Empirical Market Design - School Choice

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Introduction

- Competitive Markets:
  - Price-taking behavior
  - Homogeneous goods & perfect information
  - Walrasian auctioneer

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  - Homogeneous goods & perfect information
  - Walrasian auctioneer
  - ✓ prices clear the market
  - ✓ first and second welfare theorems
- These conditions fail in real-world markets
- Study of market failures central in many fields in economics
  - Industrial organization: monopoly, collusion
  - Contract Theory: principal-agent with hidden types and actions
  - Labor: monopsony
  - Macro: price rigidity, agency problems
  - Market Design: congestion, auctions, matching, allocation mechanisms

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- How does the market clear?
  - prices: price discovery in auctions [yesterday's lecture]
  - priority cutoffs: matching and school choice [today's lectures]
  - wait-time: queuing in organ allocation, public housing [tomorrow!]

Market Design: Objectives

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- Practicality and implementability
  - ideal of strategy-proofness
  - rules easy to codify and explain

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- Theory: Game theory, computer science
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- Practice: interpersonal skills, networking
  - learn market institutions
  - propose and implement new designs

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- Complementary to theory in evaluation of trade-offs
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- Empirical Approaches useful also in other areas of economics
  - Estimation of heterogeneous preferences and demand, e.g.,
    - What do parents value in a school?
    - What are the preferences of individuals for public housing?
  - Analysis of policy interventions, e.g.,
    - Impact of financial aid reforms given admission mechanisms
    - What are the effects of more generous public housing program?

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- I will focus on the empirical tools

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  - Deferred acceptance (a.k.a Gale and Shapley alg)
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  - Top-Trading Cycles
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- Use data on reports + behavior for non-strategy proof mechanisms

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- Interpretation of data from mechanisms
- Find tractable statistical-econometric tools

Preferences

- Students indexed by i, schools/programs indexed by j

$$v_{ij} = v\left(\boldsymbol{x}_{ij}, \xi_j, \varepsilon_{ij}\right) - d_{ij},$$

  - $\boldsymbol{x}_{ij}$ observable characteristics
  - ξ_j school quality, unobserved to the econometrician but observed to students
  - ε_{ij} i.i.d preference shock
  - d_{ij} numeraire, e.g. distance, tuition

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$$v_{ij} = \overbrace{\boldsymbol{x}_{ij}\beta + \xi_j}^{\delta_{ij}} - d_{ij} + \varepsilon_{ij}$$

  - Random coefficient models: multiple preference shocks $\varepsilon_{ij} = (\gamma_i, \omega_{ij})$

$$v_{ij} = \overbrace{\boldsymbol{x}_{ij}\beta + \xi_j + \boldsymbol{x}_{ij}\left(\bar{\gamma}\boldsymbol{z_i} + \gamma_i\right)}^{\delta_{ij}} - d_{ij} + \omega_{ij}$$

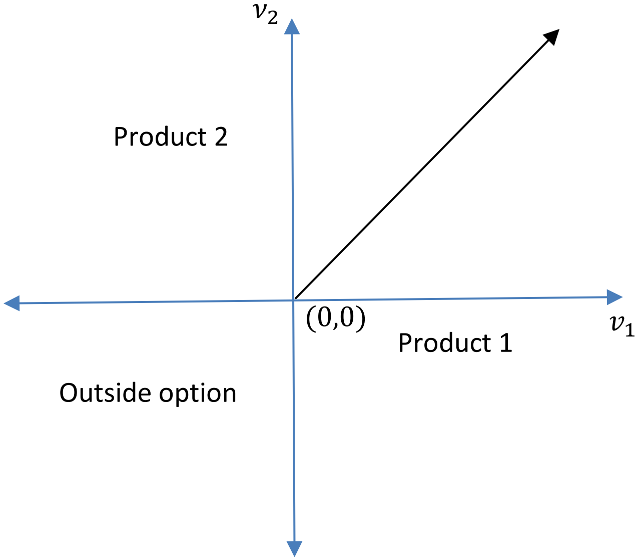
Outline

Discrete Choice Models

$$v_{ij} = v\left(\boldsymbol{x}_{ij}, \xi_j, \varepsilon_{ij}\right) - d_{ij},$$

- Consumer preferences for product
- Each consumer chooses the good with the maximum indirect utility
- The numeraire is usually price
- There are a variety of methods to estimate these models
- Rely on revealed preferences relations derived from observed choices

Revealed Preferences – Discrete Choice



Estimation Approaches – Discrete Choice

- Method of Moments (endogenous prices) [Berry 1994; Berry, Levinsohn and Pakes, 1995]
- Bayesian - Monte Carlo Markov Chain [Rossi, McCulloch and Allenby, 1996]
- Maximum Score [Manski, 1985]
- Moment Inequality [Ciliberto and Tamer, 2009; Pakes, 2010; Chernohukov, Hong and Tamer, 2007]
- Maximum Likelihood [McFadden, 1974; Train,2004]
  - In the simple linear model, with extreme value shocks: $\frac{\varepsilon_{ij}}{\sigma} \sim EV1$

$$v_{ij} = \overbrace{\boldsymbol{x}_{ij}\beta + \xi_j}^{\delta_{ij}} - d_{ij} + \varepsilon_{ij}$$

$$P\left(i \text{ chooses } j | x_{ij}; \beta\right) = \frac{exp\left(\frac{1}{\sigma}\left(\delta_{ij} - d_{ij}\right)\right)}{\sum_k exp\left(\frac{1}{\sigma}\left(\delta_{ik} - d_{ik}\right)\right)}$$

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    - students reports:
        - ★ $R_i \in \mathcal{R}$ student i's submitted rank-order list
        - ★ R_{ik} is the school ranked in position k
    - students priorities:
        - ★ $\boldsymbol{t}_i = (t_{i1}, \ldots, t_{iJ})$ is student i's priority, t_{ij} has finitely many values
        - ★ Tie-breaker: ν_{ij}

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- Step 4: Schools consider new and previously held applicants and rank them according to priority. **Provisionally** hold applicants until exhausting capacity and definitively reject the rest
- Step 5 Repeat Steps 3-4 until each student (a) is tentatively held by some school; or (ii) has been rejected by all ranked schools

Properties of DA

- Report-Specific Priority + Cutoff representation:
  - Score: $e_{ij} = f_j\left(R_i, t_i, \nu_{ij}\right)$
  - Cutoff p_j for school j
  - Each student is placed in the highest ranked school in

$$S\left(\boldsymbol{e_i}, \boldsymbol{p}\right) = \left\{j : e_{ij} > p_j\right\}$$

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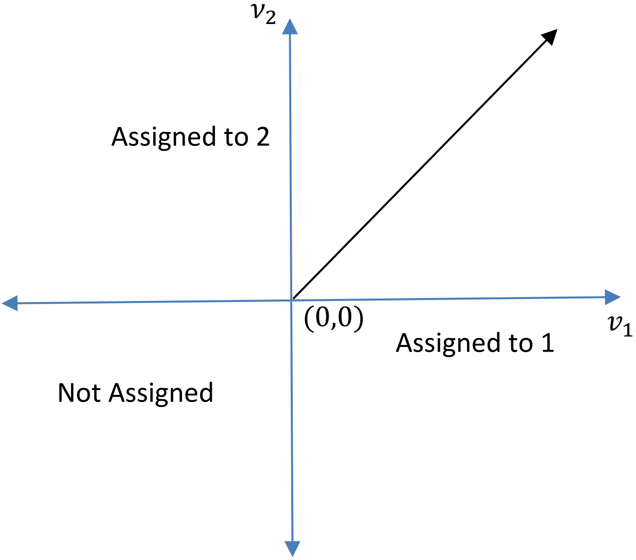
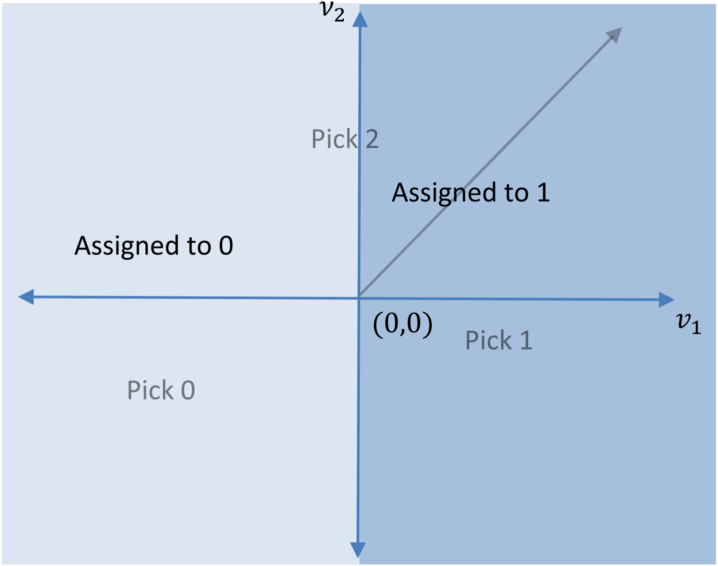
- Levels the playfield between sophisticates and naives

Revealed Preferences – Stability – Full Choice Set



Revealed Preferences – Stability – Restricted Choice Set



Stability – Estimation Methods

- Logit models: build likelihood for $\mathbb{P}\left(i \text{ is assigned to } j \middle| \delta_i, d_i; \theta\right)$:

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- Akyol and Krishna (2017) for high-schools in Turkey
- Bucarey (2018) for colleges in Chile

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	Change in average:			
	Utility	Utility Net of Price	Sticker Tuition	Received Scholarship
A. Common Price Coefficient Model				
Family Income				
Poorest Quintile	-$3,396	-$1,180	-$567	$1,137
Second Quintile	-$4,586	-$1,454	-$243	$1,458
Third Quintile	-$2,994	-$1,109	-$524	$1,274
Fourth Quintile	-$1,247	-$776	$630	$2,736
Richest Quintile	-$96	-$490	$1,460	$3,484
Test Scores				
Lowest Quartile	-$8,533	-$2,485	-$2,184	$24
Top Quartile	$1,955	$178	$3,328	$4,515
B. Income-heterogeneous Price Coefficient Model				
Family Income				
Poorest Quintile	-$6,530	-$1,078	-$506	$1,271
Second Quintile	-$3,684	-$990	-$323	$1,379
Third Quintile	-$1,461	-$778	-$25	$1,629
Fourth Quintile	$404	-$572	$675	$3,070
Richest Quintile	$1,486	-$332	$1,204	$3,832
Test Scores				
Lowest Quartile	-$10,980	-$2,178	-$2,160	$34
Top Quartile	$5,480	$614	$2,509	$5,038

Notes: This table compares the average of the variable in each column for the free tuition case and the baseline. Utilities are expressed in dollar equivalent.

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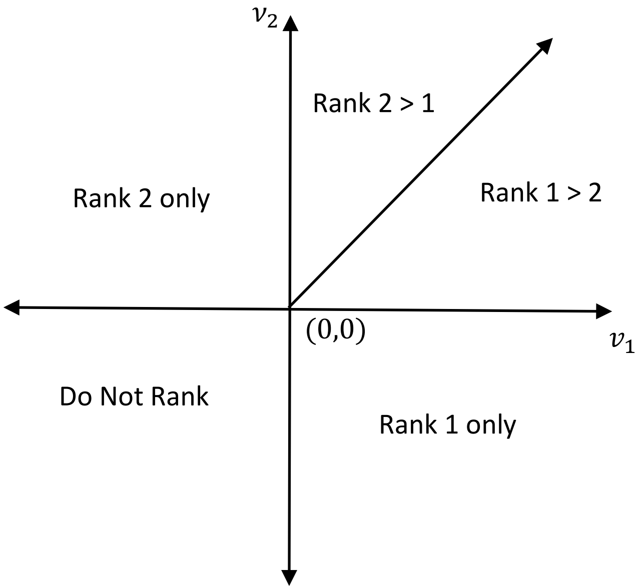

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- Abdulkadiroglu, Agarwal and Pathak, 2017: NYC High School
- Ajayi and Sidibe, 2022: High Schools in Ghana

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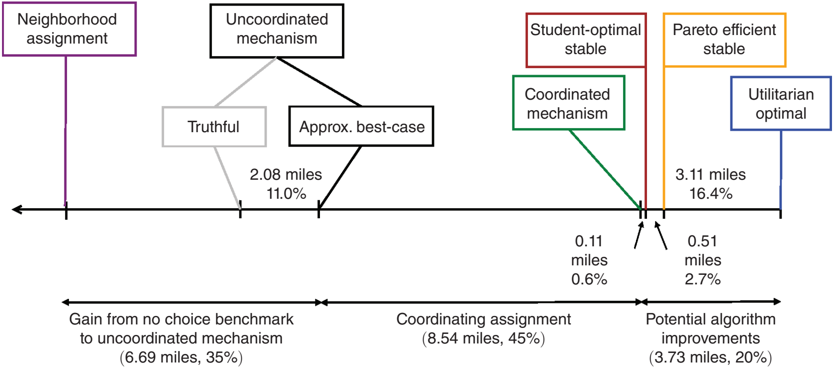
Abdulkadiroglu et. al. 2017



- Centralized (Coordinated) mechanisms perform better!

Outline

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  - DA with restricted list length

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  - Boston implemented the Immediate Acceptance mechanism (a.k.a Boston Mechanism)

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- Alternatively, take the skipping strategy more seriously
  - Require analysis attainability of each school
  - Popular schools are harder to get
  - Not ranking a unpopular school implies dislike [Hwang, 2014]

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- Step 5 Repeat Steps 3-4 until each student (a) has been accepted by some school; or (ii) has been rejected by all ranked schools

Listing to parents

- ... if I understand the impact of Gale Shapley, and I've tried to study it and I've met with BPS staff... I understood that in fact the random number... [has] preference over your choices... [Recording from the BPS Public Hearing, 6-8-05]

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- I'm troubled that you're considering a system that takes away the little power that parents have to prioritize… what you call this strategizing as if strategizing is a dirty word… [Recording from the BPS Public Hearing, 05-11-04].

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- Preferences are important!

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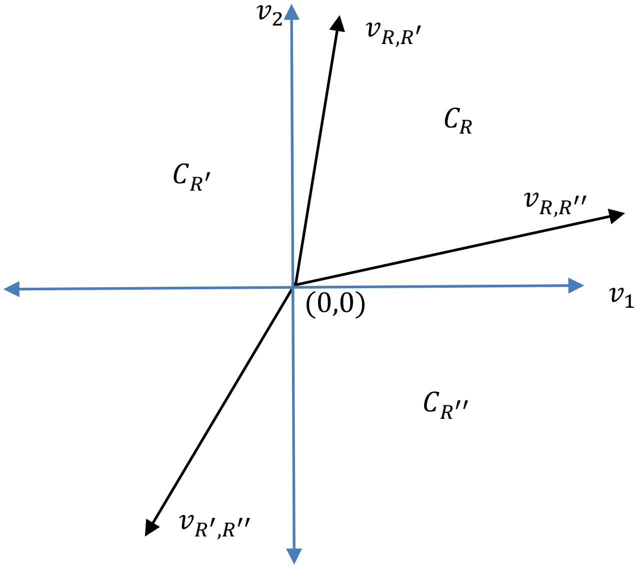
- Thus, $\boldsymbol{v}_i \in C_{R_i}$ where C_{R_i} is a cone $\left\{\boldsymbol{v}_i \in \mathbb{R}^J : \boldsymbol{v}_i \cdot \Delta L_{R_i} \geq 0\right\}$

Revealed Preferences – Strategic Behavior



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- No easy way to compute the likelihood function
- Bayesian methods do not require computation of the likelihood function
  ✓ Obtain the MLE without computing the likelihood function
  - Useful for discrete choice models [Rossi, McCulough, Allenby, 1995]
  - Can be adapted for choices over lotteries [Agarwal and Somaini, 2018]

Bayesian Methods

- Frequentist approach: $\log \mathcal{L}(\theta; data) := \log f(data; \theta)$
  - θ is a parameter
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- Bayesian Approach: $f(\theta|data) = \frac{f(data|\theta) f(\theta)}{f(data)}$
  - θ is random vector
  - $f(\theta)$ is the prior [knowledge about θ]
  - $f(\theta|data)$ is the posterior
  - $f(data) = \int f(data|\theta) f(\theta) d\theta$
  - The posterior contains all the information we want!
  - Asymptotically Gaussian posterior irrespective of prior [Bernstein von-Mises Theorem]

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  - ✓ There are other algorithms: e.g., Metropolis-Hastings, Hamiltonian Monte Carlo
- For k large enough $\theta^k = \left(\theta_1^k, \theta_2^k\right) \sim f(\theta|data)$
  - ✓ Generalizes to $\theta = (\theta_1, \theta_2, ..., \theta_d)$

Gibbs Sampler in School Choice

- Recall

$$v_{ij} = x_{ij}\beta_j - d_{ij} + \varepsilon_{ij}$$

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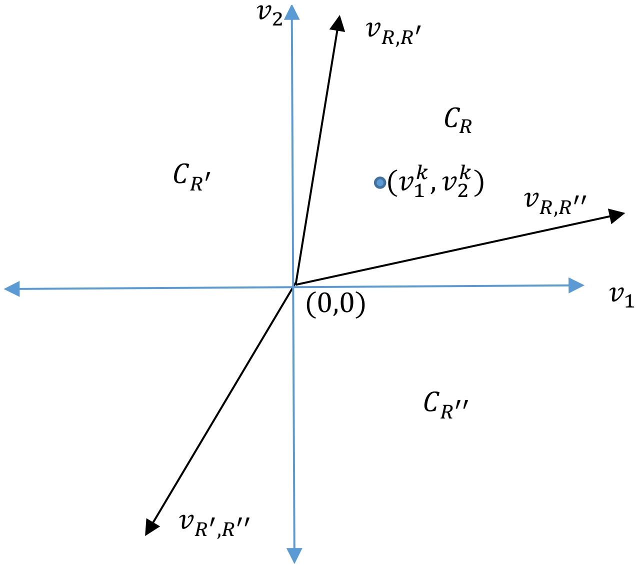
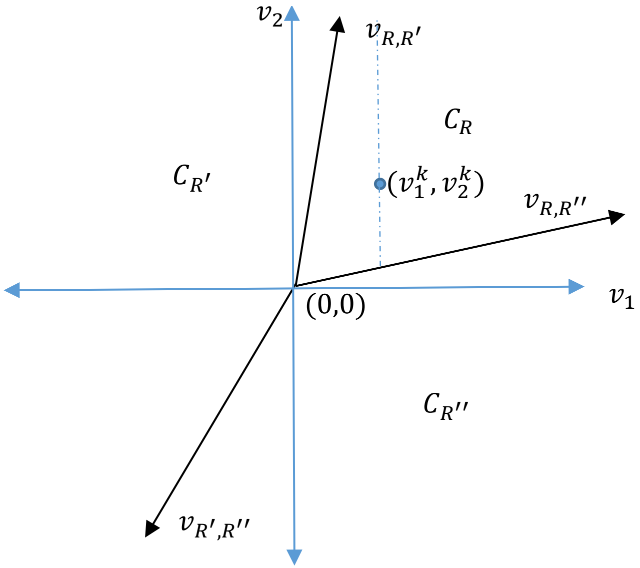
  - Update v^{k+1} given $\beta^{k+1}, \Sigma^{k+1}$

Updating v^{k+1}



We start from the previous vector v^k

Updating v^{k+1}



Draw v_2^{k+1} given $v_1^k, \beta^{k+1}, \Sigma^{k+1}$ from a truncated normal

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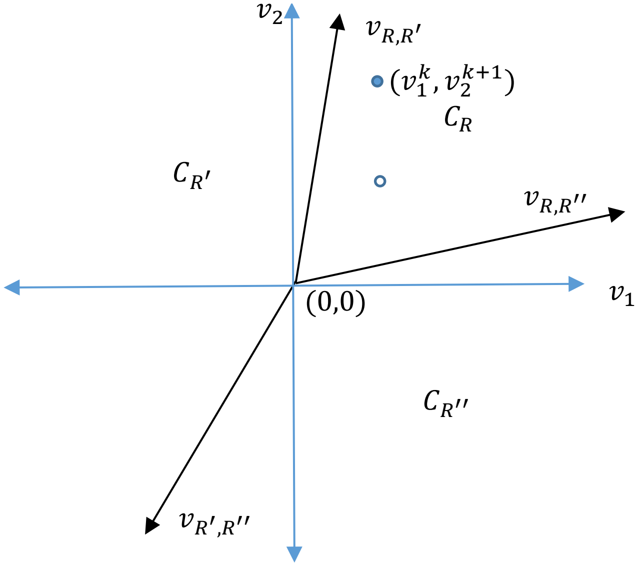
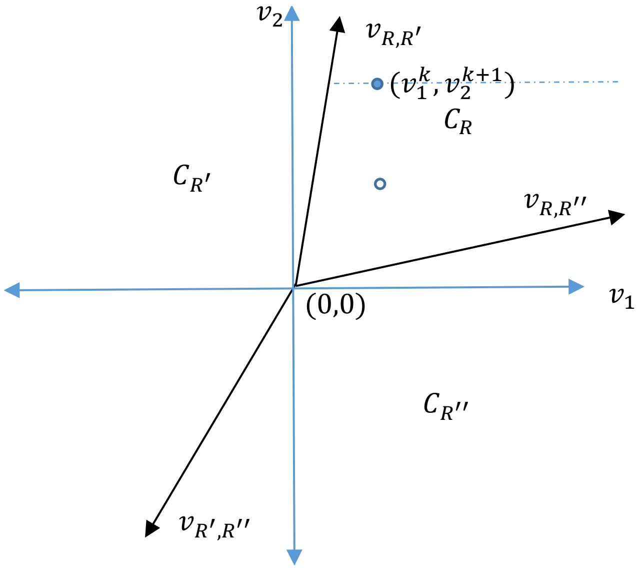


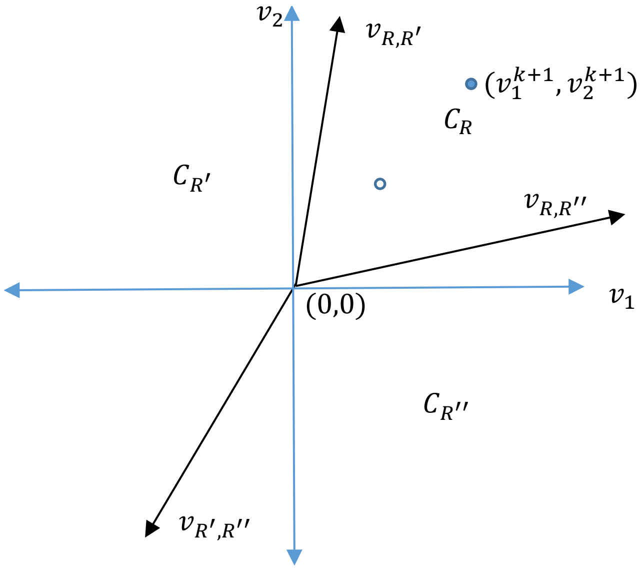
New draw of v_2^{k+1}

Updating v^{k+1}



Now, draw v_1^{k+1} given $v_2^{k+1}, \beta^{k+1}, \Sigma^{k+1}$ from a truncated normal

Updating v^{k+1}



Now, draw of v_1^{k+1}. We have v^{k+1}!

Agarwal and Somaini 2018

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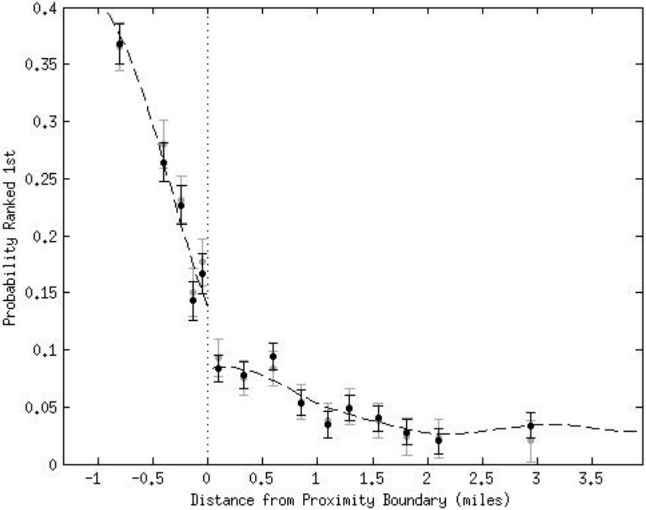
- Estimate preferences under alternative assumptions on beliefs
- Compare performance of DA vs IA

Elementary Schools and Students

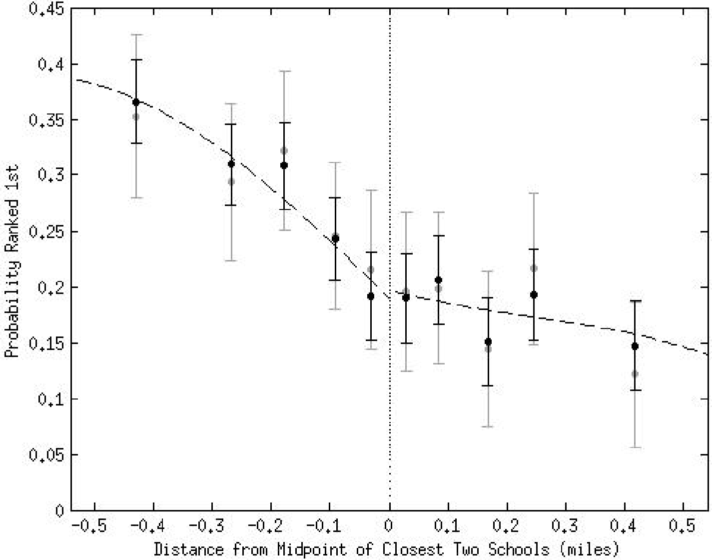
Year	2004	2005	2006	2007	2008	Average
Panel A: District Characteristics						
Schools	13	13	13	13	13	13
Programs	24	25	25	27	27	25.6
Seats	473	456	476	508	438	470
Students	412	432	397	457	431	426
Free/Reduced Lunch	32%	38%	37%	29%	32%	34%
Paid Lunch	68%	62%	63%	71%	68%	66%
Panel B: Student's Ethnicity						
White	47%	47%	45%	49%	49%	47%
Black	27%	22%	24%	22%	23%	24%
Asian	17%	18%	15%	13%	18%	16%
Hispanic	9%	11%	10%	9%	9%	10%
Panel C: Language spoken at home						
English	72%	73%	73%	78%	81%	76%
Spanish	3%	4%	4%	4%	3%	3%
Portuguese	0%	1%	1%	1%	1%	1%
Panel D: Distances(miles)						
Closest School	0.43	0.67	0.43	0.47	0.45	0.49
Average School	1.91	1.93	1.93	1.93	1.89	1.92



✓ Difficult to explain entire response with residential sorting

Strategic Behavior

Placebo with Two Closest Schools



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- Estimate assignment probabilities by resampling R_{-i}, t_{-i}, B times

$$\hat{L}_{R,t,j} = \frac{1}{B}\sum_{b=1}^{B}\int 1\{f_j(R,t,\nu) \geq p_j^b \text{ and } f_k(R,t,\nu) < p_k^b \text{ if } kRj\}\mathrm{d}\nu$$

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✓ Paper establishes consistency and asymptotic normality in a large market
  - Large number of students, fixed schools with increasing capacity
  - Target: Equilibrium of a limit game

Deferred Acceptance vs. Cambridge Mechanism

	Truthful			Rational Expectations		
	All Students	Paid Lunch	Free Lunch	All Students	Paid Lunch	Free Lunch
			Panel A: Deferred Acceptance			
Assigned to First Choice	67.7	58.2	86.6	67.9	58.1	87.5
Assigned to Second Choice	12.1	14.2	8.1	15.5	18.6	9.4
Assigned to Third Choice	5.7	8.2	0.8	5.2	7.1	1.3
			Panel B: Cambridge Mechanism			
Assigned to First Choice	79.0	74.5	87.8	72.3	63.9	88.8
Assigned to Second Choice	6.5	6.8	6.0	14.7	18.1	7.9
Assigned to Third Choice	3.1	4.0	1.4	3.9	5.1	1.3
			Panel C: Deferred Acceptance vs Cambridge			
Mean Utility DA - Cambridge	-0.004	-0.010	0.008	-0.072	-0.109	0.003
	(0.017)	(0.025)	(0.006)	(0.011)	(0.015)	(0.013)
Std. Utility DA - Cambridge	0.230	0.280	0.047	0.171	0.142	0.197
Percent DA > Cambridge	26.8	26.0	28.3	16.5	14.2	21.1
Percent DA ≈ Cambridge	31.9	26.2	43.0	30.3	27.1	36.6
Percent DA < Cambridge	41.4	47.8	28.7	53.2	58.7	42.3
Percent with Justified Envy	9.93	12.69	4.46	5.6	5.1	6.4

✓ Approach evaluates assignments, ignoring potential costs of strategizing

DA vs. Cambridge w/ Biased Beliefs

	Coarse Beliefs			Adaptive Expectations		
	All Students	Paid Lunch	Free Lunch	All Students	Paid Lunch	Free Lunch
	Panel A: Deferred Acceptance					
Assigned to First Choice	69.7	61.0	87.1	68.4	56.9	89.1
Assigned to Second Choice	11.9	13.7	8.5	13.6	17.3	7.1
Assigned to Third Choice	4.9	6.7	1.2	5.1	7.3	1.1
	Panel B: Cambridge Mechanism					
Assigned to First Choice	73.9	67.3	86.9	72.3	63.0	88.9
Assigned to Second Choice	10.2	11.1	8.3	12.1	15.3	6.4
Assigned to Third Choice	3.5	4.6	1.5	3.7	4.9	1.4
	Panel C: Deferred Acceptance vs Cambridge					
Mean Utility DA - Cambridge	-0.045	-0.074	0.013	-0.049	-0.097	0.037
	(0.011)	(0.013)	(0.016)	(0.028)	(0.035)	(0.040)
Std. Utility DA - Cambridge	0.174	0.146	0.207	0.213	0.142	0.282
Percent DA > Cambridge	22.6	21.3	25.1	19.1	16.5	23.9
Percent DA ≈ Cambridge	30.6	26.5	38.7	31.6	26.2	41.4
Percent DA < Cambridge	46.9	52.2	36.2	49.3	57.4	34.7
Percent with Justified Envy	7.1	7.8	5.6	6.7	8.0	4.4

✓ Advantage of the Cambridge mechanism are sensitive to agent information

Outline

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- Big welfare effects of centralized mechanisms
- IA can increase our measure of welfare if students strategize correctly
- Difference between the mechanisms is smaller if beliefs are biased
- Similar results in Barcelona [Calsamiglia, Guell and Fu, 2018]
- Manipulable mechanism do badly if beliefs are wrong like in New Haven [Kapor, Nielsen and Zimmerman, 2018]

Exciting avenues for research

- School choice and educational outcomes [Abdulkadiroglu, Angrist, Narita, Pathak 2017 & 2019, Abdulkadiroglu, Pathak, Schellenberg, and Walters, 2020]

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