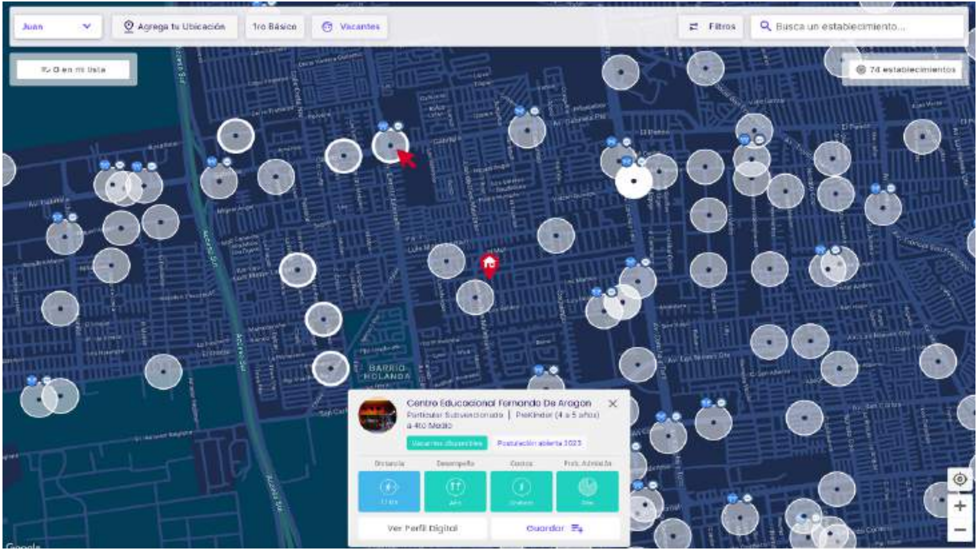

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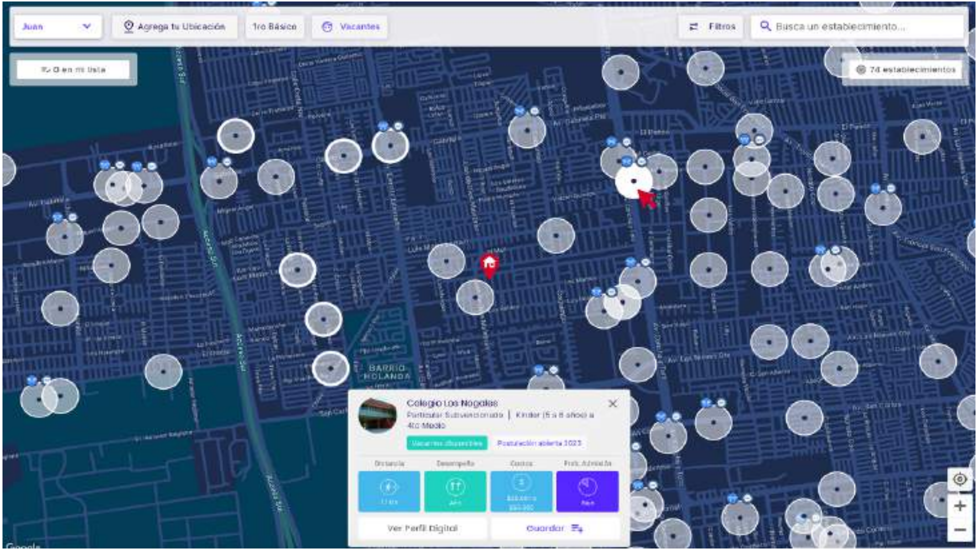

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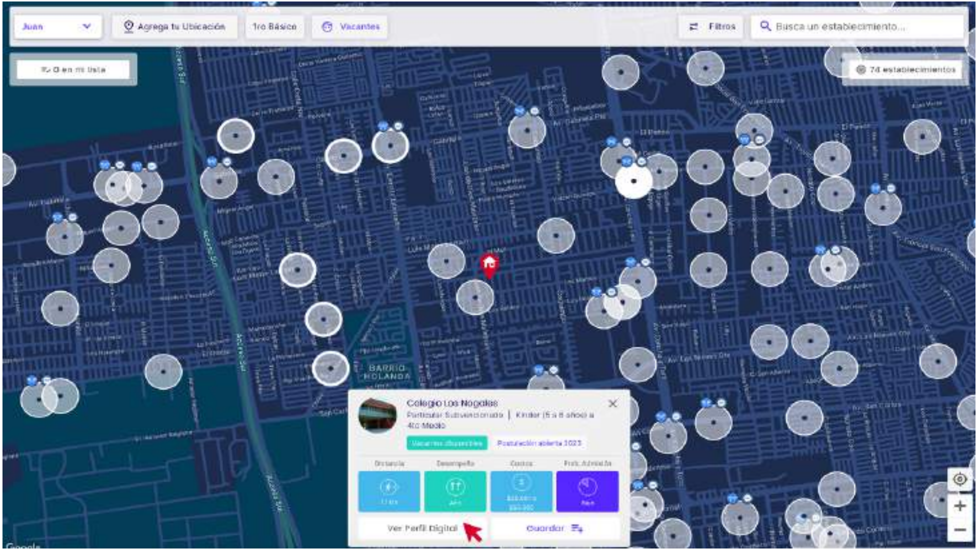
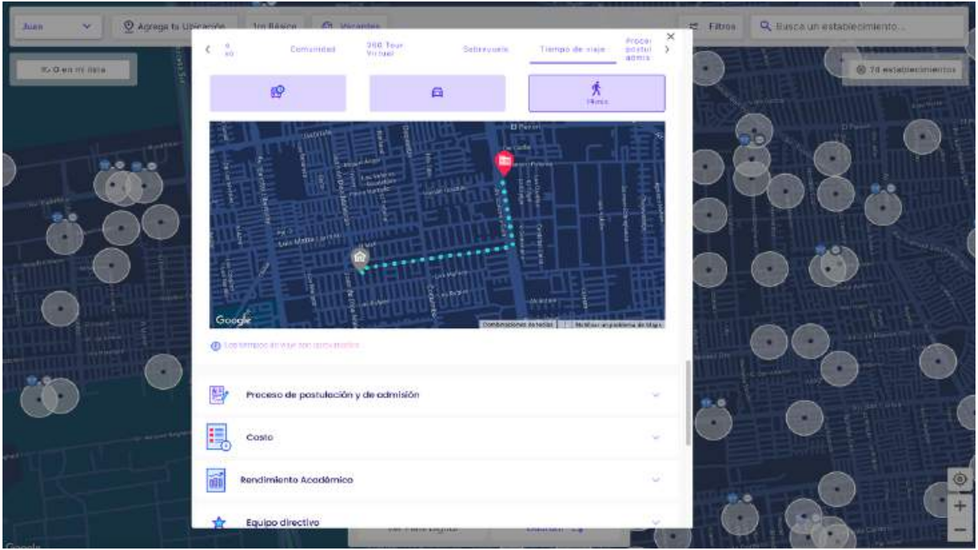


Search History



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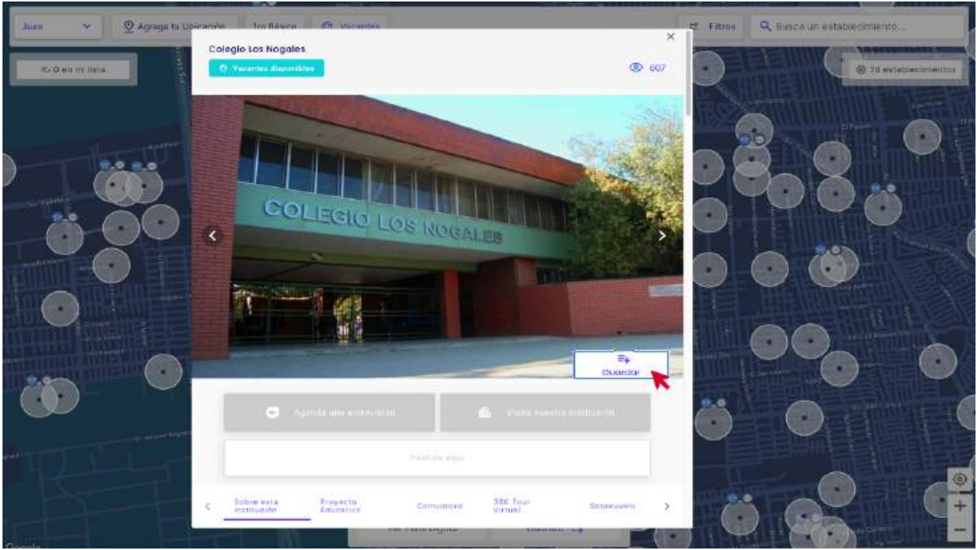

Personalized feedback

Outline

- Model
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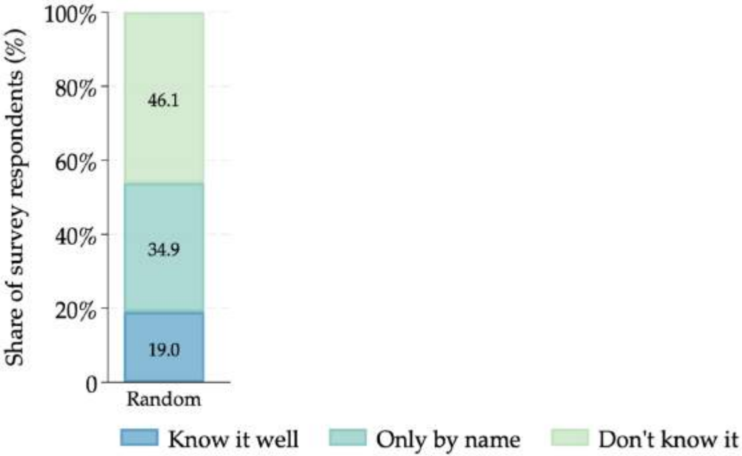
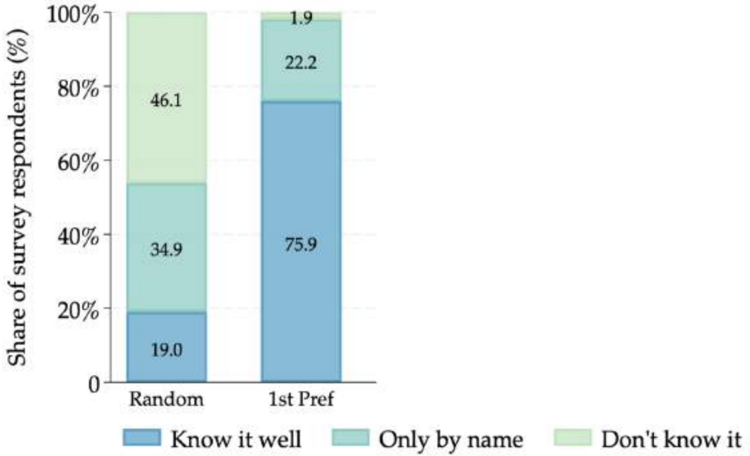
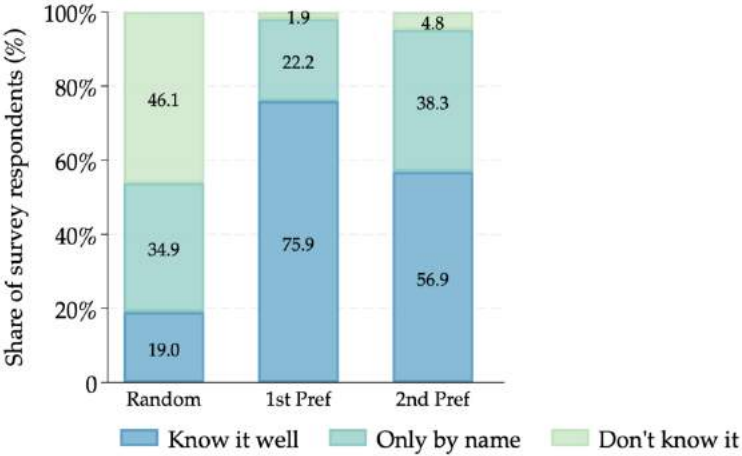
Fact 1a: households do not know all schools



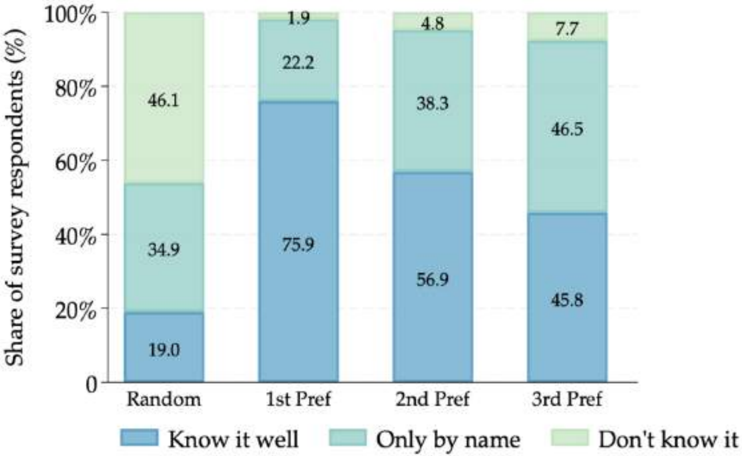
Fact 1b: First preference known well



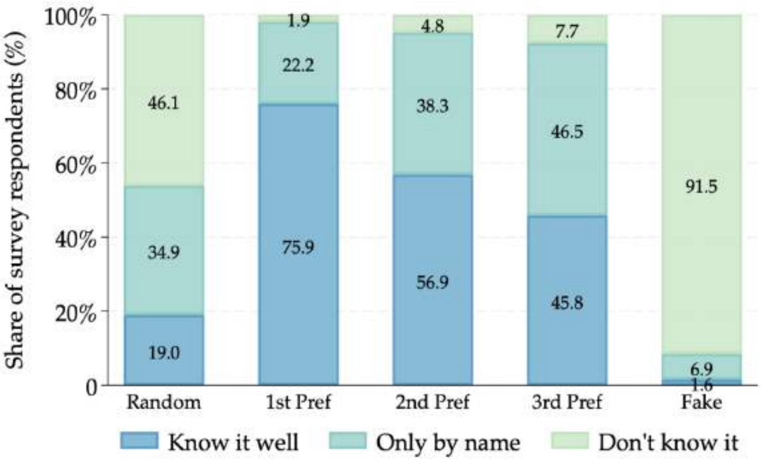
Fact 1c: Second preference known less well



Fact 1d: Third preference known less well



Fact 1e: Don't know fake school



Fact 2: Households overestimate quality and price of unknown schools

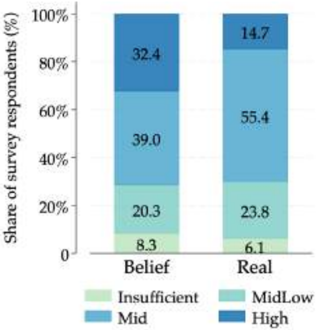


Figure 1: Quality

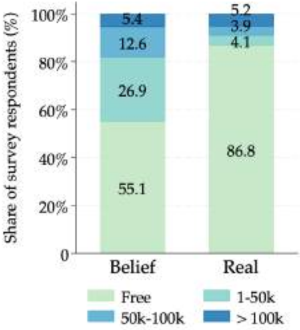
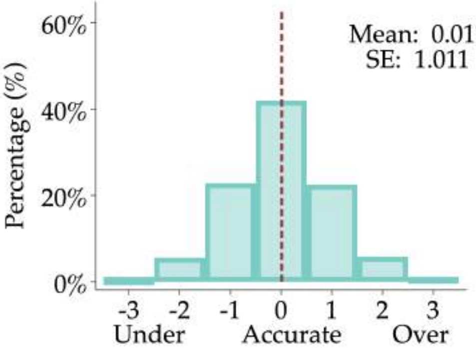


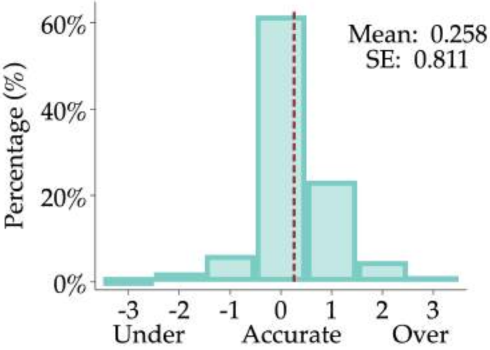
Figure 2: Price

▸ Quality index and value added

Fact 3a: Households also misinformed about price, quality of **known** schools

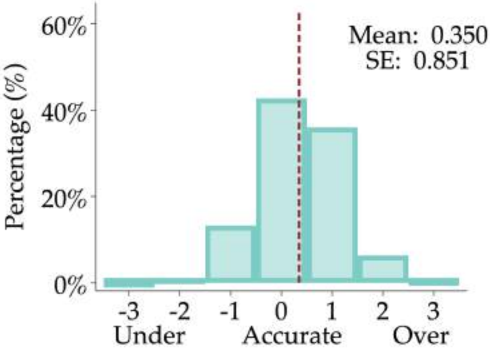


Error quality random not-in-app

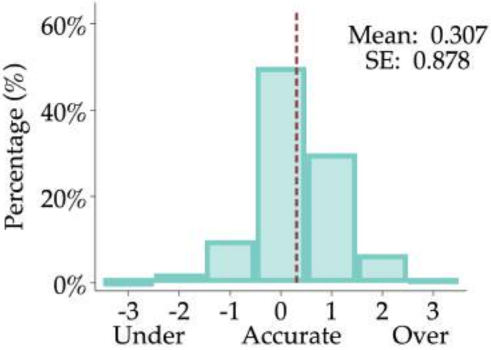


Error price random not-in-app

Fact 3b: Households overestimate quality of schools they apply to

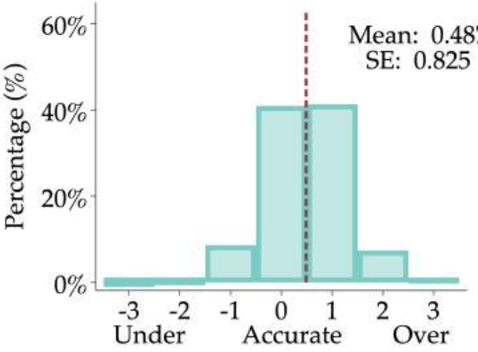


Error quality random in-app

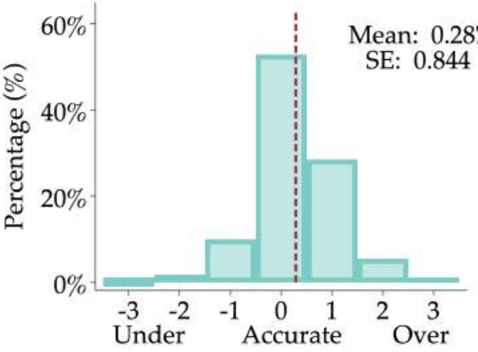


Error price random in-app

Fact 3c: Households overestimate quality of first-choice school

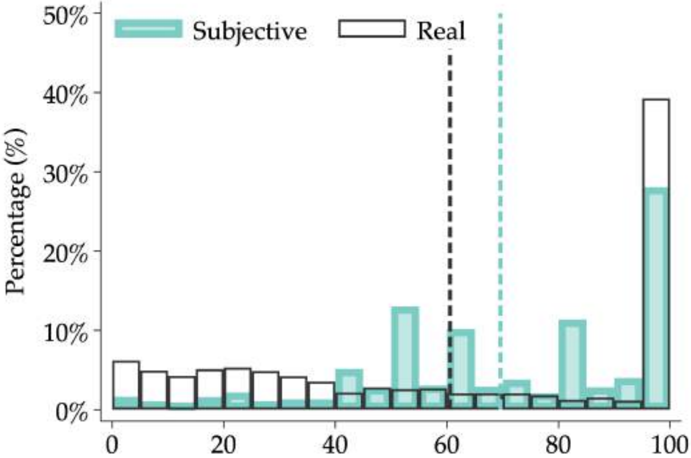


Error quality 1st pref



Error price 1st pref

Fact 4: Households also mispredict admissions chances



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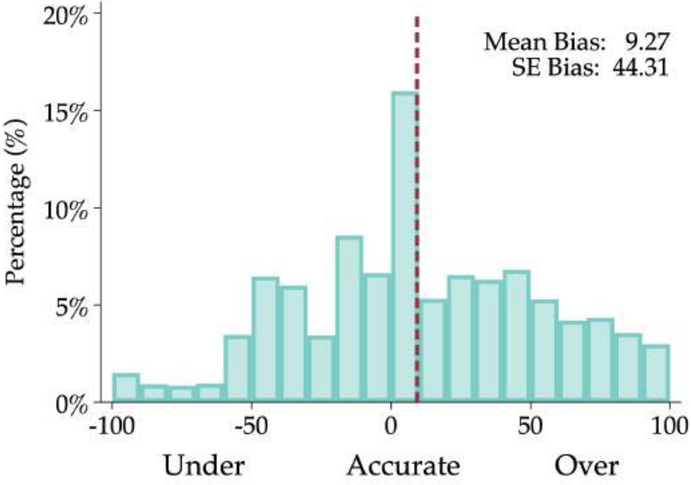
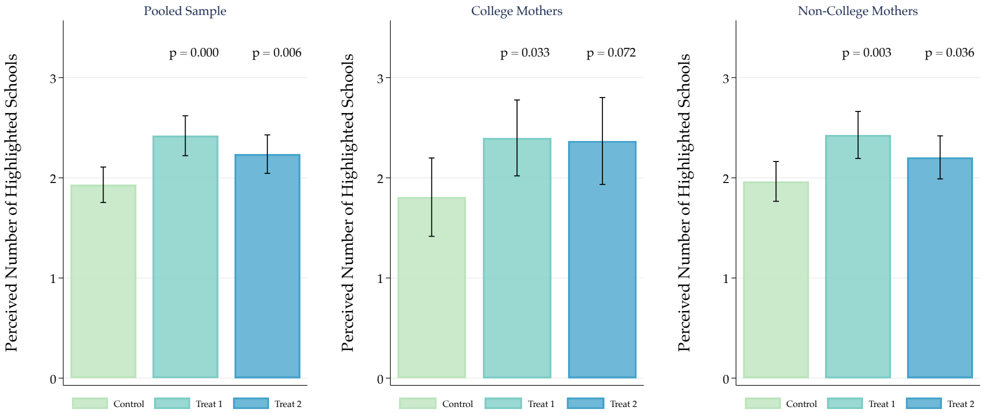


Empirical Strategy for Personalized Search Experiment

$$Y_i = \alpha + \beta_1 T1_i + \beta_2 T2_i + \lambda_i + \gamma X_i + \varepsilon_i.$$

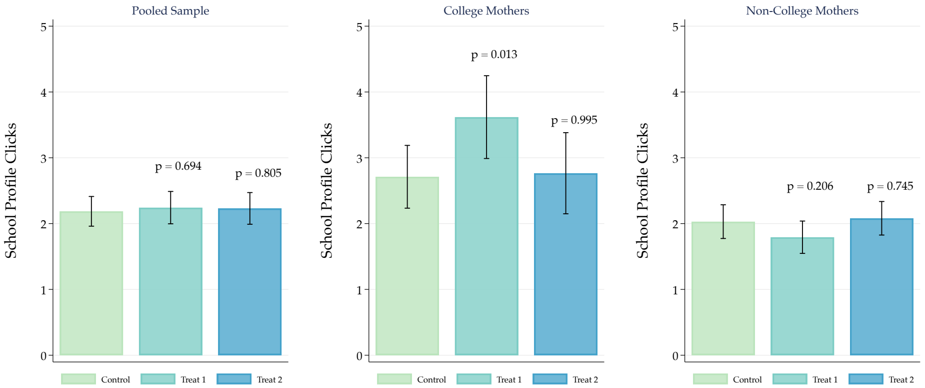
- $T1_i, T2_i$: treatment status $\quad \lambda_i$: strata fixed effect
  X_i: baseline controls (selected through double-lasso)
- Show separate results for college (23%) and non-college mothers (77%).

Treatment Affects Beliefs



▸ Regression Table

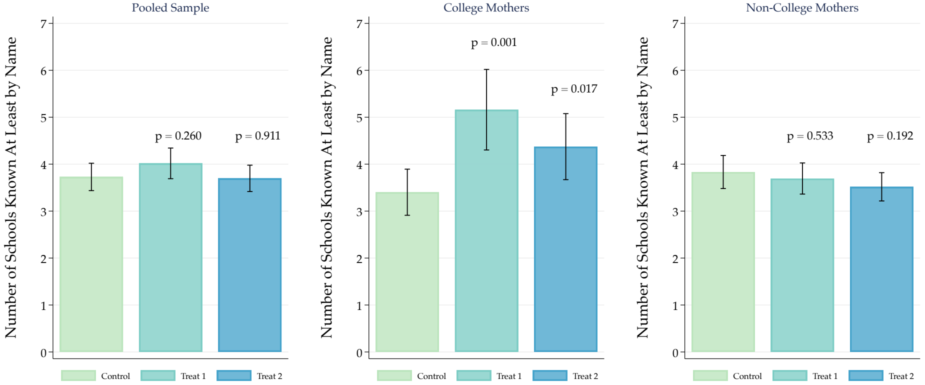
Treatment Increases Search for College Mothers



Regression Table

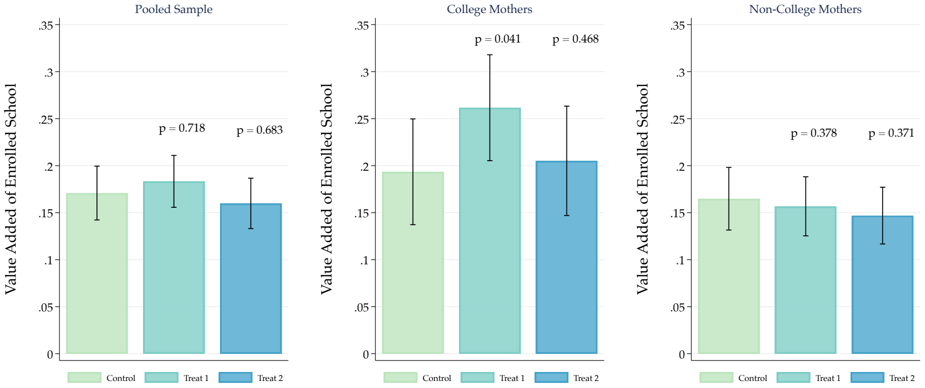
- Similar treatment effects in two follow-up experiments in Chile and DR. Details

Treatment Affects Knowledge for College Mothers



▸ Regression Table

Treatment Affects Enrollment



Regression Table

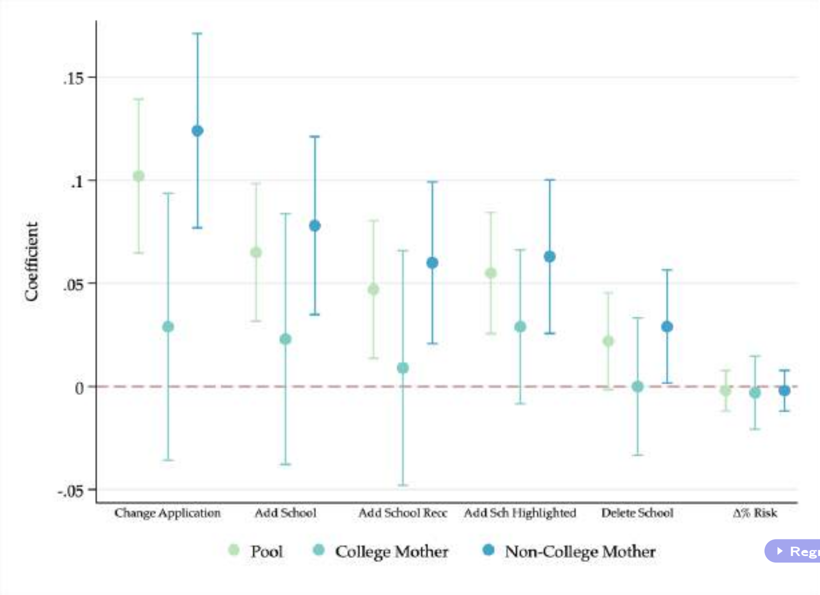
- Treatment 2 increases likelihood that 2nd ranked school in application is highlighted.

Empirical Strategy for Personalized Feedback Experiment

$$Y_i = \alpha + \beta T_i + \lambda_i + \gamma X_i + \varepsilon_i.$$

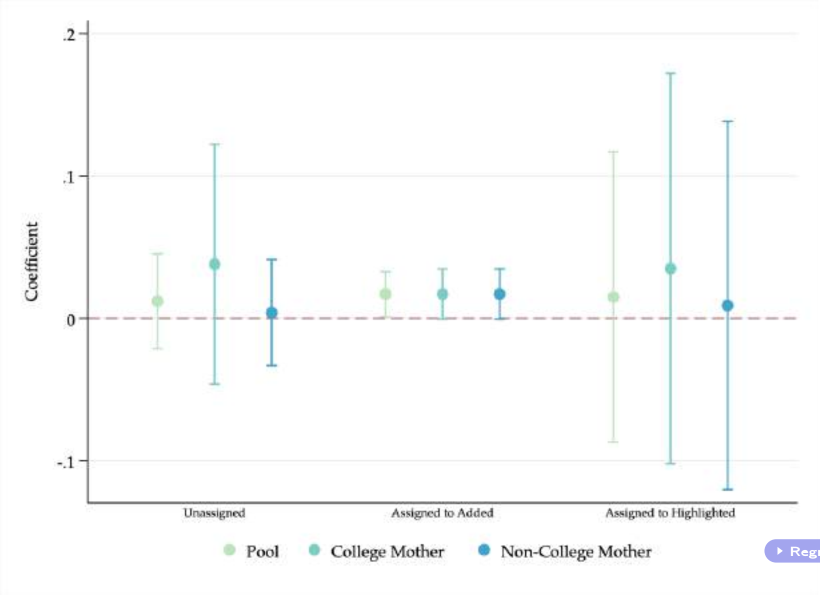
- T_i: treatment status λ_i: strata fixed effect X_i: baseline controls
- Use treatment assignment as instrument for opening feedback intervention.

Feedback Treatment Affects Application



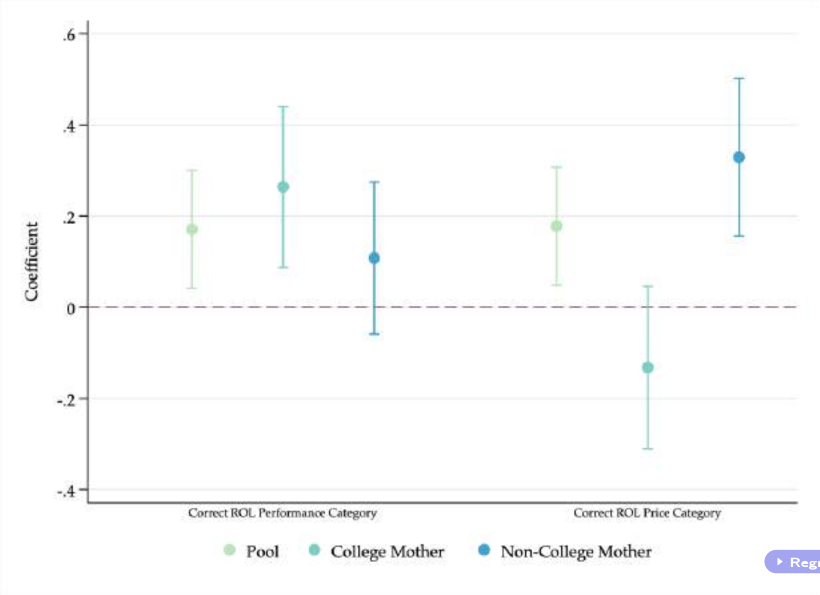
▸ Regression Table

Feedback Treatment Affects Assignment



▸ Regression Table

Feedback Treatment Affects Knowledge



▸ Regression Table

Descriptive Analysis: Summary

1. Households do not know all nearby schools.
   - In paper: high-quality schools (somewhat) more likely to be known at baseline ▸ Table
2. Households hold inaccurate beliefs:
   1. $F(\text{price}, \text{quality})$ over schools they don't know
   2. admissions chances
   3. quality and price of "known" schools
   - In paper: rankings respond to subj. beliefs not truth ▸ Table
3. Information treatments:
   1. shift beliefs (all), search effort (college moms), apps and matches (VA, college moms)
   - Sample is balanced ▸ Table
   - Heterogeneity not driven by differences in choice sets or beliefs ▸ More
4. Search activity:
   - occurs almost entirely in a short period after we prompt people ▸ Timing ▸ Search Actions
   - effort responds to subjective beliefs
   - stopping rule depends on history (i.e. search looks sequential)
   - clicks predict knowledge of schools, accurate beliefs, applications

Outline

- Model
- Setting and interventions
- Data and descriptive analysis
- Estimation and counterfactuals

Empirics: preferences (u) and awareness (π)

We specialize to three levels of knowledge, "potential utilities":

$$\pi_{ijt} = z_{ij}\alpha^{z} + w_{ijt}\alpha^{w} + w_{ijt}^{rc}\alpha_i^{rc} + \eta_j + \nu_{ijt} \qquad \text{(Awareness, time t)}$$

$$\hat{u}_{ijt} = 1(\pi_{ijt} > 1)u_{ij}^{h}(\hat{x}_{ij}^{h}) + 1(0 < \pi_{ijt} \leq 1)u_{ij}^{l}(\hat{x}_{ij}^{l}) \qquad \text{(Subj. EU, time t)}$$

Can know a school well ($\pi_{ijt} > 1$), somewhat ($0 < \pi_{ijt} \leq 1$), or not at all ($\pi_{ijt} < 0$).

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$$\hat{x}_{ij}^{l} \sim \Gamma(\cdot|x_j), \quad \hat{x}_{ij}^{h} = (x_j \text{ w.p. } p^{h}, \text{ otherwise } \hat{x}_{ij}^{l}) \qquad \text{(Perceived "observables")}$$

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"know well" $\implies$ better knowledge of match value, (stochastically) better signal of x.

- Correlated random effects: $(\eta_j, \delta_j)' \sim N\left((x_j\overline{\alpha}, x_j\overline{\beta})', \Sigma^{\eta\delta}\right)$.
- Random coefficients: $\beta_i^{rc} \sim MVN(0, \Sigma^{rc})$, $\alpha_i \sim MVN(0, \Sigma^{\alpha rc})$.
- Post-search (exogenous) off-platform learning: $\left(\nu_{ij}^0, \ldots, \nu_{ij}^T\right)' \sim N\left(\overline{\eta}, \Sigma^\pi\right)$, with $\overline{\eta}_0 = 0$.
- Shock $\varepsilon_{ij} \sim N(0, \sigma_\varepsilon^2)$. If $\pi_{ijt} \in (0,1)$, observe w/ normal noise; shrink to subj. prior.

Estimation Overview

We estimate the model in two steps:

1. Estimate $(u, \pi, \hat{x}, \beta_i^x$, associated index and VCV params) via Gibbs sampler.
    - Data:
        - baseline (survey) ROL; administrative "just-before-feedback" and "final" ROLs
        - treatment assignments and responses; explorer "detail views";
        - 3 survey waves of: "how well do you know", perceived x's; 2 waves beliefs about $F(x)$.
    - w: treatments, highlight, detail views. RC's on $(1, \text{dist}, \hat{x})$.
    - Normalizations: mean coef on distance $= -1$; $E(\varepsilon) = 0$.
    - Include (and estimate) measurement error on every survey variable.
    - ID: use repeated within-person measurements of ROL, π, $\hat{x}$; variation in treatment assignments and search outcomes.
2. Estimate remaining parameters using optimality of search decisions.
    - Estimate admissions beliefs, "x" beliefs (Λ), (click probabilities | continue) via MLE.
    - Compute subjective expected utility of search at each history using these objects and results from (1).
    - W/ SEU of search in hand, estimate search cost distribution via SMLE.

Random Effects: Mean Utility (δ) and Discoverability (η)

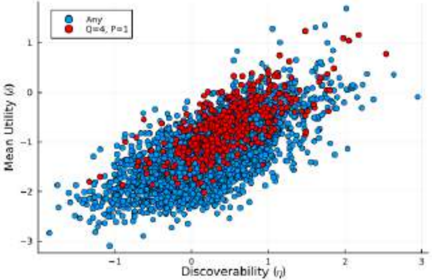

Figure 5: Non-College Mother

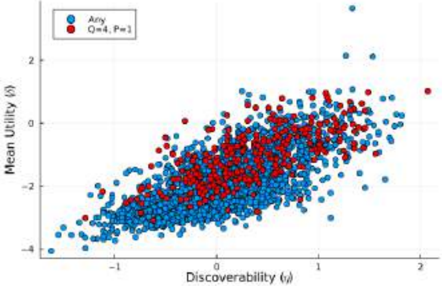

Figure 6: College Grad

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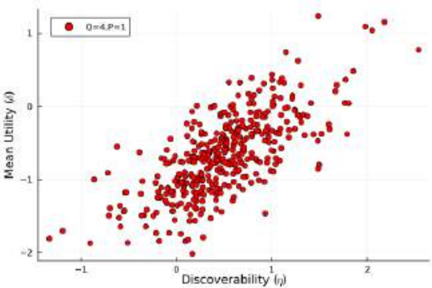

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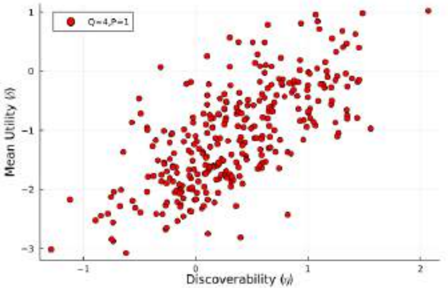

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Counterfactuals

We compare:

1. Baseline (as in data)

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5. We also estimate a specification in which we assume $\hat{x} = x$, consider "full-info benchmark" under that specification.

Main Results: Quality

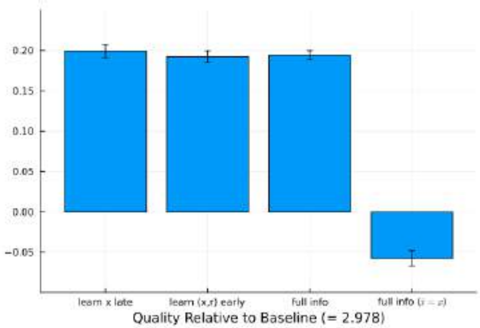

Figure 7: Non-College-Grad Mother

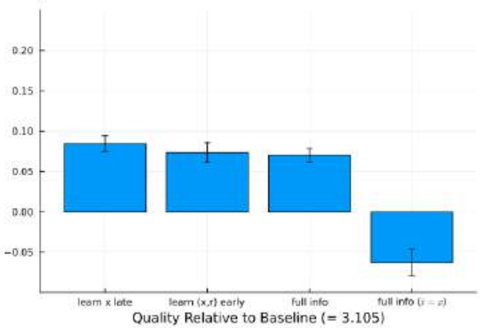

Figure 8: College Grad Mother

Main Results: Value Added

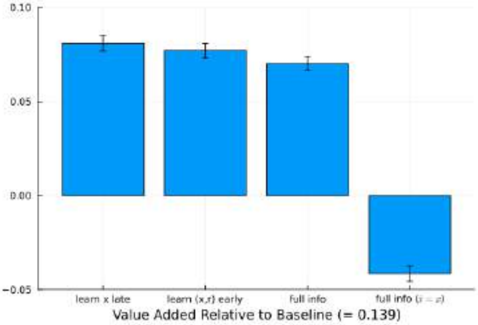

Figure 9: Non-College-Grad Mother

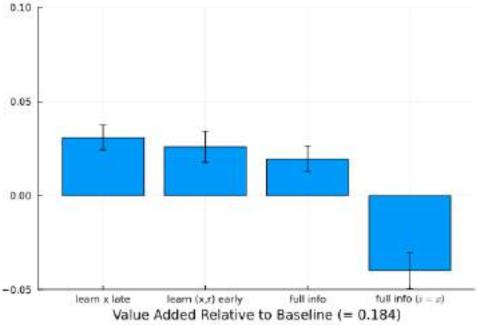

Figure 10: College Grad Mother

Main Results: Pr(Place)

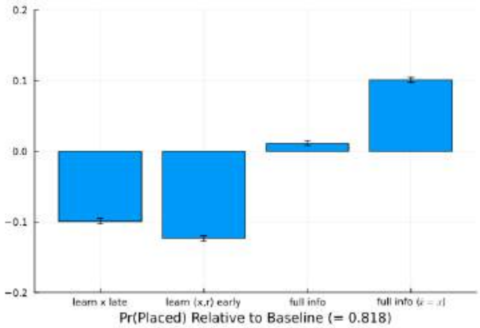

Figure 11: Non-College-Grad Mother

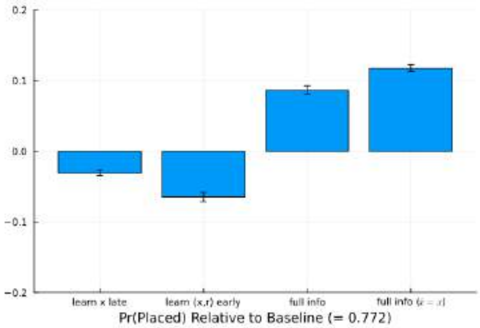

Figure 12: College Grad Mother

Main Results: Perceived Welfare

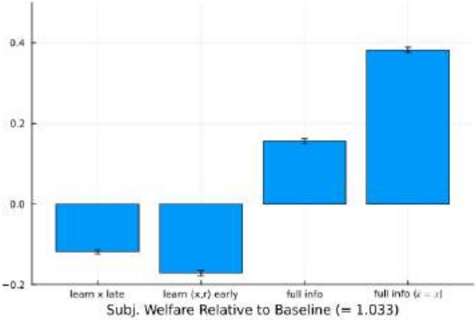

Figure 13: Non-College-Grad Mother

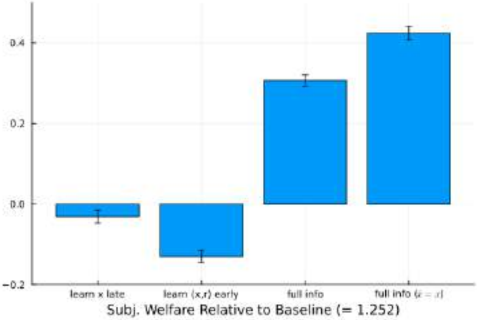

Figure 14: College Grad Mother

Main Results: Welfare

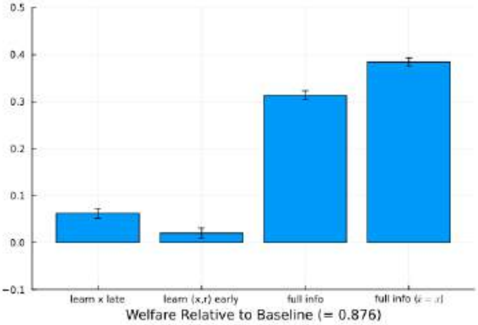

Figure 15: Non-College-Grad Mother

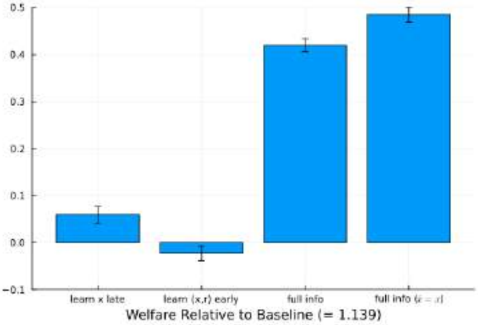

Figure 16: College Grad Mother

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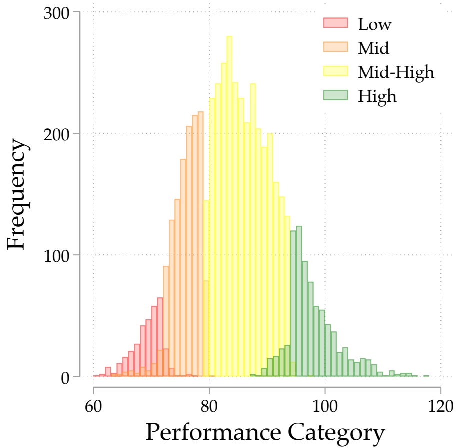
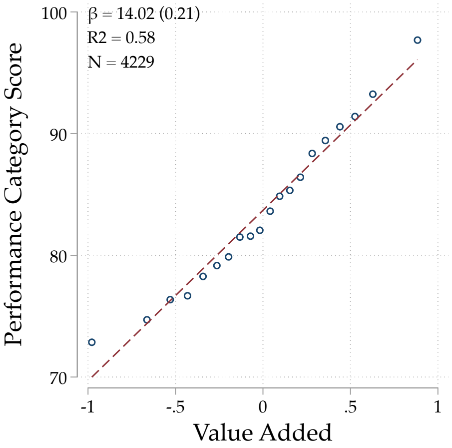
- Policy: Not obvious that we want to provide info broadly/early rather than targeted/timely (may be complements).
- Recently concluded fieldwork in additional settings (Chile 9th-grade; DR).

Performance category and Value Added





▸ Back

Baseline: Better Schools Known (Slightly) Better

	Know Well	Know by Name	Don't Know
High Performance	23.33%	38.02%	38.65%
Medium Performance	18.45%	36.26%	45.28%
Med-Low Performance	11.82%	32.39%	55.79%
Insufficient Performance	9.37%	28.07%	62.56%

Table 1: Baseline Awareness Set I

Back

Reported beliefs about p, q, not truth, predict rankings

		Partial Ranking (1)		Regular Round Ranking (2)	
Distance		-0.000	(0.003)	-0.048**	(0.020)
Perceived Price Category	1	-0.306**	(0.119)	0.280	(0.188)
	3	-0.226*	(0.133)	-0.152	(0.249)
	4	-1.269***	(0.236)	-0.329	(0.502)
Real Price Category	1	0.052	(0.118)	-0.078	(0.200)
	3	0.166	(0.134)	0.284	(0.233)
	4	0.153	(0.216)	0.295	(0.459)
Perceived Performance	1	-1.683***	(0.623)	-1.593	(1.091)
	3	1.894***	(0.176)	0.232	(0.241)
	4	3.712***	(0.202)	1.023***	(0.276)
Real Performance	1	-0.569**	(0.252)	0.020	(0.459)
	3	0.099	(0.113)	-0.113	(0.185)
	4	0.226*	(0.127)	0.028	(0.216)
Public School		-0.344***	(0.112)	-0.050	(0.172)
Observations		3568		1199	

Notes. This table presents a rank-ordered logit choice model. Column (1) refers to the partial ranking we elicited at baseline with perceived price and quality from responses to the baseline survey. Column (2) refers to the ranking from application data from SAE Regular Round, with perceived price and quality from responses to the midline survey.

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Balance Check Slides

	Control		Treatment 1		Treatment 2		
	Mean	St. Dev.	Coeff.	St. Err.	Coeff.	St. Err.	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Choice Environment							
N Schools (in SAE)	18.778	[8.903]	0.154	(0.427)	0.262	(0.433)	1,801
N Schools (Any)	42.904	[17.580]	0.124	(0.895)	0.274	(0.894)	1,801
N Highlighted (Any)	9.414	[4.785]	0.096	(0.264)	0.254	(0.260)	1,801
Panel B: Parent/Child Characteristics							
Child is female	0.483	[0.500]	0.043	(0.029)	0.040	(0.029)	1,801
Child's Birth Year	0.076	[0.541]	0.008	(0.031)	0.029	(0.031)	1,801
Mother Educ. HS	0.942	[0.234]	0.005	(0.012)	-0.006	(0.013)	1,798
Mother Educ. Coll	0.249	[0.433]	0.000	(0.017)	-0.009	(0.017)	1,798
N younger siblings	1.141	[0.401]	0.023	(0.023)	0.008	(0.023)	1,801
Has Disability	0.075	[0.263]	-0.007	(0.016)	-0.012	(0.016)	1,630
Parent Sch. Staff	0.069	[0.255]	-0.010	(0.014)	-0.012	(0.014)	1,768
SEP Household	0.373	[0.484]	-0.015	(0.014)	-0.018	(0.014)	1,781

	Control		Treatment 1		Treatment 2		
	Mean	St. Dev.	Coeff.	St. Err.	Coeff.	St. Err.	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel C: Initial Knowlege and Beliefs							
Satisfaction	5.144	[1.392]	0.053	(0.083)	0.017	(0.084)	1,679
Pref 1 (Any)	0.911	[0.286]	-0.008	(0.017)	-0.008	(0.017)	1,801
Pref 1 (HL)	0.490	[0.500]	0.044	(0.032)	0.026	(0.032)	1,402
Perceived adm.	68.089	[25.839]	1.400	(1.538)	1.358	(1.533)	1,679
N Schools known A	3.608	[2.745]	-0.027	(0.158)	0.068	(0.154)	1,801
N Schools known B	1.925	[2.126]	-0.038	(0.123)	-0.072	(0.120)	1,801
Perceived N (2km)	6.803	[8.769]	-0.441	(0.420)	-0.882	(0.391)	1,801
Perceived HL (2km)	2.086	[2.610]	0.124	(0.150)	-0.008	(0.144)	1,801
SEP Eligible (Belief)	0.139	[0.346]	-0.021	(0.019)	-0.003	(0.020)	1,801
SEP Don't Know	0.702	[0.458]	-0.009	(0.027)	0.013	(0.026)	1,801
Add info known	66.186	[30.149]	-2.104	(1.809)	-1.461	(1.787)	1,679
Add info unknown	55.858	[33.018]	1.071	(1.917)	0.454	(1.919)	1,679
Would add school	0.821	[0.384]	0.005	(0.023)	0.013	(0.022)	1,679
Add sch. as pref 1	56.129	[29.431]	0.633	(1.808)	-0.084	(1.746)	1,679
Add sch. blw last	66.264	[27.196]	1.109	(1.624)	-0.297	(1.612)	1,679

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Heterogeneity Not Driven by Different Choice Environments or Beliefs

	Number of School Pin Clicks	Number of Highlighted School Pin Clicks	Value Added of Enrolled School
	(1)	(2)	(3)
Treatment 1 × College Mother	4.561**	1.461**	0.114**
	(2.110)	(0.708)	(0.047)
Treatment 1 × Non-SEP	0.946	0.448	0.002
	(1.153)	(0.445)	(0.039)
Treatment 1 × Below-Median Perceived Admin. Chances	1.203	0.092	0.017
	(1.353)	(0.470)	(0.036)
Treatment 1 × Number of Available Schools	0.063	0.014	0.002
	(0.047)	(0.018)	(0.001)
Treatment 1 × Perceived Number of Available Schools	-0.064	0.026	0.001
	(0.178)	(0.064)	(0.003)
Treatment 1 × Number of Available Highlighted Schools	-0.100	0.025	-0.005
	(0.173)	(0.066)	(0.005)
Treatment 1 × Perceived Number of Available Highlighted Schools	0.377	0.146	0.000
	(0.277)	(0.101)	(0.008)
Observations	3,001	3,001	2,744

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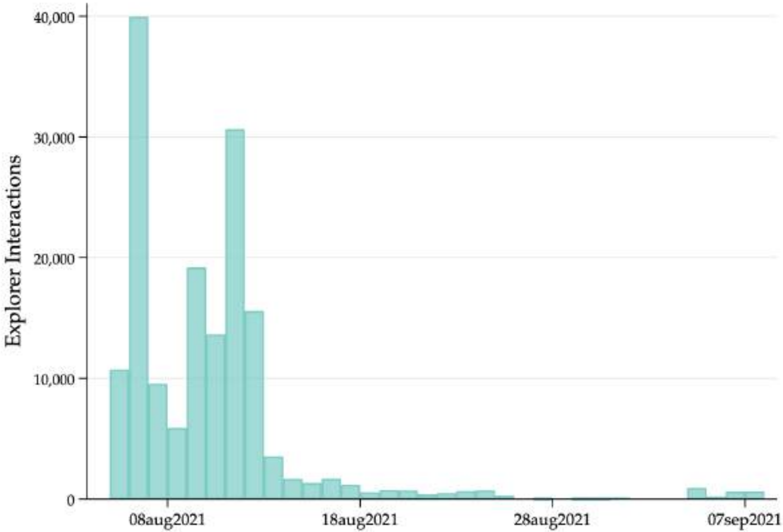
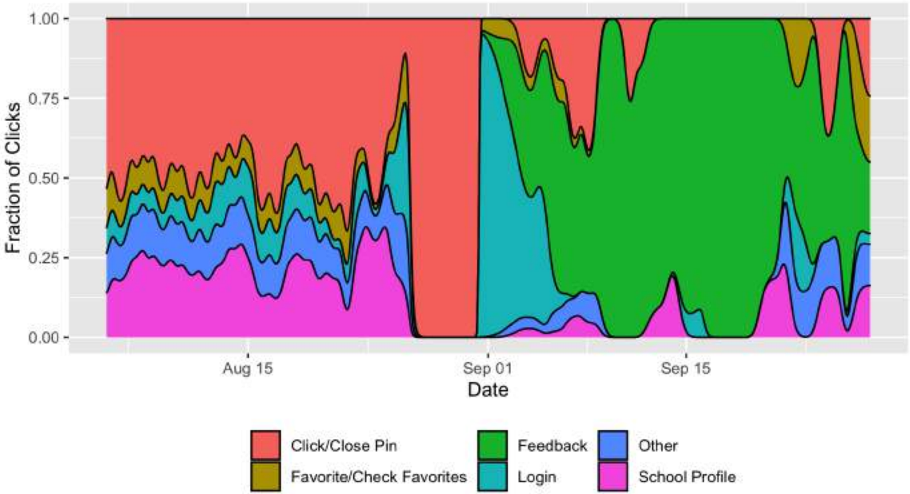
Almost all explorer use is just after we prompt households



Late explorer use is in response to “feedback” RCT



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Selected estimates - Quality Distortion Function

Table 2: Non-College-Grad Mothers

subj. quality	true quality			
	1	2	3	4
1	0.084 (0.017)	0.015 (0.003)	0.001 (0.001)	0.002 (0.001)
2	0.364 (0.026)	0.291 (0.014)	0.109 (0.004)	0.054 (0.007)
3	0.462 (0.029)	0.568 (0.012)	0.605 (0.01)	0.434 (0.014)
4	0.089 (0.015)	0.126 (0.01)	0.285 (0.008)	0.51 (0.013)

Table 3: College-Grad Mothers

subj. quality	true quality			
	1	2	3	4
1	0.119 (0.085)	0.035 (0.017)	0.007 (0.005)	0.004 (0.004)
2	0.478 (0.072)	0.451 (0.052)	0.187 (0.019)	0.085 (0.024)
3	0.349 (0.096)	0.467 (0.04)	0.615 (0.025)	0.425 (0.031)
4	0.053 (0.024)	0.047 (0.014)	0.191 (0.014)	0.485 (0.035)

Main Results: Distance

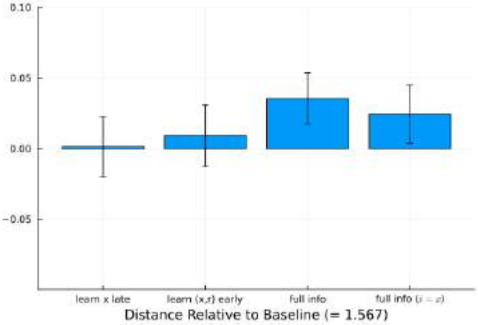

Figure 17: Non-College-Grad Mother

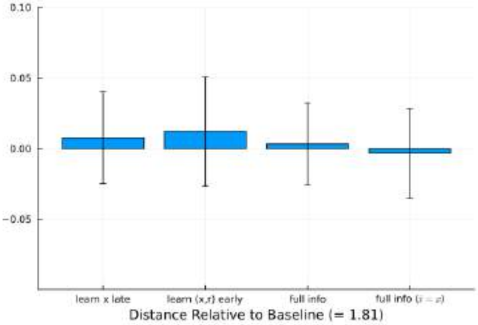

Figure 18: College Grad Mother

Main Results: Price

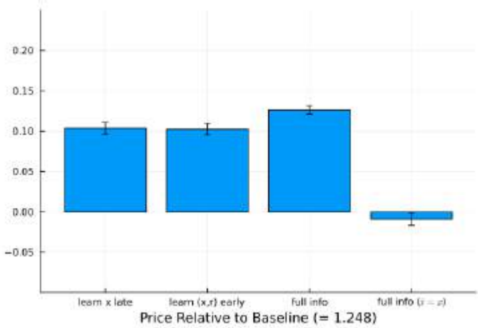

Figure 19: Non-College-Grad Mother

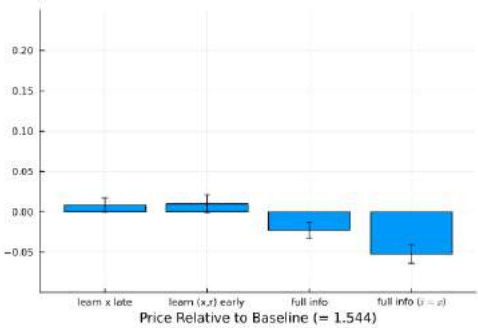

Figure 20: College Grad Mother

Main Results: Table

Table 4: Non-College-Grad Mothers

	EU	Place	E(rank)	Distance	Price	Quality	VA
baseline	0.877 (0.01)	0.818 (0.0)	1.447 (0.0)	1.567 (0.0)	1.248 (0.0)	2.978 (0.0)	0.139 (0.0)
learn x late	0.939 (0.011)	0.718 (0.006)	1.454 (0.008)	1.568 (0.021)	1.351 (0.007)	3.178 (0.008)	0.22 (0.004)
learn (x,r) early	0.896 (0.011)	0.693 (0.006)	1.44 (0.008)	1.577 (0.02)	1.35 (0.007)	3.171 (0.007)	0.217 (0.004)
full info benchmark	1.191 (0.013)	0.828 (0.006)	1.54 (0.009)	1.604 (0.021)	1.375 (0.007)	3.173 (0.009)	0.21 (0.004)
baseline ($\hat{x} = x$)	1.115 (0.035)						
full info ($\hat{x} = x$)	1.475 (0.061)	0.917 (0.004)	1.477 (0.006)	1.588 (0.014)	1.24 (0.006)	2.922 (0.008)	0.099 (0.005)

Table 5: College-Grad Mothers

	EU	Place	E(rank)	Distance	Price	Quality	VA
baseline	1.134 (0.028)	0.772 (0.0)	1.703 (0.0)	1.81 (0.0)	1.544 (0.0)	3.105 (0.0)	0.184 (0.0)
learn x late	1.193 (0.037)	0.74 (0.005)	1.684 (0.01)	1.817 (0.031)	1.553 (0.012)	3.192 (0.011)	0.216 (0.007)
learn (x,r) early	1.111 (0.033)	0.706 (0.007)	1.64 (0.012)	1.82 (0.037)	1.554 (0.014)	3.181 (0.014)	0.211 (0.009)
full info benchmark	1.555 (0.028)	0.858 (0.005)	1.792 (0.015)	1.814 (0.031)	1.523 (0.014)	3.178 (0.017)	0.204 (0.01)
baseline ($\hat{x} = x$)	1.171 (0.046)						
full info ($\hat{x} = x$)	1.64 (0.061)	0.889 (0.005)	1.742 (0.021)	1.798 (0.03)	1.492 (0.015)	3.04 (0.019)	0.145 (0.01)