Cost of Strategic Play in Centralized School Choice Mechanisms

Sepehr Ekbatani

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University of California, Los Angeles

Motivation

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- Kindergarten and Elementary School
  Boston
- High School
  New York, Boston, Chicago, Madrid, Paris, Ghana, Romania, ...
- Post-Secondary
  Norway, Chile, China, Turkey, Tunisia, Medical Schools in US, ...

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Students choose options in turns, based on their score on a centralized exam.

- Strategy-proof: No benefit in manipulating true preferences.
- Stable: Post-assignment, any preferred choice has exhausted its capacity with higher priority students.
- Pareto superior to all stable mechanisms.

Constrained DA

In practice, DA is implemented with a constraint on list size.

New York up to 12 choices

Chile up to 8 choices

Norway up to 15 choices ...

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Not strategy-proof: Students have to play strategic.

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- New York up to 12 choices
- Chile up to 8 choices
- Norway up to 15 choices ...

From a theoretical point of view,

- The mechanism is no longer strategy-proof nor stable.
  - Not strategy-proof: Students have to play strategic.
  - Not stable: Not Pareto-efficient or not fair.

This Paper

Goal:

Empirically estimate the welfare cost induced by constraint on DA.

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71,918 Applications and admissions to Iranian higher educational institutions in 2012.

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More than 4 million observations.

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Method:

A novel two-dimensional choice model that accounts for demand for majors and demand for schools separately.

Equilibrium e ects of changing the cap as counterfactual.

Related Literature

School Choice and DA Algorithm:

Gale & Shapley (1962); Abdulkadiroglu & Sonmez (2003); Haeringer & Klijn (2009); Abdulkadiroglu, Agarwal & Pathak (2017); Kapor, Neilson & Zimmerman (2018); Ajayi & Sidibe (2016); Fack, Che & He (2019).

Empirically nd welfare e ects of constrains on DA.

Estimate heterogeneous e ect of a more restrictive cap.

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College Choice Empirical Studies:

Luflade (2018); Hastings, Neilson & Zimmerman (2015); Wiswall & Zafar (2014); Drewes & Michael (2006); Artemov, Che & He (2019); De Haan, Gautier, Oosterbeek & Van der Klaauw (2015).

- Relax truth-telling assumption.
- Relax independence of unobservable taste shocks.

Independent Preference Shocks

In the literature, unobservable taste shocks are commonly assumed to be independent. It provides closed form solution and easy estimation.

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- Choosing high school and track.
- Choosing Med school and city.
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Introduce a two-dimensional choice model to relax this assumption.

Preview of the Results

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List cap of 10 instead of 100, would decrease welfare equivalent to a 453 km increase in travelled distance by an average student. (2.6 times the average)

A change from 100 to 150 would generate welfare, equivalent to a 27 km decrease in the home-university distance. (0.43 the Median)

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Less restrictive cap generates winners and losers but overall improves fairness.

Outline

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- All universities rank students the same. (serial dictatorship)
- Deferred Acceptance is executed by National Organization of Educational Testing High School Timeline
- **Data**: Students' ROLs and assignment oucomes in 2012 with list cap of 100.

Quasi Experiment Policy Change in 2013

Changed the list cap from 100 to 150 in 2013.

Use this data to:

- Provide reduced form results.
- Validate the model out of sample.

Deferred Acceptance Algorithm

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1. The rst ranked student is assigned to her rst listed choice.

(n+1). After assigning n^{th} student, the $(n+1)^{th}$ student is assigned to his highest element of his submitted list that has a vacancy. If none has a vacancy, he will be rejected.

Last. Stop when all the applications are processed.

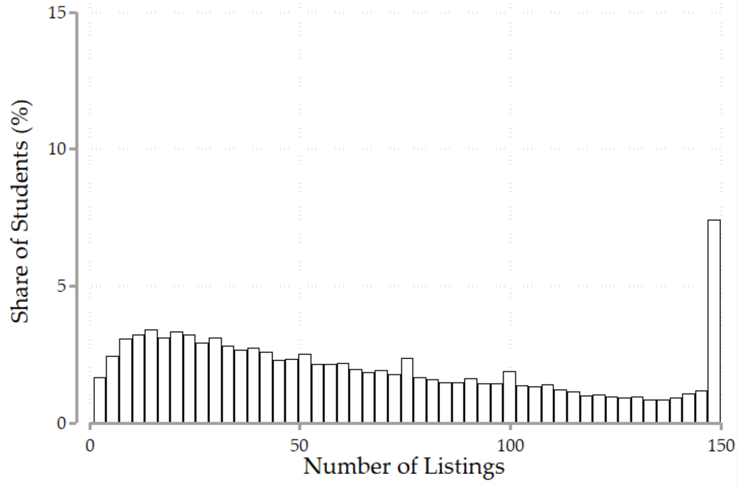
Summary Statistics (Math and Physics Concour 2012)

Table 1: Total Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Panel A. Student Characteristics				
Age	18.61	1.86	16	59
Female	0.41	0.49	0	1
Retaking the exam	0.28	0.45	0	1
Panel B. Choices				
Number of Listings	63.66	30.84	1	100
Majors Ranked (Total=241)	11.95	6.79	1	43
Universities Ranked (Total = 854)	19.78	13.23	1	93
Panel C. Outcomes				
Rejected Scatter	0.10	0.30	0	1
Row of accepted choice Histogram	30.75	25.94	1	100
Row of accepted choice *2* [1,10]	0.24	0.43	0	1
Row of accepted choice *2* [91,100]	0.03	0.15	0	1
Number of Students	71,918			
Total Number of Observations	4,461,572			

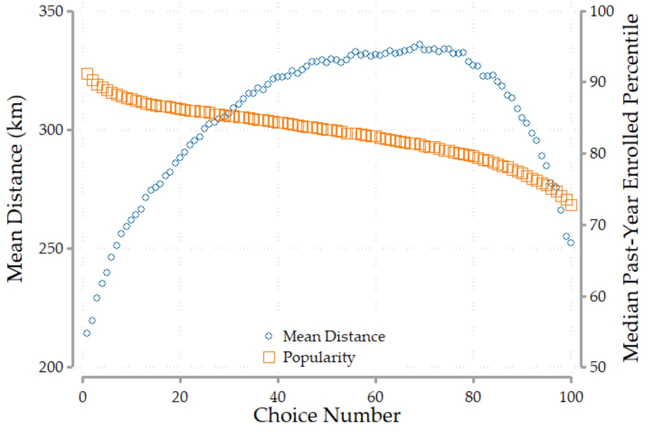
Number of Listings in 2012

Number of Listings in 2013



Students Prefer Popular Programs and Dislike Distance

Average student starts listing popular programs that are close to him. Completes his list with not-so-popular programs which are also close to his hometown.



Outline

Data and Mechanism

Model

Estimation

Counterfactual Analysis

Results

Conclusion

Rational Expectation Model for Major Choice

Student's problem is a portfolio optimization problem.

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Student's objective is to choose a portfolio of programs
$L = [l_1, \ldots, l_k, \ldots, l_K]$ with the highest expected utility:

$$EU(L) = \sum_{k=1}^{K} \left[\left(\prod_{r=1}^{k-1} (1 - p_r) \right) p_k u_k \right] + \prod_{k=1}^{K} (1 - p_k) u_0 \qquad (1)$$

p_k: Ex-ante (subjective) admission probability to k^{th} listing.

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- p_k: Ex-ante (subjective) admission probability to k^{th} listing.
- u_k: Ex-post received utility, conditional on acceptance to k^{th} listing.

Proposition: Student can not do any better but to order the *chosen programs* according to her true preference. [Haeringer & Klijn (2009)]

Estimation Steps

Assumption on revealed preferences

Recovering students' preferences u

Find subjective probabilities p

Revealed Preferences Assumptions

Truth-telling

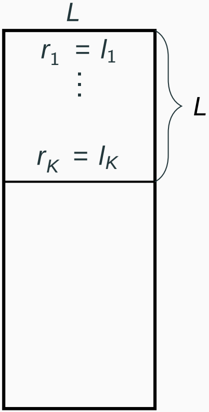
Drewes & Michael (2006); Hastings, Kane & Staiger (2009); Hallsten (2010); Kirkeboen (2012); Budish & Cantillon (2012); De Haan, Gautier, Oosterbeek & Van der Klaauw (2015); Lu ade (2018)

Undominated Strategies

Fack, Grenet & He (2019); Artemov, Che & He (2017), Agarwal & Somaini (2018)

Truth-Telling Assumption

Truthful student will rank her most desirable programs.



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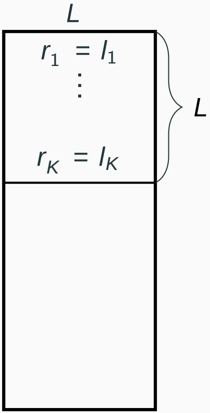
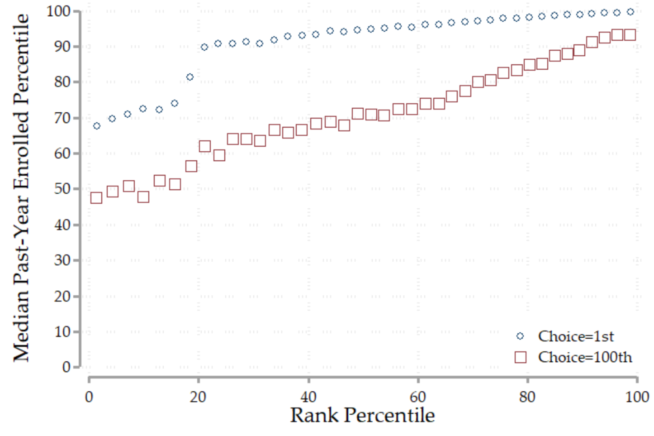


Probability of observing the submitted list:

$$
\begin{aligned}
& Pr\,(L = [l_1; \ldots; l_k; \ldots; l_K]) \\
= \; & Pr\,(u_1 > u_2 > \ldots > u_K > u_j \; : j \notin L)
\end{aligned}
\tag{2}
$$

Low-Ranked Students Do Not Seem Truthful

Top students choose all of their choices from the most popular programs. Low-ranked students have to skip the impossible.

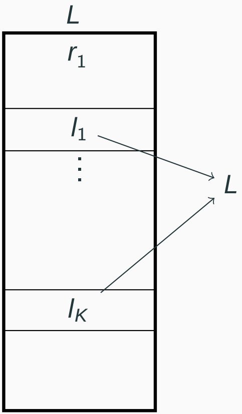


*Selectivity is proxied by the median rank of admitted students to the program in the past year.

Short-List

Undominated Strategies

Student's choices are not necessarily the most wanted ones.



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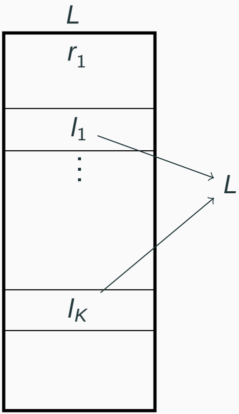


Strategic play changes the equality to an inequality:

$$
\begin{aligned}
& Pr\left(L = [l_1, \ldots, l_k, \ldots, l_K]\right) \\
= & \frac{Pr\left(u_1 > u_2 > \ldots > u_K \cap (l_1, \ldots, l_K) \in L\right)}{Pr\left(u_1 > u_2 > \ldots > u_K\right)}
\end{aligned}
\tag{3}
$$

Recovering Students' Preferences u

Rank-order Choice Model (School choice literature)

Student has preference over programs.

Two-dimensional Choice Model (This paper)

Student has preference over majors and preference over universities.

Her decision is based on the composition of the bundle.

Multinomial Logit Choice Model

Individual i receives the following utility if she is accepted to program j:

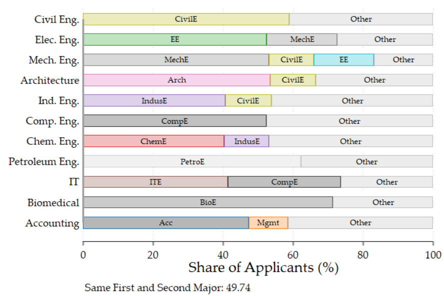
$$u_{i,j} = V(Z_{i,j}, \beta) + \epsilon_{i,j}$$

$$\epsilon_{i,j}: \textit{i.i.d} \text{ over } i \text{ and } j, \sim \text{type-I extreme value}$$

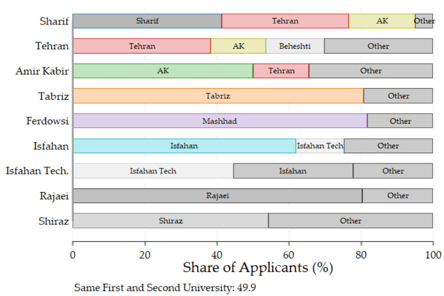
- No peer effects.
- Student's taste for *ucla mathematics* is **independent** of his taste for *ucla statistics*.

Preferences Don't Look Independent!

Second-Choice Major by First-Choice Major:



Second-Choice University by First-Choice Field:



Same First and Second Majors: 49.74%

Same First and Second Universities: 49.9%

They Look Nested

Table 2: Nestedness of Choices

		share of students who have applied to *a major* in n or more di erent universities (%) (1)	share of students who have applied to *a university* for n or more di erent majors (%) (2)
	2	99.12	99.26
	3	96.96	96.86
	4	94.01	93.48
	5	90.47	87.48
	6	86.81	80.86
n	7	82.95	71.89
	8	79.07	63.5
	9	74.86	54.15
	10	70.58	46.51
	⋮		
	100	0.01	0
Average		5.07	3.06
Median		3	2

Two-Dimensional Choice Model

Individual i receives the following utility if she is accepted to major m at school s:

$$u_{i,ms} = V(Z_{i,ms};\ ) + \ _{i,m} + \ _{i,s} + X_{ms} \tag{4}$$

$_{i,m}$: $i.i.d$ over i and m, type-I extreme value

$_{i,s}$: $i.i.d$ over i and s, type-I extreme value

- $Z_{i,ms}$: Observable individual-major-school characteristics.
- X_{ms}: Observable fixed program characteristics.
- No peer effects.
- Student's taste for *ucla mathematics* is **correlated** with his for *ucla statistics*.

Outline

Two Definitions

Definition 1- Major m_1 is revealed preferred to m_2 at school s, if (m_1, s) is listed higher in ranking compared to (m_2, s).

$$
\begin{aligned}
Pr(m_1 \succ_{i|s} m_2) &= Pr(u_{im_1s} > u_{im_2s} \;\cap\; (m_1, s), (m_2, s) \in L_i) \\
& \quad Pr(u_{im_1s} > u_{im_2s})
\end{aligned}
$$

Example

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$$Pr(u_{im_1s} > u_{im_2s})$$

Example

Definition 2- School s_1 is revealed preferred to s_2 for major m, if $(m; s_1)$ is listed higher in ranking compared to $(m; s_2)$:

$$Pr(s_1 \quad {}_{ijm}\, s_2) = Pr(u_{ims_1} > u_{ims_2} \quad \backslash \quad (m; s_1); (m; s_2)\ 2\ L_i)$$
$$Pr(u_{ims_1} > u_{ims_2})$$

Moment Inequalities

For each pair of majors the following set of inequalities can be written:

$$Pr(u_{im_1s} > u_{im_2s} j Z_{im_1s}; Z_{im_2s}; \quad) \quad \mathrm{E} \;\; 1(m_1 \quad {}_{ijs}\, m_2) j Z_{im_1s}; Z_{im_2s} \qquad 0\;;$$

$$1 \quad \mathrm{E}[1(m_2 \quad {}_{ijs}\, m_1) j Z_{im_1s}; Z_{im_2s}] \quad Pr(u_{im_1s} > u_{im_2s} j Z_{im_1s}; Z_{im_2s}; \quad) \quad 0\;:$$

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Toy Example

For each pair of schools:

$$Pr(u_{ims_1} > u_{ims_2} j Z_{ims_1}; Z_{ims_2}; \quad) \quad \mathrm{E} \quad 1(s_1 \quad {}_{ijm}\, s_2) j Z_{ims_1}; Z_{ims_2} \qquad 0\,;$$

$$1 \quad \mathrm{E}[1(s_2 \quad {}_{ijm}\, s_1) j Z_{ims_1}; Z_{ims_2}] \quad Pr(u_{ims_1} > u_{ims_2} j Z_{ims_1}; Z_{ims_2}; \quad) \quad 0\,;$$

Interact with Z_{ims} to obtain unconditional moment inequalities.

Estimation with Moment (In)equalities

Objective function based on the inequalities: [Andrews and Shi (2013)]

$$T_{MI}(\ ) = \sum_{j=1}^{M_1} \left(\frac{m_j(\ )}{\hat{\ }_j(\ )} \right)^2 \tag{5}$$

- $m_j(\ )$: mean of j^{th} moment.
- $\hat{\ }_j(\ )$: s.d. of j^{th} moment.
- $[a] \quad = min f0; ag$.

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Unfortunately, with the size of my data set, it is impossible to nd the convex hull that meets all the inequalities.

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Subsample yields uninformative bounds similar to [Fack et. al. (2019)]

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I present the results based on *moment equalities*.

Random Utility Estimation

Table 3: Utility Parameter Estimates

	(1) Two-dimensional		(2) Rank-ordered Logit	
Distance (100km)	-0.0493***	(0.000)	0.0124***	(0.000)
× Mid Cities	0.00391***	(0.000)	-0.00453***	(0.000)
× Large Cities	0.0233***	(0.000)	0.00349***	(0.000)
× Female	-0.0154***	(0.000)	-0.00981***	(0.000)
Distance (100km) Sq.	0.000545***	(0.000)	-0.00131***	(0.000)
Past-Year Median Admit	5.039***	(0.000)	3.898***	(0.000)
Same City	0.217***	(0.000)	0.0715***	(0.000)
Same Province	-0.105***	(0.000)	-0.136***	(0.000)
2-Year Program	-1.088***	(0.000)	-0.256***	(0.000)
Location: Tehran	0.829***	(0.000)	0.286***	(0.000)
× Female	-0.00887	(0.053)	0.0116***	(0.001)
× Mid Cities	0.0544***	(0.000)	0.0791***	(0.000)
× Large Cities	-0.296***	(0.000)	0.0407***	(0.000)
Major FE	x		x	
× Female	x		x	
× SES	x		x	
Observations	7,453,671		4,067,624	

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Welfare Effect of Policy Change

Based on estimated parameters in 2012, ow utility of assigned programs in 2012 and 2013:

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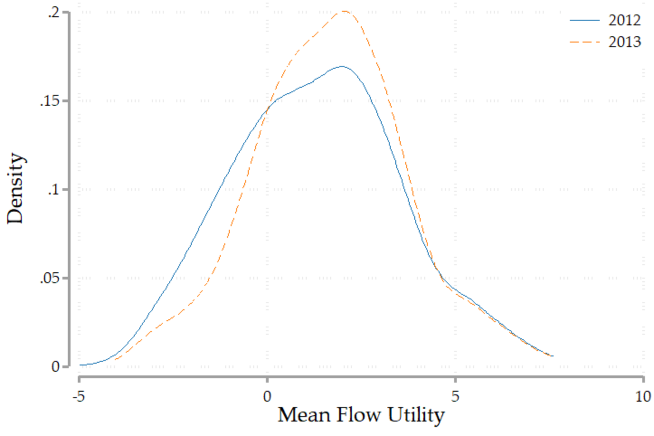

Utility is increased by an equivalent of 56 kilometers.

Subjective Probabilities

Student's admission chance to program j depends on her priority in the ranking.

$$P_j(Admission|Rank = r) = F_j(r)$$

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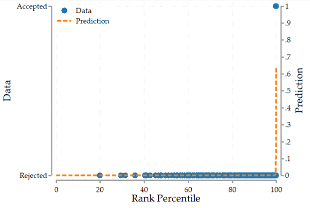
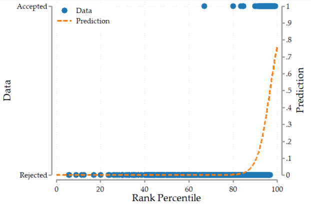
Use the historical data to estimate:

$$p_{ij} = \hat{F}_j(Rank_i) \tag{6}$$

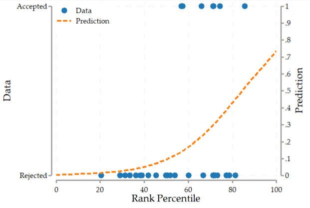
Admission Probability Examples



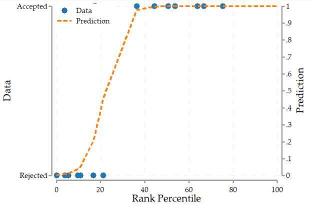
(a) E.E., Sharif Univ. Tehran



(b) Ind.E., Bu-Ali Sina Univ. Hamedan



(c) Physics, Lorestan Univ. Khorram Abad



(d) Accounting, Payam Nour Univ. Bostan Abad

Outline

Finding the Best List for Different Caps

Vectors $u_i = \{u_{ij}\}_{j=1}^{J}$ and $p_i = \{p_{ij}\}_{j=1}^{J}$ are obtained.

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- Assign students to programs using DA.
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- Problem of finding the best list with 100 choices out of 8000 is in the order of 10^{232}.

Marginal Improvement Algorithm

Optimal portfolio can be obtained by sequentially choosing the next best choice. [Chade and Smith (2006)]

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Marginal Improvement Algorithm

1. Start with $L_i = 0$; Discard all the alternatives with ow utility less than the outside option.
2. Find the program with highest expected utility; $L_i = fs_1g$
k. Select the best complement to the current list L_i:

$$\max_{s_k} \quad EU(L_i^0)$$

L_i^0 = arranged elements of (L_i [fs_kg) in decreasing order of utility.

Example

DA Assignment and Welfare

Students submit different lists in response to different list caps.

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Deferred acceptance outcome will be di erent.

DA Assignment and Welfare

- Students submit di erent lists in response to di erent list caps.
- Deferred acceptance outcome will be di erent.
- Total welfare:

$$W = \sum_{i=1}^{N} u_{ij} \tag{7}$$

  - u_{ij}: Ex-post utility of student i.
  - j: i's assignment under matching.

Outline

Data and Mechanism

Model

Estimation

Counterfactual Analysis

Results

Conclusion

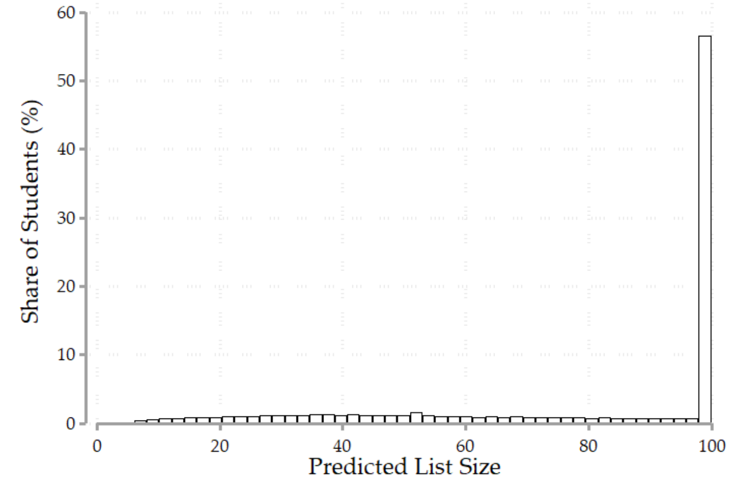
Fit and Predictions

How the model fits the data when cap is 100.

Predictions of the model for different caps.

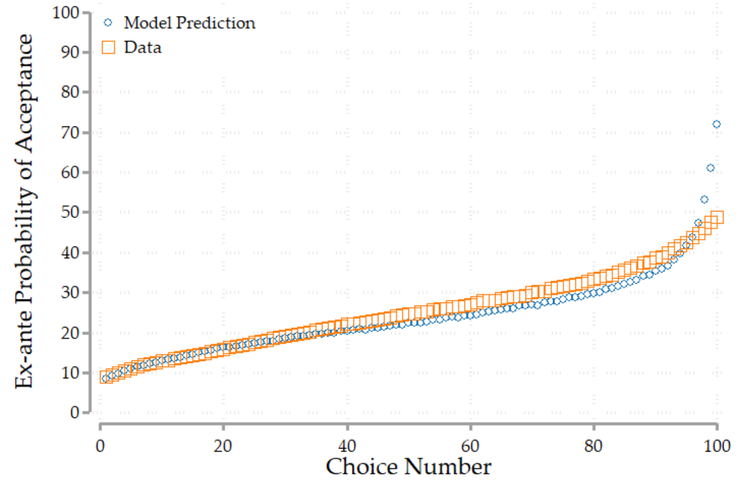
Predicted List Size

The model overestimates the number of people who submit a full list.



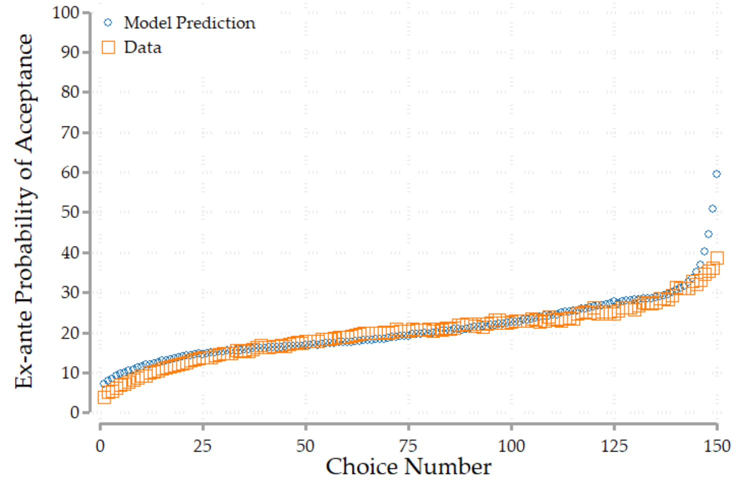
Ex-ante Probability of Acceptance Model vs Data

The model predicts data almost perfectly.

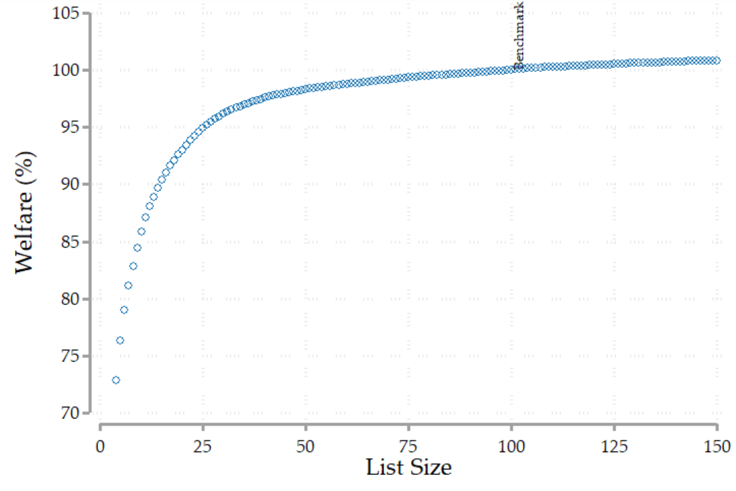


After Policy Change

Prediction of the model out of sample:

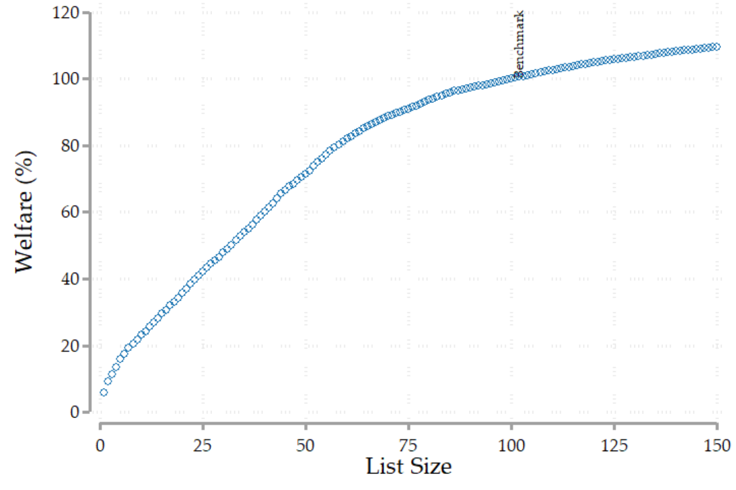


Smaller Cap, Lower Welfare



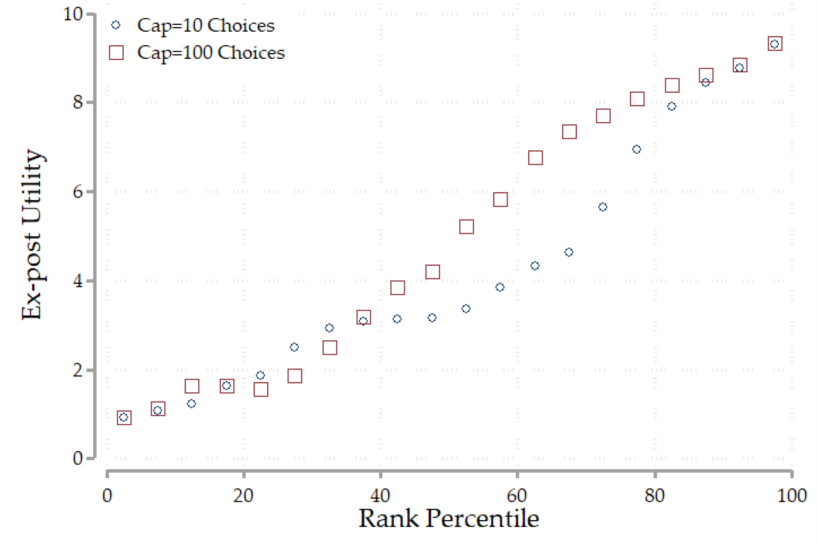
Distance

Welfare Analysis Under Rank-Ordered Logit



Winners and Losers

Students in the middle of ranking distribution bene t the most.



Outline

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Conclusion

A two-dimensional choice model is a well-suited model for college choice settings.

Truth-telling assumption generates biased estimators.

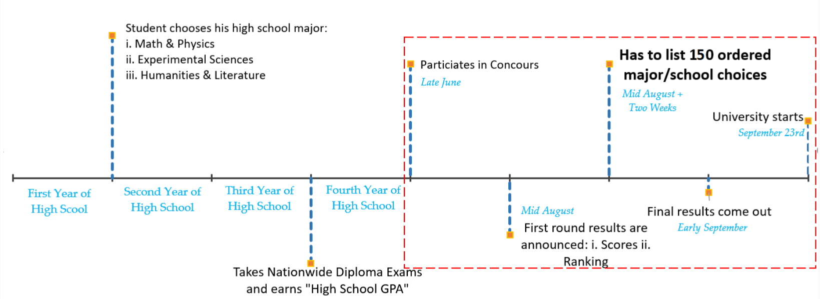
A more restrictive implementation of DA algorithm has considerable welfare loss.

This mainly comes from the students inability to submit a well-diversi ed portfolio.

Increasing the number of allowed listings, can be the cheapest and most e ective improvement to the centralized school choice systems.

Thank You!

High School and University Entrance Timeline



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Number of Listings in 2012 and 2013

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Rejection by List Size

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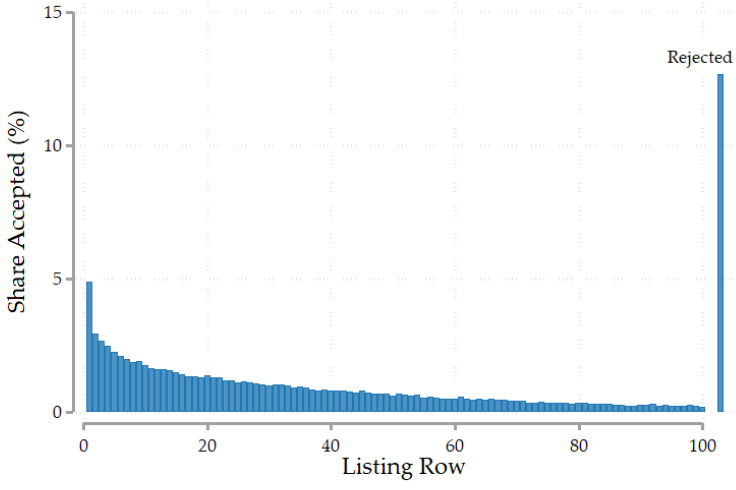
Acceptance by List Size



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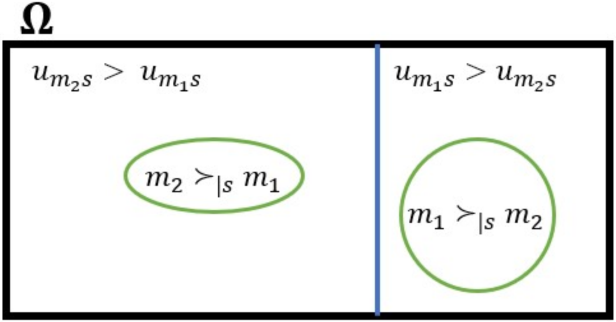
Major Inequalities at School s

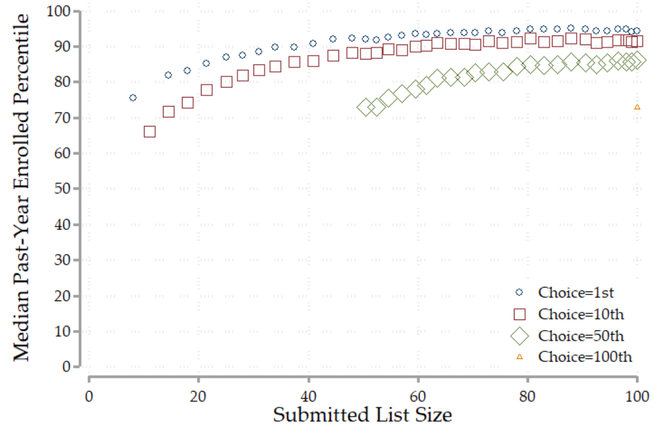
$$P(u_{m_1 s} > u_{m_2 s}) \quad P(m_1 \quad {}_{js}\, m_2)$$

$$P(u_{m_1 s} > u_{m_2 s}) \quad 1 \quad P(m_2 \quad {}_{js}\, m_1)$$



Short-List Students Are More Strategic

Submitting a short list does not imply truthfulness.



*Selectivity is proxied by the median rank of admitted students to the program in the past year.

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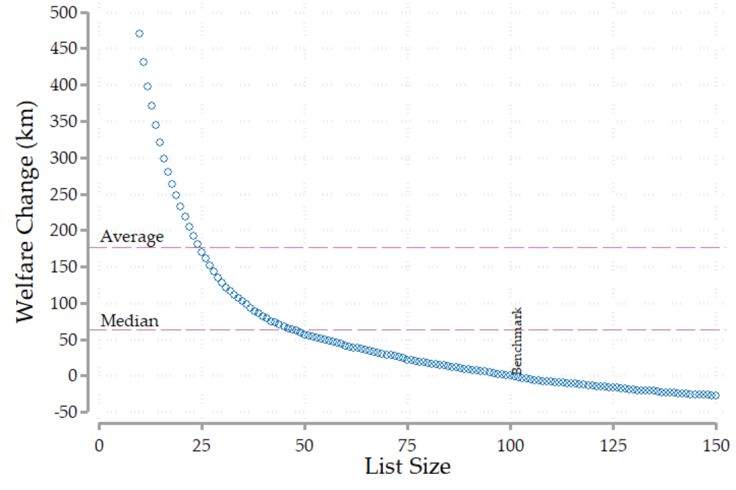
Welfare in Kilometers



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Toy Example

Original List

Row	Major	School
1	A	
2	B	
3	A	
4	B	
5	C	
6	B	

Toy Example

Original List		
Row	Major	School
1	A	
2	B	
3	A	
4	B	
5	C	
6	B	

Majors:

A	
Row	School
1	
2	

B	
Row	School
1	
2	
3	

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Toy Example

Majors:

Schools:

Original List		
Row	Major	School
1	A	
2	B	
3	A	
4	B	
5	C	
6	B	

A

Row	School
1	
2	

B

Row	School
1	
2	
3	

Row	Major
1	A
2	B

Row	Major
1	A
2	B
3	C

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Simultaneous Search Chade and Smith (2006)

Choice	p	u
I	0.12	10
II	0.2	9
III	0.15	8
IV	0.35	7
V	0.05	6
VI	0.1	5
VII	0.4	4
VIII	0.25	3
IX	0.45	2
X	0.5	1

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First Choice

Choice	p	u
I	0.12	10
II	0.2	9
III	0.15	8
IV	0.35	7
V	0.05	6
VI	0.1	5
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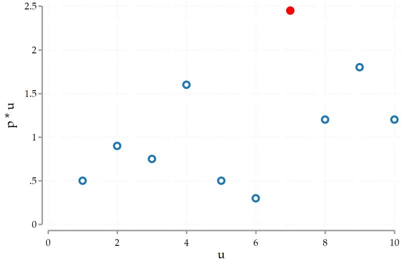

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Expected Utility Improvement

$$EU_{"} = p_{"}u_{"} + (1\quad p_{"})\ \ 0{:}35\ \ 7$$

Choice	p	u
I	0.12	10
II	0.2	9
III	0.15	8
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VII	0.4	4
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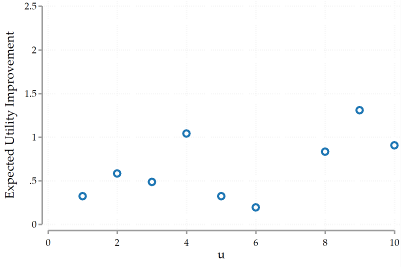
IX	0.45	2
X	0.5	1

$$EU_{\#} = 0{:}35\ \ 7 + (1\quad 0{:}35)\ \ p_{\#}\ \ u_{\#}$$



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Second Choice

Choice	p	u
I	0.12	10
II	0.2	9
III	0.15	8
IV	0.35	7
V	0.05	6
VI	0.1	5
VII	0.4	4
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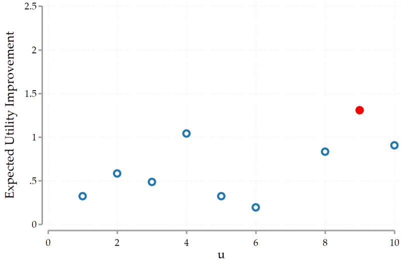

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Second Choice

Choice	p	u
I	0.12	10
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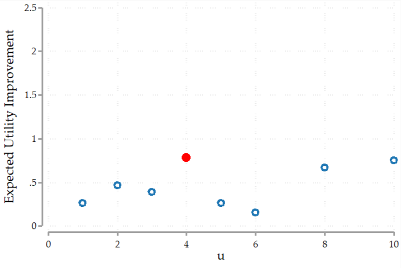

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