Dynamic College Admissions

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August 18, 2022

Outline

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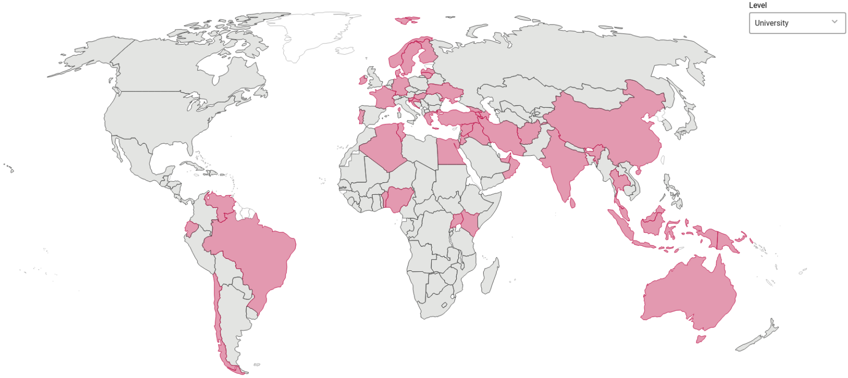
- Low retention and on-time graduation rates:
  - On-time graduation rate for OECD is 40%
  - Many students switch their majors or colleges and many dropout
- Several countries organize their college admissions via centralized assignment mechanisms

Figure 1: Centralized Systems in College Admissions



Source: Neilson, 2022

Research Question

Can centralized assignment mechanisms affect students' outcomes, such as their decisions to dropout and switch majors or colleges?

Centralized Mechanisms and Outcomes

- Scarce evidence about their effects on outcomes

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    - Excess demand + colleges care about retention → crowd-out externality
    - Ex-ante inefficient to assign students to lower-ranked programs

More

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- Dynamic structural model of students' college progression:
  - Apply, re-take tests, re-apply, switch, and dropout
  - Learn about their match-qualities through their college grades

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    - Reducing incentives to switch $\uparrow$ ex-post mismatches

Identifying Learning vs Mismatching

	Learning	Mismatching
Model		
Data		

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Data	Correlation between college grades and students' outcomes	Common prior Correlation patterns within initial preferences Causal effect of the preference of assignment on outcomes

- Results
  - Learning: 45% of switchings
  - Signaling mechanism: switchings $\downarrow$ 33%, retention rates $\uparrow$ 8%, and welfare $\uparrow$ equivalent of a 19% reduction in average tuition

Contribution to Literature

1. Empirical analysis on centralized assignment mechanisms:
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Semi-centralized market:

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Data:

- Surveys: top-true preferences and subjective beliefs
- Admission process + Enrollment + College grades + Avg. wages

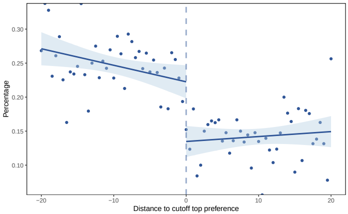
Evidence

Outline

Mismatching

- Students assigned to lower-ranked programs face lower retention rates Switching stats
- Use discontinuities created by cutoffs to estimate causal effect of assignment to the top preference

Figure 3: Re-Applications



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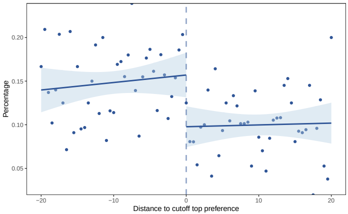

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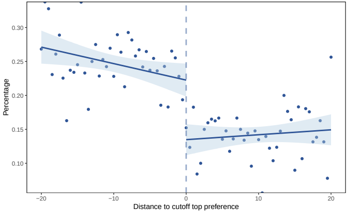

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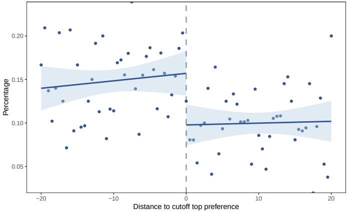

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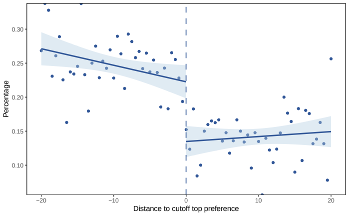

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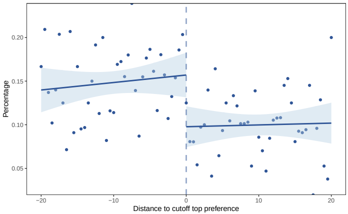

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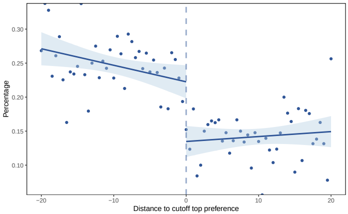

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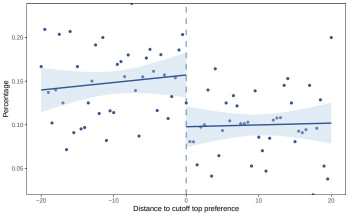

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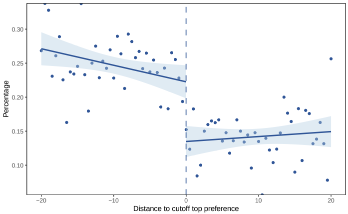

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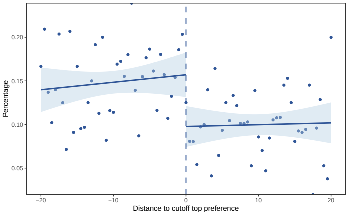

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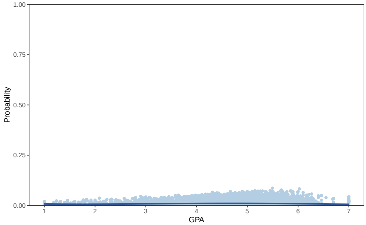
Switchings Forward-looking

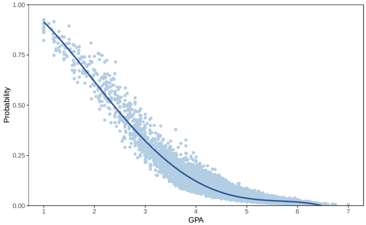
Learning: grades and outcomes

- Surveys: 60% of re-applicants change top-true preference
- Correlation patterns between grades and outcomes:

(a) Switching up



(b) Switching out



- Switching up is uncorrelated with grades
- Switching out is negatively correlated with grades

Learning

Outline

Model

Indexing: student i, program j, major m_j, college-type k_j

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Stage 1: students receive their scores and preference shocks

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Stage 3: after period two:

(i) Face a sequence of dropout and graduation probabilities

(ii) Students who graduate enter the labor force

Timeline

Learning process

Students are characterized by:

- Known major and college preferences α_{im_j} and α_{ik_j}
- Known subject-specific ability $A_i = (A_{is_m}, A_{is_v})$
- Unknown subject-specific ability , $A_i^u = (A_{is_m}^u, A_{is_v}^u)$, and major-specific ability $A_{im_j}^u$

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Ability in program j is given by:

$$A_{ij}^u = A_{im_j}^u + \sum_{l \in \{s_m, s_v\}} \underbrace{\omega_{jl}}_{\text{admission weights}} A_{il}^u, \quad A_{ij} = \sum_{l \in \{s_m, s_v\}} \omega_{jl} A_i$$

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- Comparative and absolute advantages in abilities
- Correlated learning

Learning process

Assumption (Bayesian Updating)
Students have rational expectations over the population distribution of unknown abilities for program j, and

$$A_{il}^{u} \sim N(0, \sigma_s^2) \quad \forall i, l \in \{s_m, s_v\}, \quad A_{im_j}^{u} \sim N(0, \sigma_m^2)$$

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$$A^u_{il} \sim N(0, \sigma^2_s) \quad \forall i, l \in \{s_m, s_v\}, \quad A^u_{im_j} \sim N(0, \sigma^2_m)$$

Learning
Students learn about A^u_i from their college GPA:

$$G_{ijt} = f\left(m_j, A_{ij}, Z^g_i, \alpha_{im_j}, \alpha_{ik_j}, A^u_{ij}, \varepsilon^g_{ij}\right),$$

where ε^g_{ijt} is a white noise, distributed $N(0, \sigma^2_g)$

Grade equations

Flow utility

$$u_{ijt} = \alpha_{fe_j} + \underbrace{\alpha_{im_j} + \alpha_{ik_j}}_{\text{unobserved heterogeneity}} + Z^u_{ij}\alpha - C_{ijt} + \varepsilon_{ijt},$$

with

$$Z^u_{ij}\alpha = \alpha_1 A_{ij} + \alpha_2 \underbrace{\bar{A}_j}_{\text{program quality}} + \alpha_3 D_{ij} + \alpha_4 \underbrace{\frac{(A_{ij} - \bar{A}_j)}{\bar{\sigma}_j}}_{\text{Relative position}}$$

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- C_{ijt} captures the financial cost of program with tuition c_{jt}

$$C_{ijt} = \alpha_{c0} \underbrace{(c_{jt} - \tilde{c}_{ij})}_{\text{out of pocket}}$$

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- $\varepsilon_{ijt} \sim$ T1EV(1) and $u_{i0t} = 0$

Application and Enrollment

Mixture

(i) Weak truth-tellers (ρ): report true preferences

(ii) Strategic ($1-\rho$): $R_{it} \in \operatorname{argmax}_{R' \in \mathcal{R}, |R'| \leq K} U(R')$

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Assumptions

1. Rational Expectations over cutoffs' distributions + independence
2. Do not apply to programs unless it is strictly profitable to do so

$$U(R_{it}) = p_{iR(1)t} \cdot v_{iR(1)t} + (1 - p_{iR(1)t}) \cdot p_{iR(2)t} \cdot v_{iR(2)t} + \ldots + \prod_{l=1}^{k-1} (1 - p_{iR(l)t}) \cdot p_{iR(K)t} \cdot v_{iR(K)t}.$$

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3. Enroll in their assigned program with an exogenous probability

$$v_{ikt} = P_{it}^{e} \cdot V_{ikt} + \left(1 - P_{it}^{e}\right) \cdot \max\{V_{i0t}, V_{ijt}\}$$

Student problem

Labor Market

Utility in the workforce

$$V_{ijt}^{w} = \underbrace{V_{ij}^{np}}_{\text{non-pecuniary utility}} + \underbrace{\alpha_w \log \left(E_w \left[\sum_{\tau=0}^{T-t} \beta^{\tau} \underbrace{P_{m_j}}_{\text{employment probability}} w_{ij\tau} \right] \right)}_{\text{pecuniary utility}}$$

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where

$$\log(w_{ijt}|\tau) = f\left(m_j, \bar{A}_{k_j}, \underbrace{G_{ij}\left(A_{ij}, A_{ij}^{u}\right)}_{\text{grades}}, Z_i^{w}, \underbrace{\Lambda_{m_j\tau}}_{\text{tenure}}, \epsilon_{ijt}^{w}\right)$$

Labor Market

Utility in the workforce

$$V_{ijt}^{w} = \underbrace{V_{ij}^{np}}_{\text{non-pecuniary utility}} + \underbrace{\alpha_w \log\left(E_w \left[\sum_{\tau=0}^{T-t} \beta^{\tau} \underbrace{P_{m_j}}_{\text{employment probability}} w_{ij\tau} \right] \right)}_{\text{pecuniary utility}}$$

where

$$\log(w_{ijt}|\tau) = f\left(m_j, \bar{A}_{k_j}, \underbrace{G_{ij}\left(A_{ij}, A_{ij}^{u}\right)}_{\text{grades}}, Z_i^{w}, \underbrace{\Lambda_{m_j\tau}}_{\text{tenure}}, \epsilon_{ijt}^{w} \right)$$

- V_{ij}^{np} captures the non-pecuniary utility, given by

$$V_{ij}^{np} = \alpha_1^{w}\left(\alpha_{fe_j} + \alpha_{im_j} + \alpha_{ik_j}\right) + \alpha_2^{w} A_{ij} + \alpha_3^{w} \bar{A}_{k_j} + \alpha_{4m_j}^{w} X_i^{w} + \alpha_5^{w} \underbrace{A_{ij}^{u}}_{\text{unknown ability}}$$

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- $V_0\left(X_{i0}, t\right)$ is the value function of dropping out

Estimation

Two-Step Procedure

Step 1: estimate beliefs on admission, future dropout, enrollment, graduation, and employment probabilities from the data. Bootstrap

Step 2: estimate the model parameters via Indirect Inference (II), taking students' beliefs as given. Fit

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Table 4: Estimation Results - Parameters

Parameters	Values	Std
Share of strategic ROLs	0.74	[0.022]
Variance idiosyncratic preferences by major	15.69	[0.913]
Major prior variance	0.34	[0.032]
Subject prior variance	0.48	[0.103]
Grade shock variance	0.08	[0.04]

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- Learning: 45% of switchings

Outline

Counterfactuals

Assignment mechanism

1. Constrained Deferred Acceptance with constraint K

Counterfactuals

Assignment mechanism

1. Constrained Deferred Acceptance with constraint K
    - Opportunity cost of including programs in the list

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Counterfactuals

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Re-application rules

1. Switching score penalty ψ (Turkey)

Counterfactuals

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Challenges

- How would beliefs change? $\rightarrow$ equilibrium
- How will naive students behave? $\rightarrow$ bounds

Counterfactuals

Assignment mechanisms

Student problem

Counterfactuals

Assignment mechanisms

		Constrained DA			CADA
Outcome	Baseline	$K = 3$	$K = 2$	$K = 1$	
Reapplicants [%]	34.27	0.35	1.62	10.01	
Program switchings [%]	6.48	-0.40	0.66	20.74	
Retakes PSU [%]	21.62	0.44	3.05	16.34	
Dropouts - first year [%]	3.70	-0.54	-1.48	-11.76	
Applicants in first period [%]	62.24	0.06	0.33	1.23	
Enrolls same program [%]	31.64	-0.13	-0.98	-12.14	
Assigned to top true preference [%]	10.46	0.76	2.38	-9.59	
Unassigned in first period [%]	44.17	0.33	1.09	9.69	
Difference in Ex Post Welfare Relative to Baseline (in millions of Chilean pesos)					
Overall	-	0.01	-0.08	-1.95	

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Student problem

Counterfactuals

Assignment mechanisms

Outcome	Baseline	Constrained DA	CADA $\varphi = 10\%$	CADA $\varphi = 20\%$	CADA $\varphi = 30\%$
Reapplicants [%]	34.27		-11.80	-20.92	-26.32
Program switchings [%]	6.48		-22.28	-32.84	-39.10
Retakes PSU [%]	21.62		-23.30	-34.70	-40.48
Dropouts - first year [%]	3.70		11.61	16.88	20.41
Applicants in first period [%]	62.24		1.04	1.73	2.24
Enrolls same program [%]	31.64		7.20	10.61	12.95
Assigned to top true preference [%]	10.46		16.20	22.60	23.84
Unassigned in first period [%]	44.17		-4.26	-6.30	-7.79
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Overall	-		0.62	0.77	0.78

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Student problem

Counterfactuals

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Reapplicants [%]	34.27		-11.80	-20.92	-26.32
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Student problem

Counterfactuals

Re-application rules

Student problem

Counterfactuals

Re-application rules

		Turkish Rules			Finnish Rules
Outcome	Baseline	$\psi = 10\%$	$\psi = 20\%$	$\psi = 30\%$	
Reapplicants [%]	34.27	-16.81	-29.63	-36.41	
Program switchings [%]	6.48	-33.16	-51.53	-63.34	
Retakes PSU [%]	21.62	-18.18	-27.79	-32.95	
Dropouts - first year [%]	3.70	4.22	5.70	6.92	
First enrollment in second period [%]	13.01	4.46	6.38	7.04	
Enrolls same program [%]	31.64	5.90	9.07	11.17	
Assigned to top true preference [%]	10.46	13.39	19.80	21.95	
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Retakes PSU [%]	21.62		-17.23	-24.34	-25.04
Dropouts - first year [%]	3.70		0.82	-0.53	-2.29
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Difference in Ex-Post Welfare Relative to Baseline (in millions of Chilean pesos)					
Overall	-		0.37	0.43	0.29

- Switching penalty: ↑ top-true, ↓ switchings, ↑ dropouts, ↑ welfare
- First-time bonus: ↑ top-true, ↓ switchings, ↑ delayed applications, ↑ welfare

Student problem

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Difference in Ex-Post Welfare Relative to Baseline (in millions of Chilean pesos)					
Overall	-		0.37	0.43	0.29

- Switching penalty: ↑ top-true, ↓ switchings, ↑ dropouts, ↑ welfare
- First-time bonus: ↑ top-true, ↓ switchings, ↑ delayed applications, ↑ welfare

Student problem

Counterfactuals

Re-application rules

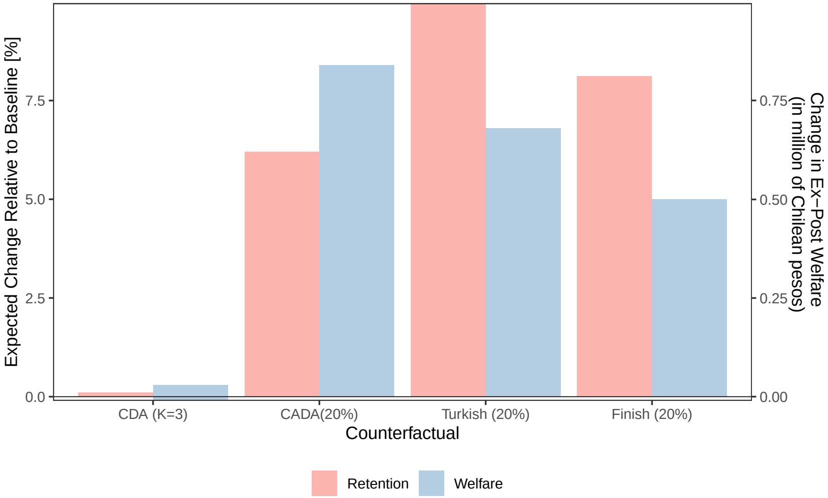
Outcome	Baseline	Turkish Rules	Finnish Rules $\varphi = 10\%$	Finnish Rules $\varphi = 20\%$	Finnish Rules $\varphi = 30\%$
Reapplicants [%]	34.27		-23.84	-34.83	-40.10
Program switchings [%]	6.48		-28.67	-40.31	-46.56
Retakes PSU [%]	21.62		-17.23	-24.34	-25.04
Dropouts - first year [%]	3.70		0.82	-0.53	-2.29
First enrollment in second period [%]	13.01		5.57	8.84	12.18
Enrolls same program [%]	31.64		4.39	5.40	5.46
Assigned to top true preference [%]	10.46		19.51	28.26	29.62
Unassigned in first period [%]	44.17		1.26	2.86	4.27
Difference in Ex-Post Welfare Relative to Baseline (in millions of Chilean pesos)					
Overall	-		0.37	0.43	0.29

- Switching penalty: ↑ top-true, ↓ switchings, ↑ dropouts, ↑ welfare
- First-time bonus: ↑ top-true, ↓ switchings, ↑ delayed applications, ↑ welfare

Student problem

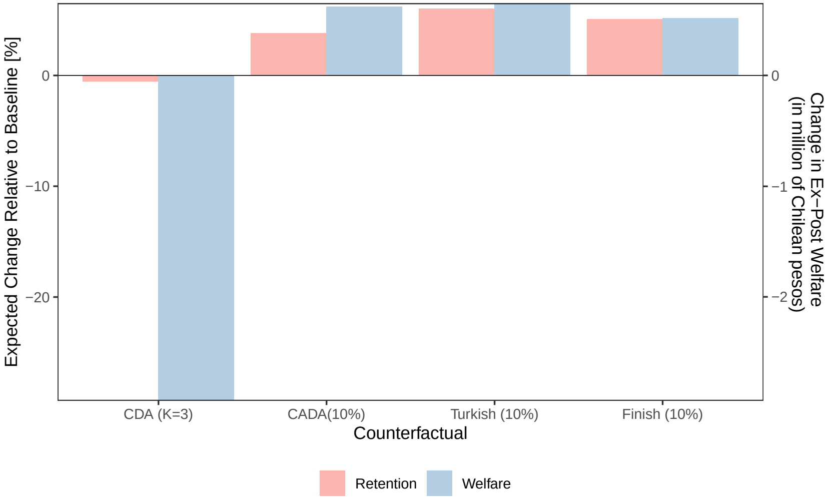
Counterfactuals

All students behave strategically



Counterfactuals

26% of students behave as truth-tellers



Outline

Introduction

Empirical facts

Model

Counterfactuals

Conclusions

Conclusions

Take-Aways

(i) Analyzed the trade-offs of designing matching markets

Conclusions

Take-Aways

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- Private information about their preferences

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Take-Aways

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  - Learn over time about their match-qualities

Conclusions

Take-Aways

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Conclusions

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(ii) Centralized systems can improve students' outcomes

Conclusions

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(ii) Centralized systems can improve students' outcomes
- Eliciting intensity on students' preferences

Conclusions

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- Learn over time about their match-qualities
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Conclusions

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  - Leveraging dynamic incentives or incorporating signals
  - Lack of sophistication reduces efficiency and welfare gains

Conclusions

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(i) Analyzed the trade-offs of designing matching markets
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- Leveraging dynamic incentives or incorporating signals
- Lack of sophistication reduces efficiency and welfare gains

Ongoing Research

- Information policies: helping students to submit optimal applications

Thank you!

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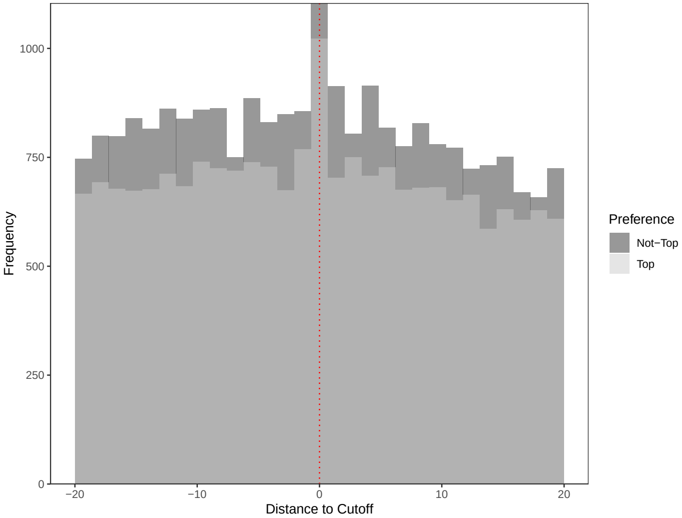
Preference of assignment

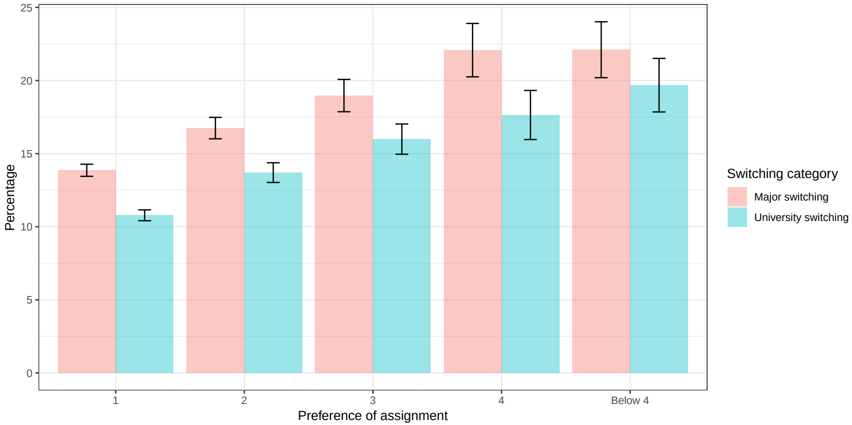
Figure 10: Distribution of preference of assignment



Channels

Mismatching

Switchings stats



Mismatching

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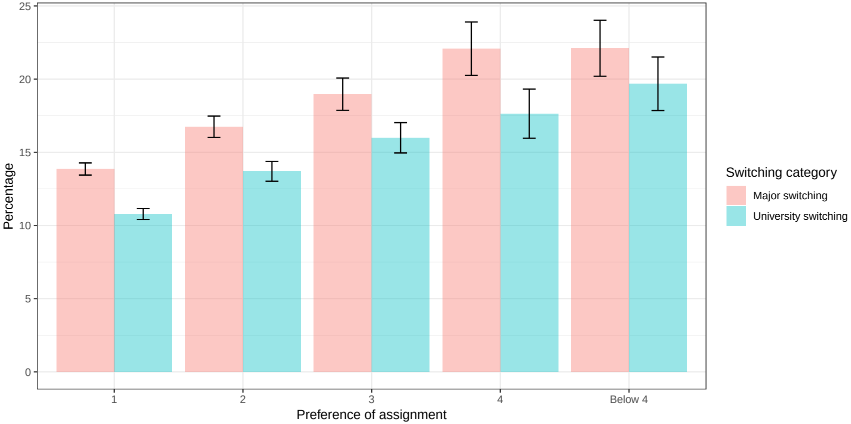
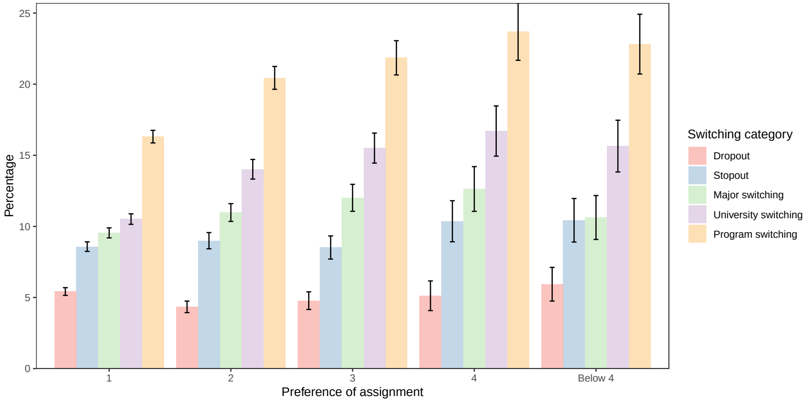


- Students assigned to lower preferences face higher switching probabilities

RDD

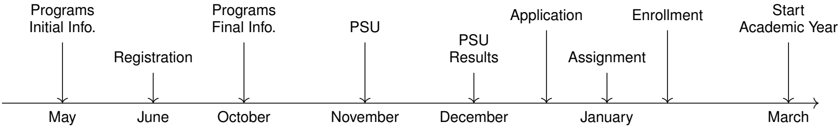
Switchings

Figure 11: Switching statistics



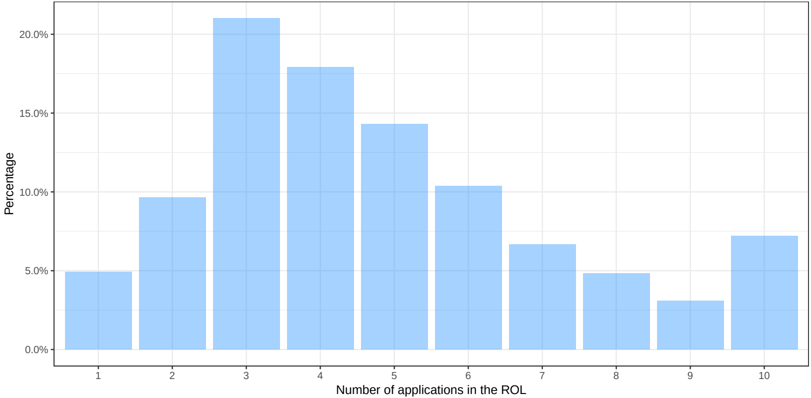
RDD

Figure 12: Timeline of the Centralized Process



Applications

Figure 13: Distribution of ROLs length

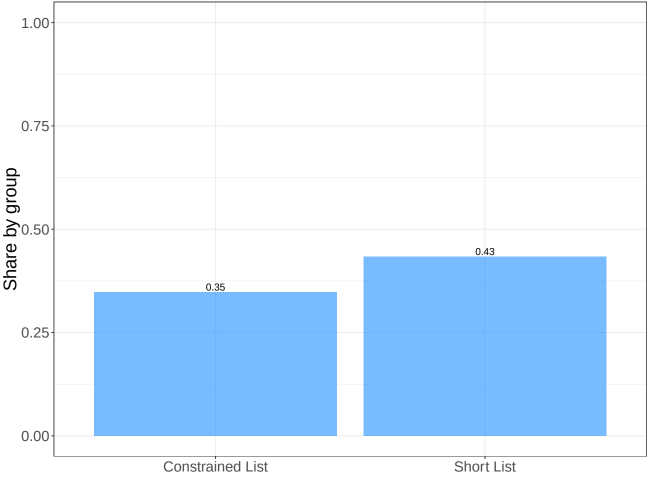


Chilean system

Misreporting preferences

Survey - Admission Process 2019

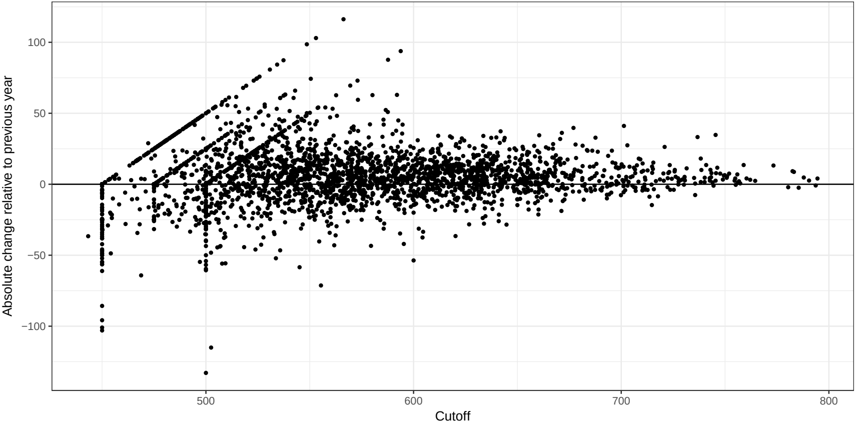
Figure 14: Percentage of truth-tellers



More evidence

Uncertainty

Figure 15: Variation in cutoffs - from 2013 to 2014

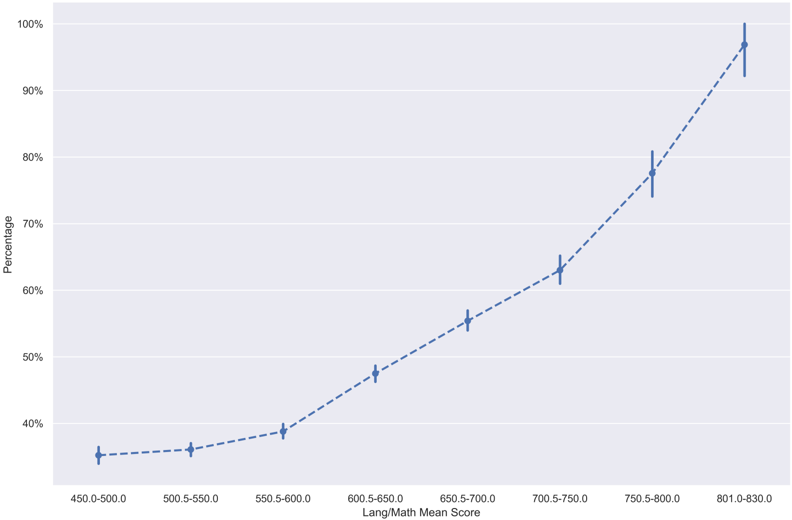


Subjective beliefs

Evidence

Survey - Admission Process 2019

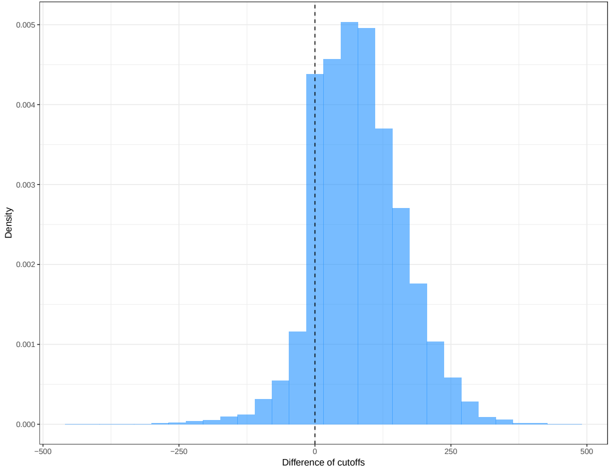
Figure 16: Share of truth-tellers by score range



Evidence

Survey - Admission Process 2019

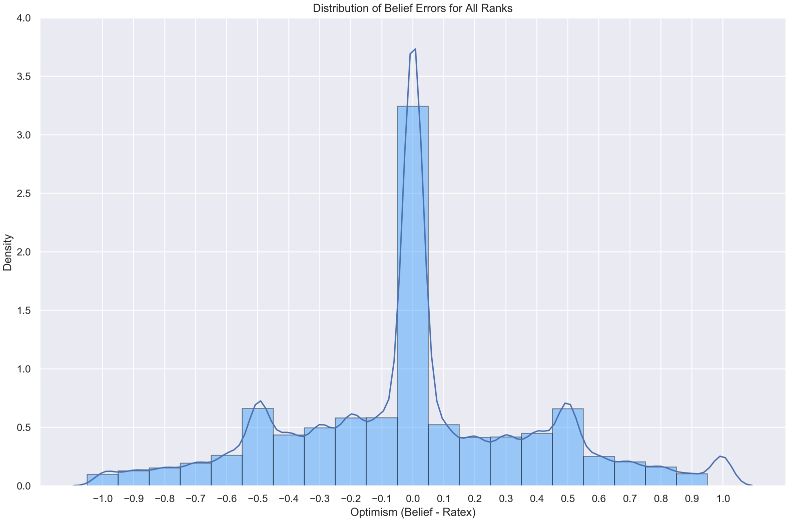
Figure 17: Expected cutoffs most desired vs. first preference



Data

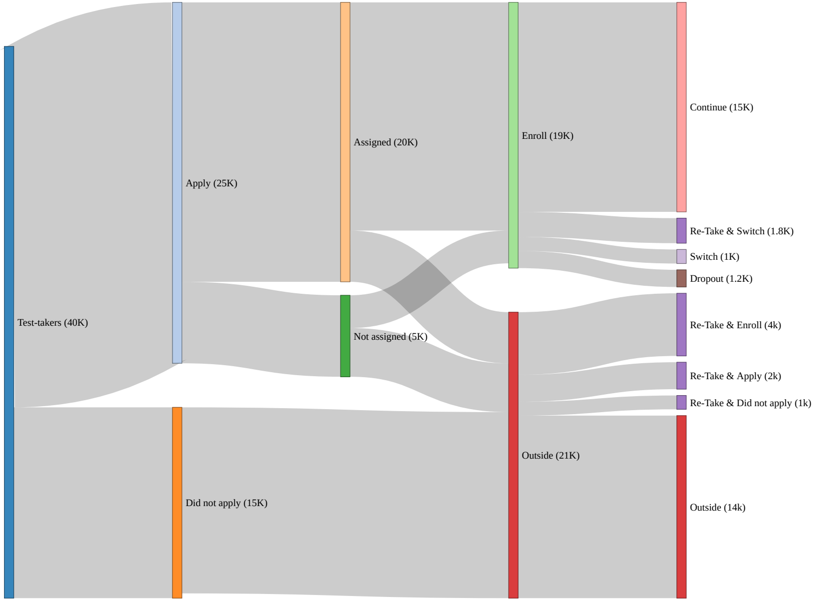
Subjective beliefs

Figure 18: Subjective beliefs



Data

Dynamics



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Apply (25K)
Did not apply (15K)
Assigned (20K)
Not assigned (5K)
Enroll (19K)
Outside (21K)
Continue (15K)
Re-Take & Switch (1.8K)
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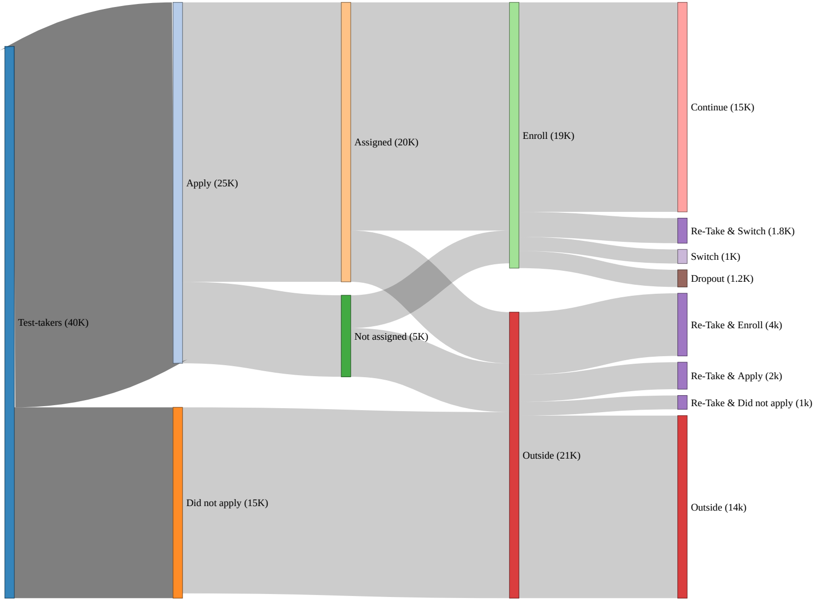
Outside (14k)

Dynamics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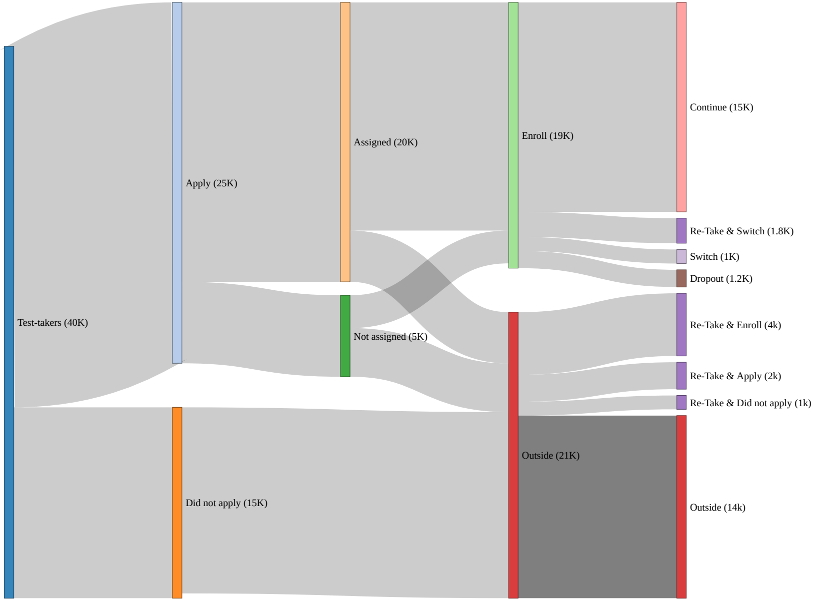

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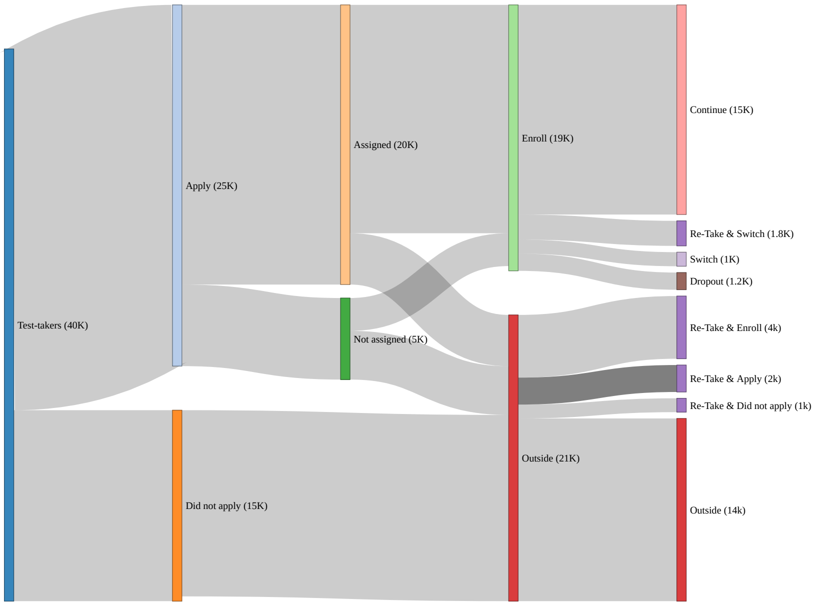
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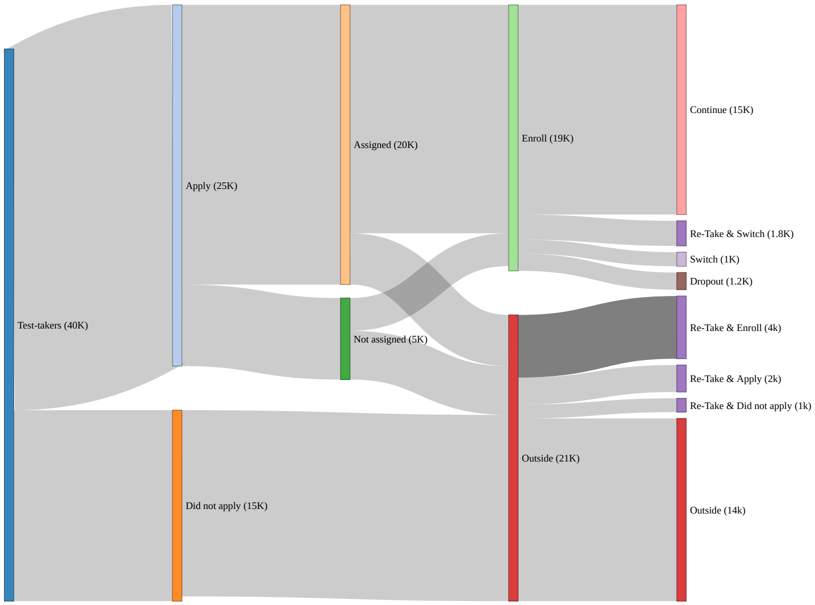

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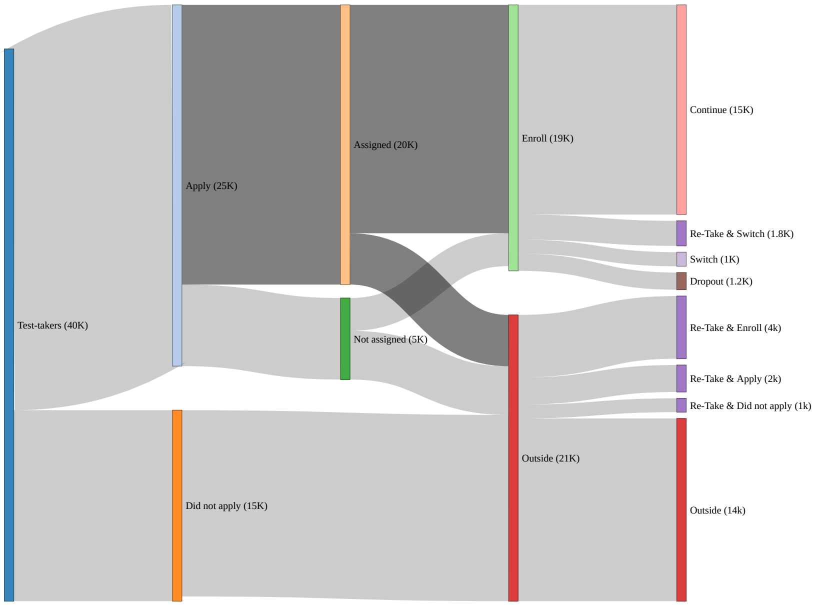

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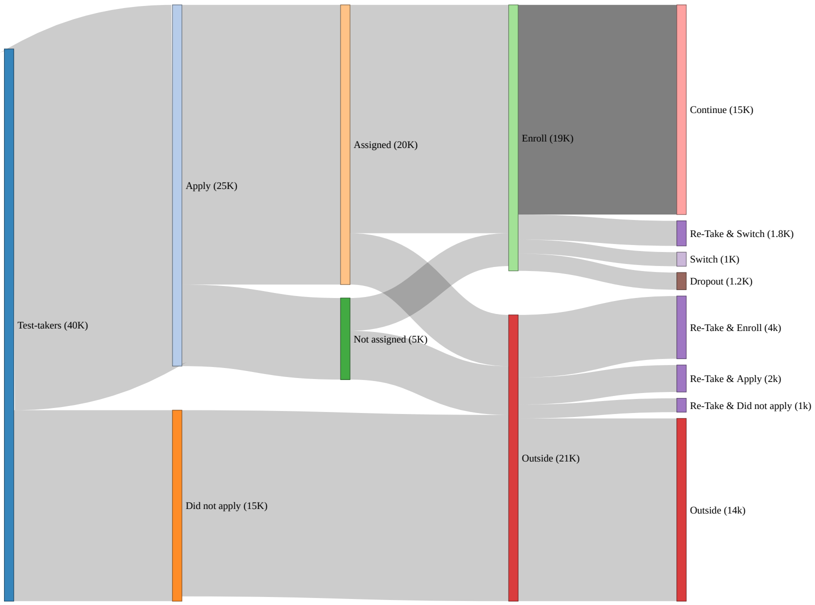

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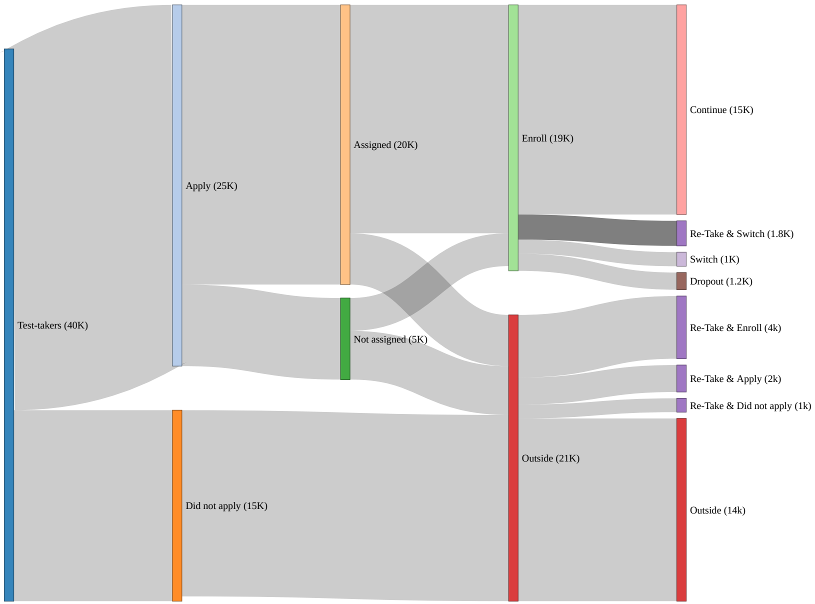
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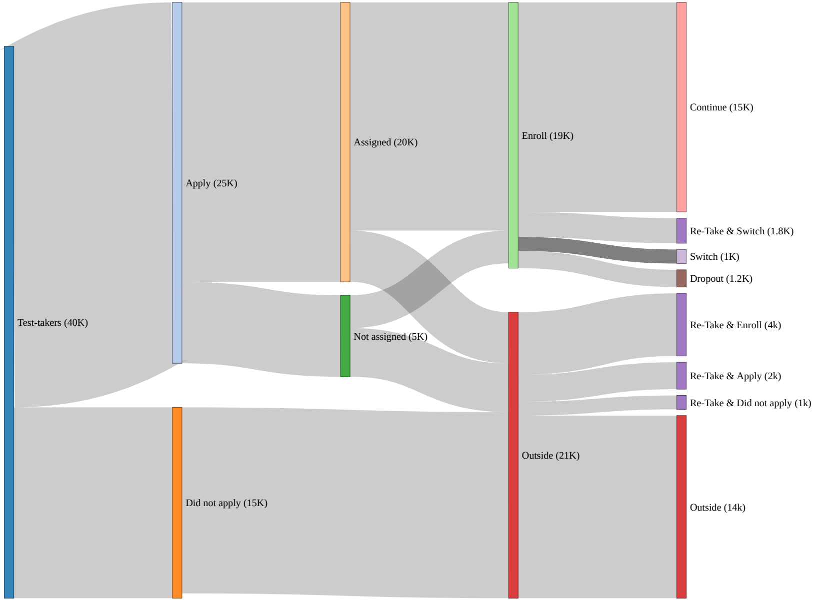

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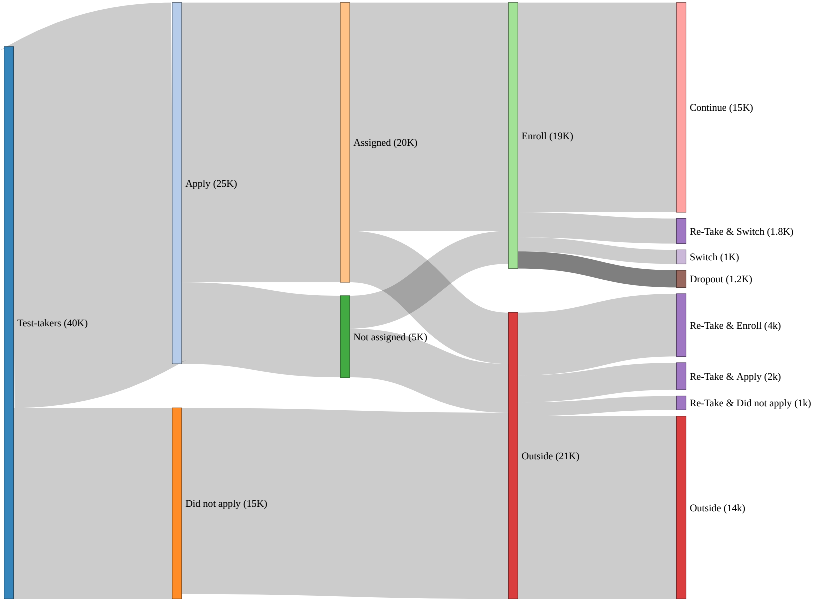
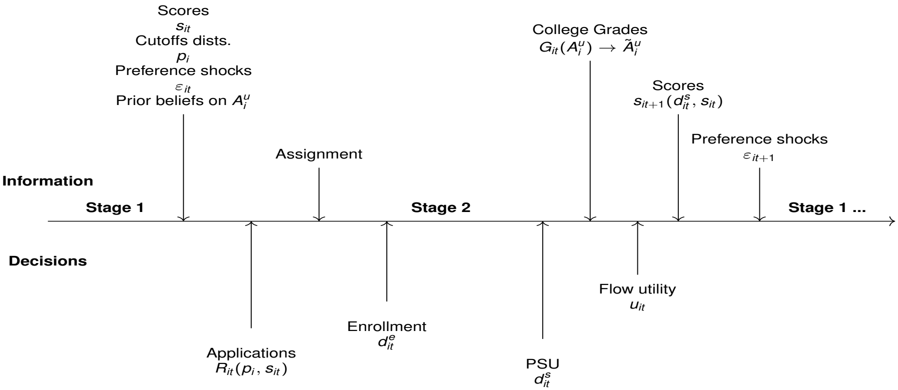


Chilean system

Timeline

- Stages 1, 2: repeat from $t = 1, ..., \bar{t}$



- Stage 3: At $\bar{t}$, students face an exogenuous graduation probability, P_{ijt}^g and receive their lifetime earnings.

Grade main

RDD

Results

	Enroll - System		Enroll - SUA		Enroll - Top		Re-Apply	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Above cutoff	0.014	0.014	0.016	0.017	0.493^{***}	0.494^{***}	-0.081^{***}	-0.076^{***}
	(0.013)	(0.013)	(0.012)	(0.012)	(0.013)	(0.013)	(0.015)	(0.017)
Program FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	38,928	38,928	38,928	38,928	38,928	38,928	38,928	38,928
R^2	0.008	0.008	0.005	0.005	0.539	0.539	0.017	0.020

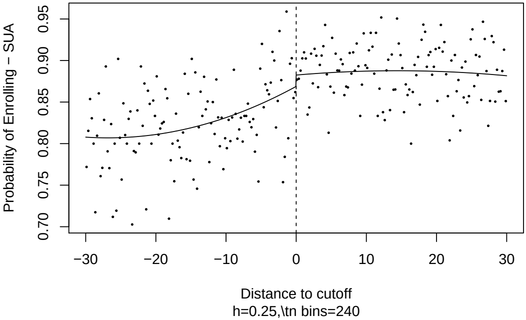
Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

RDD

Sample selection problem

- Interested in other outcome variables: Dropout, Stopout, Switches → selection problem
  - Outcomes only observed for students who enroll

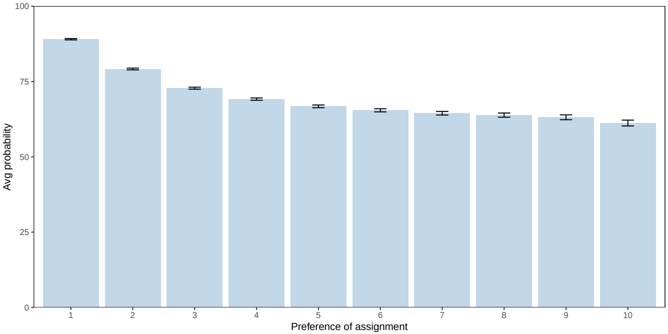
Figure 19: Enrollment



Mismatching

Survey: “What is the probability that you will remain enrolled in each of your preferences?”

Figure 20: Average “perceived” program-retention probability



- Forward-looking behavior: anticipate future switches

Match effects RDD

Mismatching: match-effects

$$P_{ij} = \alpha_i + \alpha_j + X_{ij}\beta + \beta_R R_i(j) + \varepsilon_{ij} \quad (1)$$

Table 8: Two-way Fixed Effects Regression Results

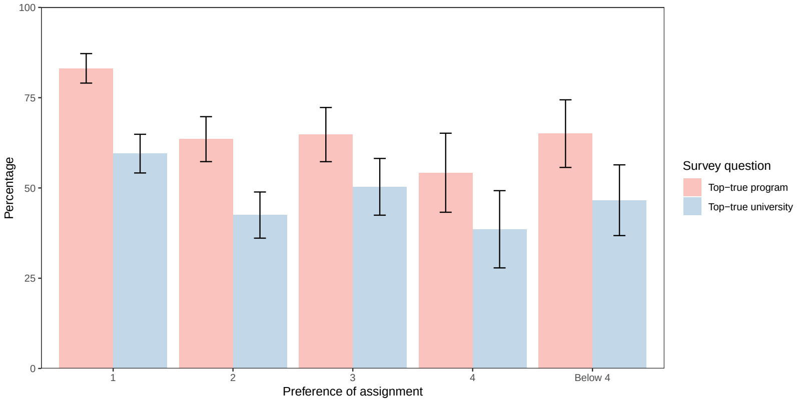
	Dependent variable: Prob. of Persistence
Preference 2	-9.891***
Preference 3	-16.844***
Preference 4	-21.355***
Preference 5	-24.831***
Preference 6	-27.148***
Preference 7	-29.164***
Preference 8	-30.329***
Preference 9	-31.995***
Preference 10	-34.757***
Constant	89.181***
Observations	159,894
R^2	0.095
Adjusted R^2	0.095

Note: Significance reported: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Forward Looking

Learning

Figure 21: Percentage of re-applicants that change their top-true preference



- Close to 60% of re-applicants change their top-true preference

Learning grades and outcomes Grades and outcomes

Learning

Table 9: Effect of Grades on Outcomes

	Re-Take PSU	Re-Apply	Switch Program	GPA
GPA	-0.904^{***}	-0.903^{***}	-1.221^{***}	-
	(0.018)	(0.018)	(0.019)	-
Preference 2	0.653^{***}	0.651^{***}	0.163^{***}	-0.057^{***}
	(0.040)	(0.040)	(0.038)	(0.011)
Preference 3	0.922^{***}	0.923^{***}	0.352^{***}	-0.061^{***}
	(0.050)	(0.050)	(0.050)	(0.015)
Preference 4	1.201^{***}	1.202^{***}	0.562^{***}	-0.070^{***}
	(0.070)	(0.070)	(0.071)	(0.022)
Preference 5	1.116^{***}	1.116^{***}	0.523^{***}	-0.013
	(0.103)	(0.103)	(0.102)	(0.032)
Preference Below 5	1.098^{***}	1.099^{***}	0.454^{***}	-0.113^{***}
	(0.112)	(0.112)	(0.115)	(0.035)
Observations	39,275	39,275	39,275	39,275

Learning: grades and outcomes

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	(0.112)	(0.112)	(0.115)	(0.035)
Observations	39,275	39,275	39,275	39,275

- Grades are negatively correlated with switching outcomes

Learning

Learning: grades and outcomes

Table 11: Effect of Grades on Outcomes

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	(0.112)	(0.112)	(0.115)	(0.035)
Observations	39,275	39,275	39,275	39,275

- Preference of assignment has a small negative correlation with grades

Learning

Model solution

Period $t = 3$**:**

$$V_{ijt}(\mu_{ij2}, \tau_{ijt}) = E_t \left[\sum_{t'=\tau_{ijt}+1}^{T_f} P^g_{ijt'} \left(\mathbb{E}_\varepsilon \left[\sum_{t''=0}^{t'-(\tau_{ijt}+1)} \beta^{t''} u_{ij(t+t'')} \right] + \beta^{t'-\tau_{ijt}} \underbrace{V^w_{ij(t+t'-\tau_{ijt})}(\mu_{ij2})}_{\text{Value fcn Labor market}} \right) \right]$$

$$+ E_t \left[\sum_{t'=\tau_{ijt}+1}^{T_f} P^d_{ijt'} \left(\mathbb{E}_\varepsilon \left[\sum_{t''=0}^{t'-(\tau_{ijt}+1)} \beta^{t''} u_{ij(t+t'')} \right] + \beta^{t'-\tau_{ijt}} \underbrace{V_{i0(t+t'-\tau_{ijt})}}_{\text{Value fcn Dropout}} \right) \right]$$

Period $t = 2$**:**
Indirect utility of enrolling in j:

$$V_{ijt}(\mu_{ij2}, \tau_{ijt}) = u_{ijt} - \mathbb{1}_{\{(j \neq 0) \cap (\tau_{ijt} = 0)\}} C^e + \beta \mathbb{E}_\varepsilon \left[V_{ijt+1}(\mu_{ij2}, \tau_{ijt+1}) \right]$$

Model solution

Period $t = 1$:

$$V_{ijt}(\mu_{ij1}, \tau_{ijt}, \vec{s}_{it}) = \max_{d^s_{it}} E_0 \Big[u_{ijt} - d^s_{it} C^{psu} - \mathbb{1}_{\{j \neq 0\}} C^e +$$

$$\beta \int_{a_{ij1}} \int_{\vec{s}_{it+1}} \underbrace{EmaxROL(\tau_{ijt} + 1, \vec{s}_{it+1}, \mu_{i2}(a_{ij1}))}_{\text{continuation value of reapplications}} \underbrace{d\pi(a_{ij1})}_{\text{signal}} \underbrace{dF(\vec{s}_{it+1} | \vec{s}_{it}, d^s_{it})}_{\text{future scores}} \Big]$$

Application Counterfactuals Mechanisms Counterfactuals Re-applications

Pairwise-stability

Proposition (Fack et al (2018))

In a large market, the allocation of Constrained DA satisfies pairwise-stability, i.e,

$$\mu(i|\varepsilon_i, \{P_j\}_{j\in\mathcal{J}}) = \underset{j\in J_i(\{P_j\}_{j\in\mathcal{J}})}{\text{argmax}} \ \bar{u}_{ij} + \varepsilon_{ij}$$

$$J_i(\{P_j\}_{j\in\mathcal{J}}) := \{j \in \mathcal{J} : s_{ij} \geq P_j\} \bigcup \{j = 0\}$$

Proposition (EmaxROL)

$$EmaxROL = \mathbb{E}_{\{P_j\}_{j\in\mathcal{J}}} \left[\log \left(\sum_{j\in J_i(\{P_j\}_{j\in\mathcal{J}})} \exp\left(\bar{u}_{ij}\right) \right) + \gamma \right]$$

Identification

Bootstrap

Agarwal and Somaini (2018) show that a consistent estimator of these beliefs can be obtained using the following bootstrap procedure:

- For each period t and each bootstrap simulation $b = 1, \dots, B$,
  - Sample with replacement a set N_t^b of N_t students with their corresponding ROLs and scores.
  - Run the mechanism to obtain the allocation μ_t^b.
  - Obtain the set of cutoffs $\left\{\bar{s}_{jt}^b\right\}_{j\in J}$ from the allocation μ_t^b, i.e., for each $j \in J$,

$$\bar{s}_{jt}^b = \min\left\{s_{ijt} : i \in N_t^b,\ \mu_t^b(i) = j\right\}$$

- We can estimate the admission probability of student $i \in N_t$ in program $j \subset J$ as

$$\hat{p}_{ijt} = \frac{1}{B}\sum_{b=1}^{B} \mathbb{1}_{\left\{s_{ijt} \geq \bar{s}_{jt}^b\right\}}$$

We estimate these probabilities running $B = 10,000$ bootstrap simulations for every application process Estimation

Goodness of fit

Table 12: Correlation between grades and outcomes

	Model	Data
Dropout	-0.055	-0.086
Switching programs	-0.152	-0.148
Switching broad majors	-0.092	-0.075
Switching majors	-0.172	-0.107
Switching math type	-0.079	-0.044
Switching Up	-0.008	0.002
Switching Down	-0.029	-0.032
Switching Out feasible	-0.084	-0.089
Switching Out unfeasible	-0.032	-0.011

Table 13: Causal effect RDDs

	Model	Data
RDD switch program 1 (level)	0.205	0.1622
RDD switch program 1 (coeff.)	-0.07	-0.0478
RDD reapplications 1 (level)	0.488	0.2261
RDD reapplications 1 (coeff.)	-0.104	-0.0840

Estimation

Algorithm: Computing $Q(\theta)$

input : Value of the structural parameters θ, and first-stage estimates $\hat{p}$, $\hat{P}^e$, $\hat{P}^d$, $\hat{P}^g$, and $\hat{P}^w$.
output: Value of the objective function $Q(\theta)$

foreach *student i in the sample* **do**
  foreach *simulation* $m_{rc} \in \{1, \ldots, N_{rc}\}$ **do**
    Draw a vector of random coefficients $\alpha_i^{m_{rc}}$;
    Solve the model by backward-induction;
    foreach *simulation* $m_s \in \{1, \ldots, N_s\}$ **do**
      foreach *state* **do**
        Draw a vector of preference shocks $\varepsilon_i^{m_s, m_{rc}}$, enrollment shocks $\varepsilon_i^{e, m_s, m_{rc}}$, wage shocks $\epsilon_i^{m_s, m_{rc}}$, vector of random cutoff scores $P^{m_s, m_{rc}}$ from the empirical distribution of cutoffs, vector of PSU score shocks $\nu_i^{m_s, m_{rc}}$, vector of unknown abilities $A_i^{u, m_s, m_{rc}}$, and grade shocks $\varepsilon_i^{g, m_s, m_{rc}}$;
      end
      Forward-simulate the model and obtain a set of outcomes $y_i^{m_s, m_{rc}}$;
    end
  end
end
foreach $m_s \in \{1, \ldots, N_s\}$ *and* $m_{rc} \in \{1, \ldots, N_{rc}\}$ **do**
  Estimate the *auxiliary* model parameters, $\hat{\beta}^{m_s, m_{rc}}(\theta)$, on the simulated sample ;
end
Compute $\bar{\beta}(\theta) = \frac{1}{N_{rc} \times N_s} \sum_{m_{rc}} \sum_{m_s} \hat{\beta}^{m_s, m_{rc}}(\theta)$;
Return $Q(\theta) := \left(\bar{\beta}(\theta) - \hat{\beta}\right)^T W \left(\bar{\beta}(\theta) - \hat{\beta}\right)$;

Table 14: Estimation moments

Moment description	Targeted parameters
Share of students who retake the PSU	C^{psu}
Share of students who dropout by gender and income level	$\{\alpha_d\}_d$, α^w, C^e, σ_s^2
Grade auxiliary models' coefficients	γ, σ_g^2
Wage auxiliary models' coefficients	λ
Switchings and dropout auxiliary models' coefficients	σ_g^2, σ_m^2, σ_s^2, α_4^w
RDD auxiliary models' coefficients	V_{α^m}, V_{α^k}, C^e
Share of students who reapply	
Share of students who switch programs	σ_m^2, σ_s^2, V_{α^m}, V_{α^k}, C^e
Share of students who switch majors	σ_m^2, V_{α^m}
Share of students who switch majors within math-types	σ_m^2, V_{α^m}
Share of students who switch math-types within majors	σ_s^2
Share of students who switch college-types	V_{α^k}
Share of students who dropout at the end of the first year of college	α^w
Share of students who choose the outside option every year	α^w
Share of students who start college in the second year	
Share of students who remain in the same program after two years	
Share of top-reported preferences by program	$\{\alpha_{fe}\}_j$
Share of students whose top-reported preference is their top-true preference in R_1	ρ
Share of students whose top-reported preference is their top-true preference in R_2	ρ
Share of students whose top-reported preference has zero admission probability	ρ
Share of students with a positive risk of being unassigned given R_1	ρ
Share of ROLs R_1 with length 10	ρ
Share of ROLs R_2 with length 10	ρ
Share of students assigned to their top-true preference in the first period	ρ
Share of students who apply in the first year	
Share of students who apply in the second year	
Share of reapplications that change in their top-true preference	σ_m^2, σ_s^2, V_{α^m}, V_{α^k}
Shares of majors within R_1	V_{α^m}
Shares of college-types within R_1	V_{α^k}
Shares of majors within R_2	V_{α^m}
Shares of college-types within R_2	V_{α^k}

Table 15: Estimation moments

Moment description	Targeted parameters
[1] Norm of the difference between the vectors of college-type shares for students who reapply	V_{α^k}
Norm of the difference between the vectors of major shares for students who reapply	σ_m^2, V_{α^m}
[1] Norm of the difference between the vectors of ω shares for students who reapply	σ_s^2, V_{α^m}, V_{α^k}
Correlation between first-year grades and the norm of the difference between the vectors of major shares for students who reapply	σ_m^2, σ_g^2
[1] Correlation between first-year grades and the norm of the difference between the vectors of ω shares for students who reapply	σ_s^2, σ_g^2
Share of applications by major and college-type, grouped by gender in R_1	Δ^m, Δ^k
Share of applications by major and college-type, grouped by gender in R_2	Δ^m, Δ^k
Share reapplications from top-reported preferences	
Share reapplications from top-true preferences	
Mean of tuition for top-reported preferences, grouped by students' scores and income groups	$\{\alpha_c\}_c$
Mean of observed ability for top-reported preferences	α_1
Mean of average observed ability at the college level for top-reported preferences	α_2
Mean of distance for top-reported preferences	α_3
Mean of relative observed ability position for topreported preferences	α_4
Mean and variance of $\log\left(\frac{s_{lt+1}}{s_{lt}}\right)$ for positive PSU scores	$\{\alpha_l\}_l$, σ_{psu}
Mean and variance of $\log\left(\frac{s_{lt+1}}{\bar{s}_t}\right)$ for PSU scores wit zero value in the first year	$\{\alpha_{0l}\}_l$,σ_{psu}

Estimation

Table 16: Estimation Results - Parameters

Parameters	Values	Std
Application behavior and Dropout		
Share of strategic ROLs $(1-\rho)$	0.74	[0.022]
Cost of retaking PSU (C^{psu})	4.46	[0.219]
Dropout flow-utility for females $(\alpha^{dropout}_{female})$	19	[1.262]
Dropout flow-utility for males $(\alpha^{dropout}_{male})$	41.8	[1.756]
Dropout flow-utility for low-income $(\alpha^{dropout}_{low-income})$	15.8	[0.83]
First-time enrollment cost (C^{e})	32.16	[0.944]
Flow-utility and Priors		
Tuition (α_c)	-0.14	[0.049]
Relative position (α_4)	-0.28	[0.022]
Distance (α_3)	-1.09	[0.056]
Student observed ability (α_1)	12.92	[0.86]
Program observed ability (α_2)	4.65	[0.26]
Gender effect by major (Δ^m)	(-4.93 -2.46 3.28 1.48)	([0.363] [0.171] [0.256] [0.237])
Variance major random coefficient (σ^{2m}_{α})	15.69	[0.913]
Income effect by college (Δ^k)	(-0.11 -0.12 9.06)	([0.215] , [0.218] , [0.449])
Variance college random coefficient (σ^{2k}_{α})	0.43	[0.075]
Major prior variance (σ^2_m)	0.34	[0.032]
Subject prior variance (σ^2_s)	0.48	[0.103]

Notes: the order of majors is Social Sciences, Science, Education and Humanities, and Health.
The order of colleges is CRUCH-Public, CRUCH-Private, and Non-CRUCH.

Estimation

Table 17: Estimation Results - Parameters

Parameters	Values	Std
Grade equations		
Constant by major (γ_{1m_j})	(3.91 4.32 3.81 3.43)	([0.105] [0.229] [0.14] [0.208])
Student observed ability (γ_2)	0.52	[0.053]
Gender effect (γ_3)	0.36	[0.052]
Random coefficient effect on grades (major) (γ_4)	0.05	[0.015]
Grade shock variance (σ_g^2)	0.08	[0.04]
Evolution of scores		
Std. of ν (σ_{psu})	0.1	[0.007]
Mean prop. change ($\{\alpha_l\}_l$)	(1.06 1.07 1.05 1.02)	([0.004] [0.007] [0.006] [0.001])
Mean prop. change from zero score ($\{\alpha_{0l}\}_l$)	(1.07 1.08)	([0.024] [0.021])
Non-pecuniary work utility		
Major random coefficient (α_1^w)	8.72	[0.363]
Student observed ability (α_2^w)	71.58	[2.688]
College observed ability (α_3^w)	-1.86	[0.592]
Non-pecuniary work value of unknown ability (α_4^w)	178.57	[6.852]
Pecuniary work utility parameter (α_5^w)	75.95	[5.247]
Wage parameters		
Constant by major (λ_{1m_j})	(1.78 1.17 1.07 1.63)	([0.073] , [0.083] , [0.1] , [0.059])
College observed ability (λ_2)	0.03	[0.011]
Grades (λ_3)	0.13	[0.017]
Gender effects (λ_4)	-0.19	[0.094]
Wage shock variance (σ_w^2)	0.68	[0.08]
Wage growth		
Linear term by major (λ_{5m_j})	(0.11 0.18 0.14 0.24)	(-)
Quadratic term by major (λ_{6m_j})	(0 -0.01 -0.01 -0.02)	(-)

Notes: the order of majors is Social Sciences, Science, Education and Humanities, and Health.
The order of colleges is CRUCH-Public, CRUCH-Private, and Non-CRUCH.

Switching equations:

$$O_{ij} = \beta^{o}_{1m_j} + \beta^{o}_{2} A_{ij} + \beta^{o}_{3} Z^{g}_{i} + \underbrace{\beta^{o}_{4} \mathbb{1}\{j = R_{1i}(1)\} + \beta^{o}_{5} s_{1im_j} + \beta^{o}_{6} s_{1ik_j}}_{\text{correlated with } \alpha_{im_j} \quad \alpha_{ik_j}} + \underbrace{\beta^{o}_{7} G_{ij1}}_{\text{correlated with } A^{u}_{ij}} + \varepsilon^{o}_{ij},$$

Grade equations:

$$G_{ij1} = \beta^{\gamma}_{1m_j} + \beta^{\gamma}_{2} A_{ij} + \beta^{\gamma}_{3} Z^{g}_{i} + \underbrace{\beta^{\gamma}_{4} \mathbb{1}\{j = R_{1i}(1)\} + \beta^{\gamma}_{5} s_{1im_j} + \beta^{\gamma}_{6} s_{1ik_j}}_{\text{correlated with } \alpha_{im_j} \quad \alpha_{ik_j}} + \varepsilon^{g}_{ij1},$$

$$G_{ij2} = \left(\beta^{\gamma}_{7} + \beta^{\gamma}_{8} S\right) G_{ij1} + \beta^{\gamma}_{9} + \gamma_{10} S + \varepsilon^{g}_{ij2}.$$

Pecuniary:

$$\log(\bar{w}_{j(\tau=4)}) = \beta^{\lambda}_{1m_j} + \beta^{\lambda}_{2} \bar{A}_{k_j} + \beta^{\lambda}_{3} \bar{G}_{j} + \beta^{\lambda}_{4} \bar{Z}^{w} + \epsilon_{j(\tau=4)},$$

$$\log(\bar{w}_{m_j\tau}) = \beta^{\lambda}_{5m_j} + \beta^{\lambda}_{6m_j}\tau + \beta^{\lambda}_{7m_j}\tau^{2} + \epsilon_{m_j\tau},$$

Non-pecuniary:

$$y_{ij} = \beta^{w}_{1} s_{1im_j} + \beta^{w}_{2} \mathbb{1}\{j = R_{1i}(1)\} + \beta^{w}_{3} A_{ij} + \beta^{w}_{4} \bar{A}_{k_j} + \beta^{w}_{5} Z^{g}_{i} + \varepsilon^{w}_{ij}$$

Auxiliary models