Empirical Mechanism Design

Paulo Somaini

Stanford

DSE 2022

Introduction

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

Introduction

- Competitive Markets:
    - Price-taking behavior
    - Homogeneous goods & perfect information
    - Walrasian auctioneer
    - ✓ prices clear the market

Introduction

- Competitive Markets:
  - Price-taking behavior
  - Homogeneous goods & perfect information
  - Walrasian auctioneer
  - ✓ prices clear the market
  - ✓ first and second welfare theorems

Introduction

- Competitive Markets:
  - Price-taking behavior
  - Homogeneous goods & perfect information
  - Walrasian auctioneer
  - ✓ prices clear the market
  - ✓ first and second welfare theorems

- These conditions fail in real-world markets

Introduction

- Competitive Markets:
    - Price-taking behavior
    - 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

Market Design: How do markets really work?

- Abandon mythical Walrasian auctioneer

Market Design: How do markets really work?

- Abandon mythical Walrasian auctioneer

- Take market institutions seriously
  - congestion, coordination failures, other frictions
  - market failues: collusion, market power, inperfect information
  - rules, laws, political or institutional constraints

Market Design: How do markets really work?

- Abandon mythical Walrasian auctioneer
- Take market institutions seriously
  - congestion, coordination failures, other frictions
  - market failues: collusion, market power, inperfect information
  - rules, laws, political or institutional constraints
- What are participant's incentives?

Market Design: How do markets really work?

- Abandon mythical Walrasian auctioneer
- Take market institutions seriously
  - congestion, coordination failures, other frictions
  - market failues: collusion, market power, inperfect information
  - rules, laws, political or institutional constraints
- What are participant's incentives?
- How does the market clear?

Market Design: How do markets really work?

- Abandon mythical Walrasian auctioneer
- Take market institutions seriously
  - congestion, coordination failures, other frictions
  - market failues: collusion, market power, inperfect information
  - rules, laws, political or institutional constraints
- What are participant's incentives?
- 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

- Efficiency
  - ideal of Pareto optimality, c.f. first welfare theorem

Market Design: Objectives

- Efficiency
  - ideal of Pareto optimality, c.f. first welfare theorem
- Fairness and distributional concerns
  - notions of fairness in the process or in the allocation
  - notions of equity achieved via redistribution, c.f. second welfare theorem

Market Design: Objectives

- Efficiency
  - ideal of Pareto optimality, c.f. first welfare theorem
- Fairness and distributional concerns
  - notions of fairness in the process or in the allocation
  - notions of equity achieved via redistribution, c.f. second welfare theorem
- Practicality and implementability
  - ideal of strategy-proofness
  - rules easy to codify and explain

Market Design: Tools

- Theory: Game theory, computer science
  - Relevant equilibrium notions: stability
  - Properties: efficiency, fairness, strategy-proofness
  - identify tradeoffs: e.g. efficiency vs. equity

Market Design: Tools

- Theory: Game theory, computer science
  - Relevant equilibrium notions: stability
  - Properties: efficiency, fairness, strategy-proofness
  - identify tradeoffs: e.g. efficiency vs. equity
- Empirical Analysis: statistics, econometrics
  - Test hypothesis
  - Estimate economic primitives
  - Evaluate alternative designs

Market Design: Tools

- Theory: Game theory, computer science
  - Relevant equilibrium notions: stability
  - Properties: efficiency, fairness, strategy-proofness
  - identify tradeoffs: e.g. efficiency vs. equity
- Empirical Analysis: statistics, econometrics
  - Test hypothesis
  - Estimate economic primitives
  - Evaluate alternative designs
- Practice: interpersonal skills, networking
  - learn market institutions
  - propose and implement new designs

Emprical Market Design

- Complementary to theory in evaluation of trade-offs
  - Testing theoretical predictions
  - Quantify tradeoffs
  - Analysis when theory is ambiguous
  - Document effect of designs, market failures
  - Evaluate alternative designs

Emprical Market Design

- Complementary to theory in evaluation of trade-offs
  - Testing theoretical predictions
  - Quantify tradeoffs
  - Analysis when theory is ambiguous
  - Document effect of designs, market failures
  - Evaluate alternative designs
- Organized marketplaces present a unique opportunity for analysis
  - Well-understood rules
  - Administrative data

Emprical Market Design

- Complementary to theory in evaluation of trade-offs
  - Testing theoretical predictions
  - Quantify tradeoffs
  - Analysis when theory is ambiguous
  - Document effect of designs, market failures
  - Evaluate alternative designs
- Organized marketplaces present a unique opportunity for analysis
  - Well-understood rules
  - Administrative data
- 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?

School Choice

- Education instrumental for economic progress and social mobility

School Choice

- Education instrumental for economic progress and social mobility
- Public school systems aim for universal access

School Choice

- Education instrumental for economic progress and social mobility
- Public school systems aim for universal access
- Ideal of equal opportunity
  - efficiency
  - equity, fairness

School Choice

- Education instrumental for economic progress and social mobility
- Public school systems aim for universal access
- Ideal of equal opportunity
    - efficiency
    - equity, fairness
- Economic inequities tilt the playing field

School Choice

- Education instrumental for economic progress and social mobility
- Public school systems aim for universal access
- Ideal of equal opportunity
  - efficiency
  - equity, fairness
- Economic inequities tilt the playing field
- Apply the market design tool-kit:
  - Theory: properties mechanisms for student allocation
  - Empirical analysis: preferences for school characteristics
  - Practice: implement new designs, inform students

School Choice

- Education instrumental for economic progress and social mobility
- Public school systems aim for universal access
- Ideal of equal opportunity
  - efficiency
  - equity, fairness
- Economic inequities tilt the playing field
- Apply the market design tool-kit:
  - Theory: properties mechanisms for student allocation
  - Empirical analysis: preferences for school characteristics
  - Practice: implement new designs, inform students
- I will focus on the empirical tools

Mechanisms in School Choice

- School districts rely on algorithms for student allocation
- Algorithms use student reports to generate allocation

Mechanisms in School Choice

- School districts rely on algorithms for student allocation
- Algorithms use student reports to generate allocation
- Schools have coarse priorities

Mechanisms in School Choice

- School districts rely on algorithms for student allocation
- Algorithms use student reports to generate allocation
- Schools have coarse priorities
- Many different algorithms implemented/studied (example):
    - Deferred acceptance (a.k.a Gale and Shapley alg)
    - Immediate acceptance (a.k.a Boston Mechanism)
    - Top-Trading Cycles
    - Serial Dictator

Mechanisms in School Choice

- School districts rely on algorithms for student allocation
- Algorithms use student reports to generate allocation
- Schools have coarse priorities
- Many different algorithms implemented/studied (example):
  - Deferred acceptance (a.k.a Gale and Shapley alg)
  - Immediate acceptance (a.k.a Boston Mechanism)
  - Top-Trading Cycles
  - Serial Dictator
- Mechanisms have different properties

Empirical Approaches - Summary

- Exploit properties of the mechanism to derive revealed preferences

Empirical Approaches - Summary

- Exploit properties of the mechanism to derive revealed preferences
- Use data on allocation for stable mechanisms

Empirical Approaches - Summary

- Exploit properties of the mechanism to derive revealed preferences
- Use data on allocation for stable mechanisms
- Use data on reports for strategy-proof mechanisms

Empirical Approaches - Summary

- Exploit properties of the mechanism to derive revealed preferences
- Use data on allocation for stable mechanisms
- Use data on reports for strategy-proof mechanisms
- Use data on reports + behavior for non-strategy proof mechanisms

Challenges

- Demand estimation for schools, prestigious programs
  - Market does not clear on prices: $D(p)$ is not the full picture

Challenges

- Demand estimation for schools, prestigious programs
  - Market does not clear on prices: $D(p)$ is not the full picture
- Interpretation of data from mechanisms

Challenges

- Demand estimation for schools, prestigious programs
  - Market does not clear on prices: $D(p)$ is not the full picture
- 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

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

- Examples:
  - Simple linear model

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

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

- Examples:
  - Simple linear model

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

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

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

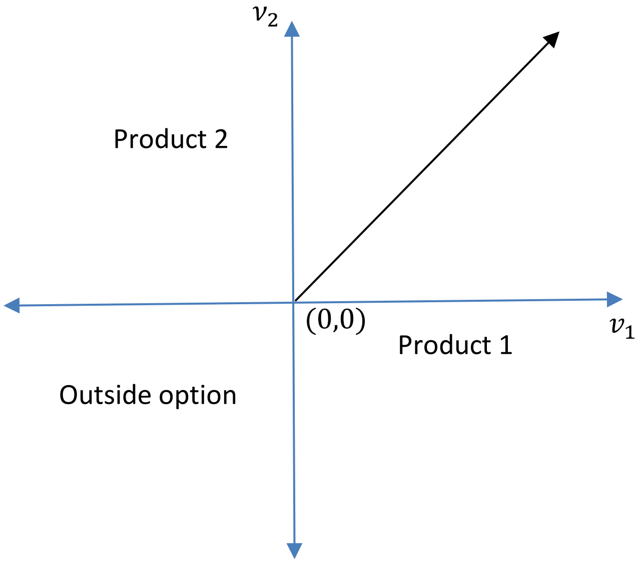
Outline

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: $\frac{\varepsilon_{ij}}{\sigma} \sim EV1$

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

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

Outline

Back to School Choice

- Students cannot just pick the school that they want the most

Back to School Choice

- Students cannot just pick the school that they want the most
- Prices do not clear the market

Back to School Choice

- Students cannot just pick the school that they want the most
- Prices do not clear the market
- An algorithm $\mu = \Phi(\boldsymbol{R}, \boldsymbol{t}, \boldsymbol{\nu})$ determines the allocation given:
  - students reports:
    - ★ $R_i \in \mathcal{R}$ student i's submitted rank-order list
    - ★ R_{ik} is the school ranked in position k

Back to School Choice

- Students cannot just pick the school that they want the most
- Prices do not clear the market
- An algorithm $\mu = \Phi(\boldsymbol{R}, \boldsymbol{t}, \boldsymbol{\nu})$ determines the allocation given:
  - 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}

Student Proposing Deferred Acceptance (DA)

- Step 1: Students apply to the first school in their list

Student Proposing Deferred Acceptance (DA)

- Step 1: Students apply to the first school in their list
- Step 2: Schools consider applicants and rank them according to priority. **Provisionally** hold applicants until exhausting capacity and definitively reject the rest

Student Proposing Deferred Acceptance (DA)

- Step 1: Students apply to the first school in their list
- Step 2: Schools consider applicants and rank them according to priority. **Provisionally** hold applicants until exhausting capacity and definitively reject the rest
- Step 3: Students apply to the highest school that has not reject them

Student Proposing Deferred Acceptance (DA)

- Step 1: Students apply to the first school in their list
- Step 2: Schools consider applicants and rank them according to priority. **Provisionally** hold applicants until exhausting capacity and definitively reject the rest
- Step 3: Students apply to the highest school that has not reject them
- 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

Student Proposing Deferred Acceptance (DA)

- Step 1: Students apply to the first school in their list
- Step 2: Schools consider applicants and rank them according to priority. **Provisionally** hold applicants until exhausting capacity and definitively reject the rest
- Step 3: Students apply to the highest school that has not reject them
- 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

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

  - DA: score does not depend on R_i

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

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

  - DA: score does not depend on R_i

- Deferred Acceptance has some desirable properties:
  - strategy-proofness: incentives to report ordinal preferences truthfully
  - stable allocation: i allocated to preferred school in $S\left(\boldsymbol{e_i}, \boldsymbol{p}\right)$

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

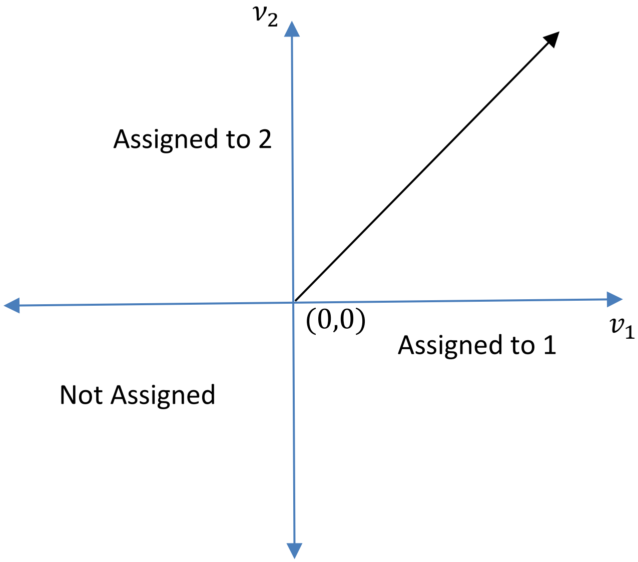
$$S\left(\boldsymbol{e_i}, \boldsymbol{p}\right) = \{j : e_{ij} > p_j\}$$

  - DA: score does not depend on R_i

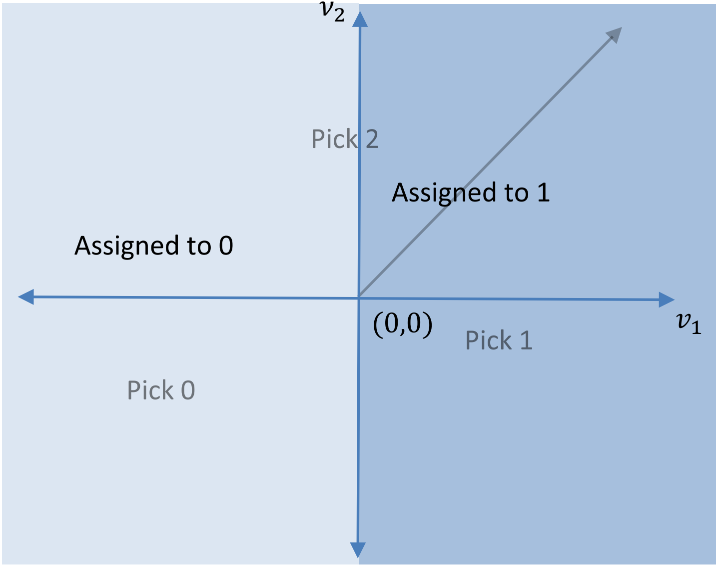
- Deferred Acceptance has some desirable properties:
  - strategy-proofness: incentives to report ordinal preferences truthfully
  - stable allocation: i allocated to preferred school in $S\left(\boldsymbol{e_i}, \boldsymbol{p}\right)$

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

$$\frac{\exp\left(\frac{1}{\sigma}\left(\delta_{ij} - d_{ij}\right)\right)}{\sum 1\left\{k \in S\left(\boldsymbol{e}_i, \boldsymbol{p}\right)\right\} \exp\left(\frac{1}{\sigma}\left(\delta_{ik} - d_{ik}\right)\right)}$$

Stability – Estimation Methods

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

$$\frac{\exp\left(\frac{1}{\sigma}\left(\delta_{ij} - d_{ij}\right)\right)}{\sum 1\left\{k \in S\left(\boldsymbol{e}_i, \boldsymbol{p}\right)\right\} \exp\left(\frac{1}{\sigma}\left(\delta_{ik} - d_{ik}\right)\right)}$$

- Random coefficients γ_i, $\mathbb{P}\left(i \text{ is assigned to } j|\boldsymbol{x}_j, \boldsymbol{z}_i; \theta\right)$ is:

$$\int \mathbb{P}\left(i \text{ is assigned to } j|\delta_i, d_i; \theta, \gamma\right) \phi\left(\gamma; \Sigma_\gamma\right) d\gamma.$$

Stability – Estimation Methods

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

$$\frac{\exp\left(\frac{1}{\sigma}\left(\delta_{ij} - d_{ij}\right)\right)}{\sum 1\left\{k \in S\left(\boldsymbol{e}_i, \boldsymbol{p}\right)\right\} \exp\left(\frac{1}{\sigma}\left(\delta_{ik} - d_{ik}\right)\right)}$$

- Random coefficients γ_i, $\mathbb{P}\left(i \text{ is assigned to } j | \boldsymbol{x}_j, \boldsymbol{z}_i; \theta\right)$ is:

$$\int \mathbb{P}\left(i \text{ is assigned to } j | \delta_i, d_i; \theta, \gamma\right) \phi\left(\gamma; \Sigma_\gamma\right) d\gamma.$$

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

Bucarey (2018) Who pays for free college?

- In 2014 the Chilean government promised to make college free

Bucarey (2018) Who pays for free college?

- In 2014 the Chilean government promised to make college free
- Low-income students already received financial aid

Bucarey (2018) Who pays for free college?

- In 2014 the Chilean government promised to make college free
- Low-income students already received financial aid
- Thus, low-income students' tuition was lower

Bucarey (2018) Who pays for free college?

- In 2014 the Chilean government promised to make college free
- Low-income students already received financial aid
- Thus, low-income students' tuition was lower
- Hypothesis: If college is free for all students
  - high-income students will face same price as low-income students
  - Low-income students will be displaced from highly demanded majors

Bucarey (2018) Who pays for free college?

- In 2014 the Chilean government promised to make college free
- Low-income students already received financial aid
- Thus, low-income students' tuition was lower
- Hypothesis: If college is free for all students
  - high-income students will face same price as low-income students
  - Low-income students will be displaced from highly demanded majors
- Approach:
  - Data on student enrollment

Bucarey (2018) Who pays for free college?

- In 2014 the Chilean government promised to make college free
- Low-income students already received financial aid
- Thus, low-income students' tuition was lower
- Hypothesis: If college is free for all students
  - high-income students will face same price as low-income students
  - Low-income students will be displaced from highly demanded majors
- Approach:
  - Data on student enrollment
  - DA generates a stable assignment

Bucarey (2018) Who pays for free college?

- In 2014 the Chilean government promised to make college free
- Low-income students already received financial aid
- Thus, low-income students' tuition was lower
- Hypothesis: If college is free for all students
  - high-income students will face same price as low-income students
  - Low-income students will be displaced from highly demanded majors
- Approach:
  - Data on student enrollment
  - DA generates a stable assignment
  - Estimate preferences

Bucarey (2018) Who pays for free college?

- In 2014 the Chilean government promised to make college free
- Low-income students already received financial aid
- Thus, low-income students' tuition was lower
- Hypothesis: If college is free for all students
  - high-income students will face same price as low-income students
  - Low-income students will be displaced from highly demanded majors
- Approach:
  - Data on student enrollment
  - DA generates a stable assignment
  - Estimate preferences
  - Simulate allocation with free-tuition

Bucarey (2018) Who pays for free college?

- In 2014 the Chilean government promised to make college free
- Low-income students already received financial aid
- Thus, low-income students' tuition was lower
- Hypothesis: If college is free for all students
  - high-income students will face same price as low-income students
  - Low-income students will be displaced from highly demanded majors
- Approach:
  - Data on student enrollment
  - DA generates a stable assignment
  - Estimate preferences
  - Simulate allocation with free-tuition
  - Who pays for free college?

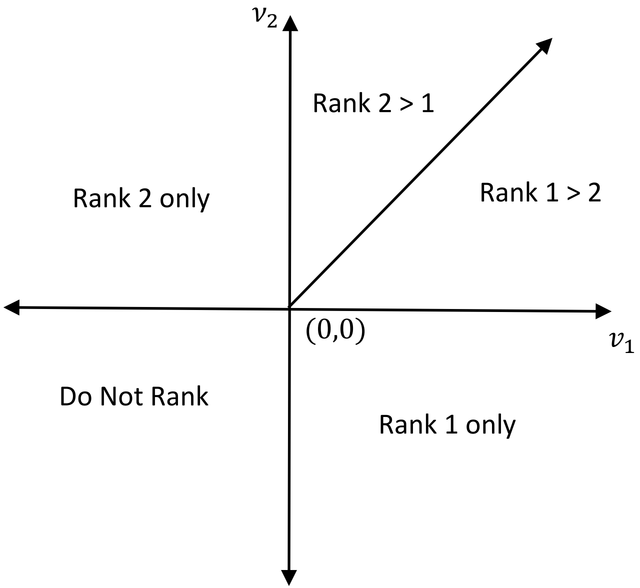
Bucarey (2018) Who pays for free college?

	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.

Outline

Revealed Preferences – Truthtelling



Truthtelling – Estimation Methods

- In logit models, likelihood built on $\mathbb{P}\left(i \text{ submits } R_i | \delta_i, d_i; \theta\right)$:

$$\prod_{k=1}^{K_i} \frac{\exp\left(\frac{1}{\sigma}\left(\delta_{R_{ik}} - d_{iR_{ik}}\right)\right)}{\sum 1\left\{j \neq R_{ik'} \text{ for } k' < k\right\} \exp\left(\frac{1}{\sigma}\left(\delta_j - d_{ij}\right)\right)}$$

Truthtelling – Estimation Methods

- In logit models, likelihood built on $\mathbb{P}\left(i \text{ submits } R_i | \delta_i, d_i; \theta\right)$:

$$\prod_{k=1}^{K_i} \frac{\exp\left(\frac{1}{\sigma}\left(\delta_{R_{ik}} - d_{iR_{ik}}\right)\right)}{\sum 1\left\{j \neq R_{ik'} \text{ for } k' < k\right\} \exp\left(\frac{1}{\sigma}\left(\delta_j - d_{ij}\right)\right)}$$

- Random coefficients γ_i, $\mathbb{P}\left(i \text{ submits } R_i | \delta_i, d_i; \theta\right)$ is:

$$\int \mathbb{P}\left(i \text{ submits } R_i | \delta_i, d_i; \theta, \gamma\right) \phi\left(\gamma; \Sigma_\gamma\right) d\gamma.$$

Truthtelling – Estimation Methods

- In logit models, likelihood built on $\mathbb{P}\left(i \text{ submits } R_i | \delta_i, d_i; \theta\right)$:

$$\prod_{k=1}^{K_i} \frac{\exp\left(\frac{1}{\sigma}\left(\delta_{R_{ik}} - d_{iR_{ik}}\right)\right)}{\sum 1\left\{j \neq R_{ik'} \text{ for } k' < k\right\} \exp\left(\frac{1}{\sigma}\left(\delta_j - d_{ij}\right)\right)}$$

- Random coefficients γ_i, $\mathbb{P}\left(i \text{ submits } R_i | \delta_i, d_i; \theta\right)$ is:

$$\int \mathbb{P}\left(i \text{ submits } R_i | \delta_i, d_i; \theta, \gamma\right) \phi\left(\gamma; \Sigma_\gamma\right) d\gamma.$$

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

Abdulkadiroglu et. al. 2017:

- Until 2003, students applied to 5 programs out of 600

Abdulkadiroglu et. al. 2017:

- Until 2003, students applied to 5 programs out of 600
- Many students were rejected and administratively placed

Abdulkadiroglu et. al. 2017:

- Until 2003, students applied to 5 programs out of 600
- Many students were rejected and administratively placed
- In 2003 the district adopts DA

Abdulkadiroglu et. al. 2017:

- Until 2003, students applied to 5 programs out of 600
- Many students were rejected and administratively placed
- In 2003 the district adopts DA
- What are the welfare effects of coordinated assignment?

Abdulkadiroglu et. al. 2017:

- Until 2003, students applied to 5 programs out of 600
- Many students were rejected and administratively placed
- In 2003 the district adopts DA
- What are the welfare effects of coordinated assignment?
- Approach:
  - Data on student reports to the DA mechanism

Abdulkadiroglu et. al. 2017:

- Until 2003, students applied to 5 programs out of 600
- Many students were rejected and administratively placed
- In 2003 the district adopts DA
- What are the welfare effects of coordinated assignment?
- Approach:
  - Data on student reports to the DA mechanism
  - DA is strategy-proof: no gains from misreporting preferences

Abdulkadiroglu et. al. 2017:

- Until 2003, students applied to 5 programs out of 600
- Many students were rejected and administratively placed
- In 2003 the district adopts DA
- What are the welfare effects of coordinated assignment?
- Approach:
    - Data on student reports to the DA mechanism
    - DA is strategy-proof: no gains from misreporting preferences
    - Estimate preferences assuming truthful reports

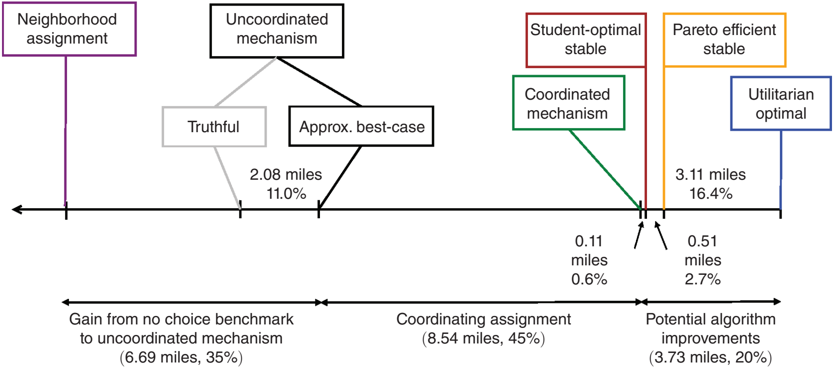
Abdulkadiroglu et. al. 2017:

- Until 2003, students applied to 5 programs out of 600
- Many students were rejected and administratively placed
- In 2003 the district adopts DA
- What are the welfare effects of coordinated assignment?
- Approach:
  - Data on student reports to the DA mechanism
  - DA is strategy-proof: no gains from misreporting preferences
  - Estimate preferences assuming truthful reports
  - Simulate allocation under alternative allocation systems
    - Neighborhood assignment
    - Uncoordinated assignment
    - Deferred Acceptance

Abdulkadiroglu et. al. 2017:

- Until 2003, students applied to 5 programs out of 600
- Many students were rejected and administratively placed
- In 2003 the district adopts DA
- What are the welfare effects of coordinated assignment?
- Approach:
  - Data on student reports to the DA mechanism
  - DA is strategy-proof: no gains from misreporting preferences
  - Estimate preferences assuming truthful reports
  - Simulate allocation under alternative allocation systems
    - Neighborhood assignment
    - Uncoordinated assignment
    - Deferred Acceptance
  - Calculate aggregate welfare and distributional consequences

Abdulkadiroglu et. al. 2017



- Centralized (Coordinated) mechanisms perform better!

Outline

Manipulable Mechanisms

- Many school districts implemented manipulable centralized mechanisms

Manipulable Mechanisms

- Many school districts implemented manipulable centralized mechanisms
- Districts that implemented DA restrict the length of lists

Manipulable Mechanisms

- Many school districts implemented manipulable centralized mechanisms

- Districts that implemented DA restrict the length of lists
- Boston implemented the Immediate Acceptance mechanism

Manipulable Mechanisms

- Many school districts implemented manipulable centralized mechanisms
- Districts that implemented DA restrict the length of lists
- Boston implemented the Immediate Acceptance mechanism
- a.k.a Boston Mechanism

Restricted List DA

- The mechanism is manipulable
  - Students should rank schools according to their ordinal preferences
  - They should skip schools that are unattainable [Haeringer and Klijn 2009]

Restricted List DA

- The mechanism is manipulable
  - Students should rank schools according to their ordinal preferences
  - They should skip schools that are unattainable [Haeringer and Klijn 2009]

- Infer revealed preference relations from ranked lists

Restricted List DA

- The mechanism is manipulable
  - Students should rank schools according to their ordinal preferences
  - They should skip schools that are unattainable [Haeringer and Klijn 2009]
- Infer revealed preference relations from ranked lists
- How should we treat schools that are not ranked on the list?
  - Only infer relations from ranked lists?
  - Assume any ranked school is preferred to any non-ranked school?
  - Assume non-ranked schools are worse than the outside option?
  - Default back to using stability [Fack et al, 2019]?
- 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]

Immediate Acceptance (IA)

- Step 1: Students apply to the first school in their list

Immediate Acceptance (IA)

- Step 1: Students apply to the first school in their list
- Step 2: Schools consider applicants and rank them according to priority. **Immediately** admit applicants until exhausting capacity and reject the rest

Immediate Acceptance (IA)

- Step 1: Students apply to the first school in their list
- Step 2: Schools consider applicants and rank them according to priority. **Immediately** admit applicants until exhausting capacity and reject the rest
- Step 3: Students apply to the highest school that has not reject them

Immediate Acceptance (IA)

- Step 1: Students apply to the first school in their list
- Step 2: Schools consider applicants and rank them according to priority. **Immediately** admit applicants until exhausting capacity and reject the rest
- Step 3: Students apply to the highest school that has not reject them
- Step 4: Schools with spare capacity consider new applicants and rank them according to priority. **Immediately** admit applicants until exhausting capacity and reject the rest

Immediate Acceptance (IA)

- Step 1: Students apply to the first school in their list
- Step 2: Schools consider applicants and rank them according to priority. **Immediately** admit applicants until exhausting capacity and reject the rest
- Step 3: Students apply to the highest school that has not reject them
- Step 4: Schools with spare capacity consider new applicants and rank them according to priority. **Immediately** admit applicants until exhausting capacity and reject the rest
- 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

Listening 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]

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]

- 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].

Were they right?

- Abdulkadiroglu, Che, Yasuda (2011):
  - Students have the similar ordinal preferences

Were they right?

- Abdulkadiroglu, Che, Yasuda (2011):
  - Students have the similar ordinal preferences
  - Schools have no priorities
  - IA Pareto dominates DA in ex ante welfare

Were they right?

- Abdulkadiroglu, Che, Yasuda (2011):
  - Students have the similar ordinal preferences
  - Schools have no priorities
  - IA Pareto dominates DA in ex ante welfare
  - IA may not harm but rather benefit those who don not strategize

Were they right?

- Abdulkadiroglu, Che, Yasuda (2011):
  - Students have the similar ordinal preferences
  - Schools have no priorities
  - IA Pareto dominates DA in ex ante welfare
  - IA may not harm but rather benefit those who don not strategize
  - IA facilitates access to good schools for students with no priority

Were they right?

- Abdulkadiroglu, Che, Yasuda (2011):
  - Students have the similar ordinal preferences
  - Schools have no priorities
  - IA Pareto dominates DA in ex ante welfare
  - IA may not harm but rather benefit those who don not strategize
  - IA facilitates access to good schools for students with no priority
- Preferences are important!

Choice under uncertainty

- Report R_i is associated with lottery L_{R_i}

Choice under uncertainty

- Report R_i is associated with lottery L_{R_i}
- Agents form beliefs about lotteries $\hat{L}_{R_i}$ associated to each report

Choice under uncertainty

- Report R_i is associated with lottery L_{R_i}
- Agents form beliefs about lotteries $\hat{L}_{R_i}$ associated to each report
  - Rational expectations: $\hat{L}_{R_i} = L_{R_i}$
  - Adaptive expectations $\hat{L}_{R_i,t} = L_{R_i,t-1}$
  - Elicit beliefs through survey [Kapor, Nielsen and Zimmerman, 2018]

Choice under uncertainty

- Report R_i is associated with lottery L_{R_i}
- Agents form beliefs about lotteries $\hat{L}_{R_i}$ associated to each report
  - Rational expectations: $\hat{L}_{R_i} = L_{R_i}$
  - Adaptive expectations $\hat{L}_{R_i,t} = L_{R_i,t-1}$
  - Elicit beliefs through survey [Kapor, Nielsen and Zimmerman, 2018]
- Revealed Preferences:

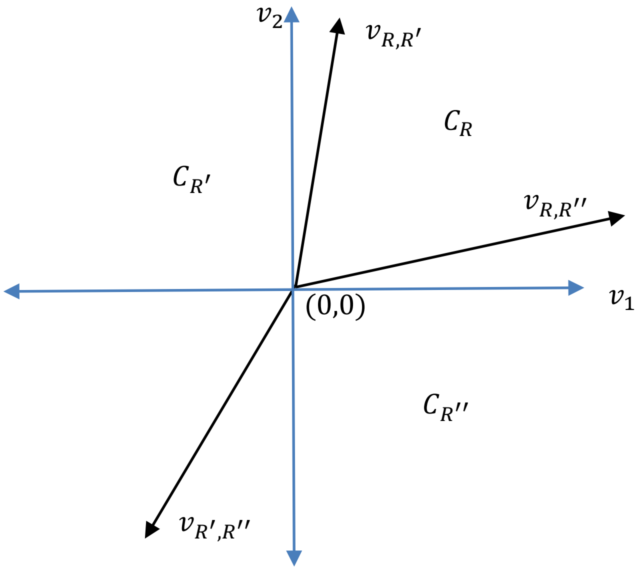
$$\boldsymbol{v}_i \cdot \boldsymbol{L}_{R_i} \geq \boldsymbol{v}_i \cdot \boldsymbol{L}_R$$

- Report R_i is associated with lottery L_{R_i}
- Agents form beliefs about lotteries $\hat{L}_{R_i}$ associated to each report
  - Rational expectations: $\hat{L}_{R_i} = L_{R_i}$
  - Adaptive expectations $\hat{L}_{R_i,t} = L_{R_i,t-1}$
  - Elicit beliefs through survey [Kapor, Nielsen and Zimmerman, 2018]
- Revealed Preferences:

$$\boldsymbol{v}_i \cdot \boldsymbol{L}_{R_i} \geq \boldsymbol{v}_i \cdot \boldsymbol{L}_R$$

- 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



Strategic Behavior – Estimation Methods

- Arbitrary integration regions: Logit models lose their appeal
- Probit Models still do not provide close form solutions
- No easy way to compute the likelihood function

Strategic Behavior – Estimation Methods

- Arbitrary integration regions: Logit models lose their appeal
- Probit Models still do not provide close form solutions
- 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
  - $\theta_{MLE} = \arg\max_{\theta} \mathcal{L}(\theta; data)$
  - Consistence and asymptotic normality of θ_{MLE}

Bayesian Methods

- Frequentist approach: $\log \mathcal{L}(\theta; data) := \log f(data|\theta)$
  - θ is a parameter
  - $\theta_{MLE} = \arg\max_\theta \mathcal{L}(\theta; data)$
  - Consistence and asymptotic normality of θ_{MLE}
- 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]

Markov Monte Carlo Chain (MCMC)

- Sampling from the posterior $f\left(\theta|data\right)$?

Markov Monte Carlo Chain (MCMC)

- Sampling from the posterior $f\left(\theta | data\right)$?
- Sampling from conditional posteriors:
  - Suppose that $\theta = (\theta_1, \theta_2)$
  - and $f\left(\theta_1 | \theta_2, data\right)$ and $f\left(\theta_2 | \theta_1, data\right)$ have closed-form solutions

Markov Monte Carlo Chain (MCMC)

- Sampling from the posterior $f(\theta|data)$?
- Sampling from conditional posteriors:
  - Suppose that $\theta = (\theta_1, \theta_2)$
  - and $f(\theta_1|\theta_2, data)$ and $f(\theta_2|\theta_1, data)$ have closed-form solutions
- How to construct a MCMC?
  - pick some θ_1^0
  - sample θ_2^k from $f\left(\theta_2|\theta_1^k, data\right)$
  - sample θ_1^{k+1} from $f\left(\theta_1|\theta_2^k, data\right)$

Markov Monte Carlo Chain (MCMC)

- Sampling from the posterior $f(\theta|data)$?
- Sampling from conditional posteriors:
  - Suppose that $\theta = (\theta_1, \theta_2)$
  - and $f(\theta_1|\theta_2, data)$ and $f(\theta_2|\theta_1, data)$ have closed-form solutions
- How to construct a MCMC?
  - pick some θ_1^0
  - sample θ_2^k from $f\left(\theta_2|\theta_1^k, data\right)$
  - sample θ_1^{k+1} from $f\left(\theta_1|\theta_2^k, data\right)$
- This algorithm is called Gibbs Sampler
  - ✓ There are other algorithms: e.g., Metropolis-Hastings, Hamiltonian Monte Carlo

Markov Monte Carlo Chain (MCMC)

- Sampling from the posterior $f(\theta|data)$?
- Sampling from conditional posteriors:
  - Suppose that $\theta = (\theta_1, \theta_2)$
  - and $f(\theta_1|\theta_2, data)$ and $f(\theta_2|\theta_1, data)$ have closed-form solutions
- How to construct a MCMC?
  - pick some θ_1^0
  - sample θ_2^k from $f\left(\theta_2|\theta_1^k, data\right)$
  - sample θ_1^{k+1} from $f\left(\theta_1|\theta_2^k, data\right)$
- This algorithm is called Gibbs Sampler
  - ✓ 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

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

where $\varepsilon_{ij} \sim N(0, \Sigma)$, $\beta \sim N(\overline{\beta}, \Sigma_\beta)$ and $\Sigma \sim IW(u_0, S)$

Gibbs Sampler in School Choice

- Recall
$$v_{ij} = x_{ij}\beta_j - d_{ij} + \varepsilon_{ij}$$
where $\varepsilon_{ij} \sim N(0, \Sigma)$, $\beta \sim N(\overline{\beta}, \Sigma_\beta)$ and $\Sigma \sim IW(u_0, S)$
- Data augmentation: $v = \{v_{11}, v_{12}, ...v_{1J}, ..., v_{ij}, ..., v_{NJ}\}$
- $\theta = (v, \Sigma, \beta)$

Gibbs Sampler in School Choice

- Recall

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

  where $\varepsilon_{ij} \sim N(0, \Sigma)$, $\beta \sim N(\overline{\beta}, \Sigma_\beta)$ and $\Sigma \sim IW(u_0, S)$

- Data augmentation: $v = \{v_{11}, v_{12}, ...v_{1J}, ..., v_{ij}, ..., v_{NJ}\}$

- $\theta = (v, \Sigma, \beta)$
  - $\beta|\Sigma, v$ has a Normal posterior

Gibbs Sampler in School Choice

- Recall

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

  where $\varepsilon_{ij} \sim N(0, \Sigma)$, $\beta \sim N(\overline{\beta}, \Sigma_\beta)$ and $\Sigma \sim IW(u_0, S)$

- Data augmentation: $v = \{v_{11}, v_{12}, ...v_{1J}, ..., v_{ij}, ..., v_{NJ}\}$

- $\theta = (v, \Sigma, \beta)$
  - $\beta|\Sigma, v$ has a Normal posterior
  - $\Sigma|\beta, v$ has a Inverse Wishart posterior

Gibbs Sampler in School Choice

- Recall

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

  where $\varepsilon_{ij} \sim N(0, \Sigma)$, $\beta \sim N(\overline{\beta}, \Sigma_\beta)$ and $\Sigma \sim IW(u_0, S)$

- Data augmentation: $v = \{v_{11}, v_{12}, ...v_{1J}, ..., v_{ij}, ..., v_{NJ}\}$

- $\theta = (v, \Sigma, \beta)$
  - $\beta|\Sigma, v$ has a Normal posterior
  - $\Sigma|\beta, v$ has a Inverse Wishart posterior
  - $v_{ij}|v_{i-j}, \beta_j, \Sigma, C_i$ has a truncated normal posterior

Gibbs Sampler in School Choice

- Recall
$$v_{ij} = x_{ij}\beta_j - d_{ij} + \varepsilon_{ij}$$
where $\varepsilon_{ij} \sim N(0, \Sigma)$, $\beta \sim N(\overline{\beta}, \Sigma_\beta)$ and $\Sigma \sim IW(u_0, S)$
- Data augmentation: $v = \{v_{11}, v_{12}, ...v_{1J}, ..., v_{ij}, ..., v_{NJ}\}$
- $\theta = (v, \Sigma, \beta)$
  - $\beta|\Sigma, v$ has a Normal posterior
  - $\Sigma|\beta, v$ has a Inverse Wishart posterior
  - $v_{ij}|v_{i-j}, \beta_j, \Sigma, C_i$ has a truncated normal posterior
- Initialize Σ^0 and v^0 so that $v_i^0 \in C_i$ for every student

Gibbs Sampler in School Choice

- Recall

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

  where $\varepsilon_{ij} \sim N(0, \Sigma)$, $\beta \sim N(\overline{\beta}, \Sigma_\beta)$ and $\Sigma \sim IW(u_0, S)$

- Data augmentation: $v = \{v_{11}, v_{12}, ...v_{1J}, ..., v_{ij}, ..., v_{NJ}\}$

- $\theta = (v, \Sigma, \beta)$
  - $\beta|\Sigma, v$ has a Normal posterior
  - $\Sigma|\beta, v$ has a Inverse Wishart posterior
  - $v_{ij}|v_{i-j}, \beta_j, \Sigma, C_i$ has a truncated normal posterior

- Initialize Σ^0 and v^0 so that $v_i^0 \in C_i$ for every student

- For every k:
  - Draw $\beta^{k+1}|\Sigma^k, v^k$ from its normal posterior

Gibbs Sampler in School Choice

- Recall
$$v_{ij} = x_{ij}\beta_j - d_{ij} + \varepsilon_{ij}$$
where $\varepsilon_{ij} \sim N(0, \Sigma)$, $\beta \sim N(\overline{\beta}, \Sigma_\beta)$ and $\Sigma \sim IW(u_0, S)$
- Data augmentation: $v = \{v_{11}, v_{12}, ...v_{1J}, ..., v_{ij}, ..., v_{NJ}\}$
- $\theta = (v, \Sigma, \beta)$
  - $\beta|\Sigma, v$ has a Normal posterior
  - $\Sigma|\beta, v$ has a Inverse Wishart posterior
  - $v_{ij}|v_{i-j}, \beta_j, \Sigma, C_i$ has a truncated normal posterior
- Initialize Σ^0 and v^0 so that $v_i^0 \in C_i$ for every student
- For every k:
  - Draw $\beta^{k+1}|\Sigma^k, v^k$ from its normal posterior
  - Draw $\Sigma^{k+1}|\beta^{k+1}, v^k$ from its normal posterior

Gibbs Sampler in School Choice

- Recall
$$v_{ij} = x_{ij}\beta_j - d_{ij} + \varepsilon_{ij}$$
where $\varepsilon_{ij} \sim N(0, \Sigma)$, $\beta \sim N(\overline{\beta}, \Sigma_\beta)$ and $\Sigma \sim IW(u_0, S)$

- Data augmentation: $v = \{v_{11}, v_{12}, ...v_{1J}, ..., v_{ij}, ..., v_{NJ}\}$

- $\theta = (v, \Sigma, \beta)$
  - $\beta|\Sigma, v$ has a Normal posterior
  - $\Sigma|\beta, v$ has a Inverse Wishart posterior
  - $v_{ij}|v_{i-j}, \beta_j, \Sigma, C_i$ has a truncated normal posterior

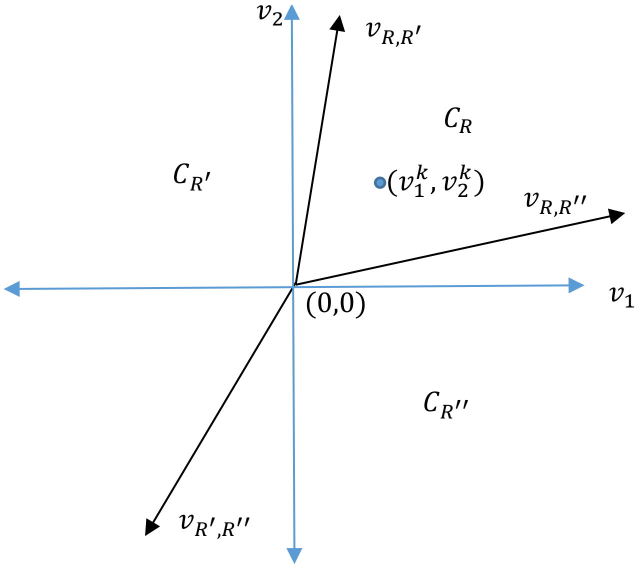
- Initialize Σ^0 and v^0 so that $v_i^0 \in C_i$ for every student

- For every k:
  - Draw $\beta^{k+1}|\Sigma^k, v^k$ from its normal posterior
  - Draw $\Sigma^{k+1}|\beta^{k+1}, v^k$ from its normal posterior
    - ✓ "Bayesian regression" of $v_{ij} + d_{ij}$ on x_{ij}

Gibbs Sampler in School Choice

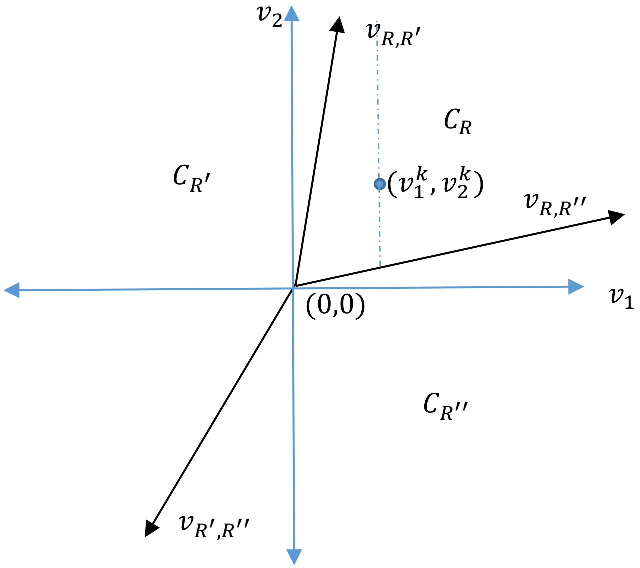
- Recall
$$v_{ij} = x_{ij}\beta_j - d_{ij} + \varepsilon_{ij}$$
where $\varepsilon_{ij} \sim N(0, \Sigma)$, $\beta \sim N(\overline{\beta}, \Sigma_\beta)$ and $\Sigma \sim IW(u_0, S)$
- Data augmentation: $v = \{v_{11}, v_{12}, ...v_{1J}, ..., v_{ij}, ..., v_{NJ}\}$
- $\theta = (v, \Sigma, \beta)$
  - $\beta|\Sigma, v$ has a Normal posterior
  - $\Sigma|\beta, v$ has a Inverse Wishart posterior
  - $v_{ij}|v_{i-j}, \beta_j, \Sigma, C_i$ has a truncated normal posterior
- Initialize Σ^0 and v^0 so that $v_i^0 \in C_i$ for every student
- For every k:
  - Draw $\beta^{k+1}|\Sigma^k, v^k$ from its normal posterior
  - Draw $\Sigma^{k+1}|\beta^{k+1}, v^k$ from its normal posterior
    - ✓ "Bayesian regression" of $v_{ij} + d_{ij}$ on x_{ij}
  - Update v^{k+1} given $\beta^{k+1}, \Sigma^{k+1}$

Updating v^{k+1}



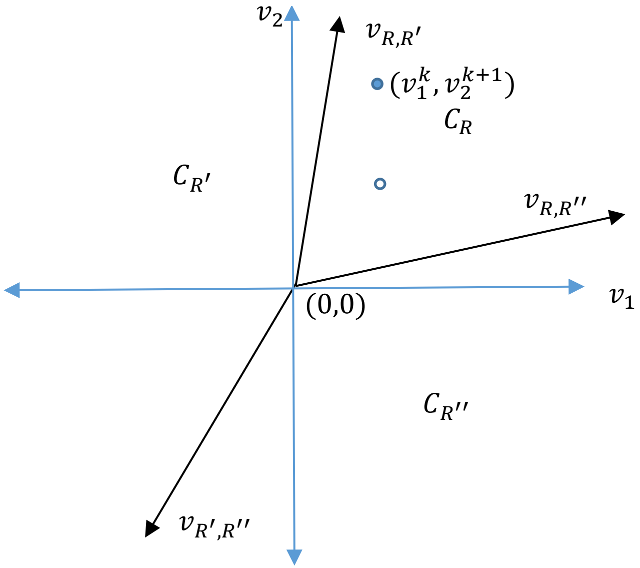
We start from the previous vector v^k

Updating v^{k+1}



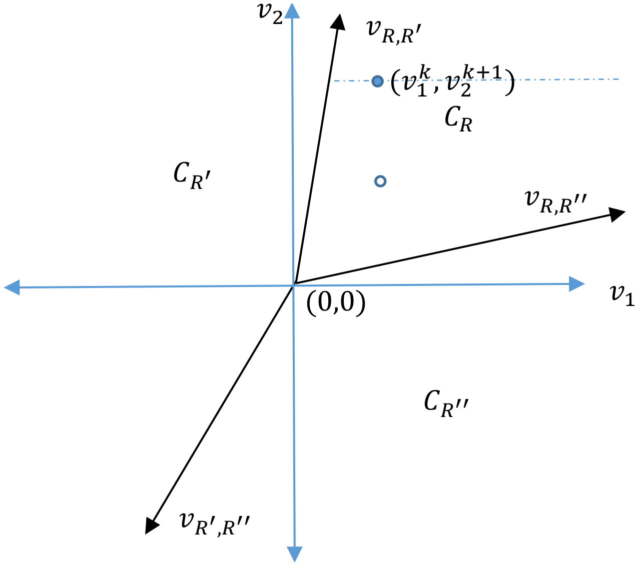
Draw v_2^{k+1} given $v_1^k, \beta^{k+1}, \Sigma^{k+1}$ from a truncated normal

Updating v^{k+1}



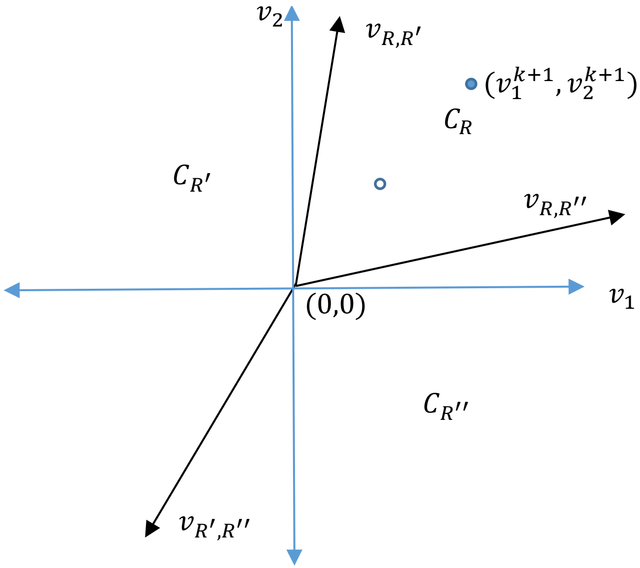
New draw of v_2^{k+1}

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

- Use data from the Immediate Acceptance algorithm used in Cambridge

Agarwal and Somaini 2018

- Use data from the Immediate Acceptance algorithm used in Cambridge
- There are two sets of schools:
  - Competitive: they are very likely to clear in first round
  - Non-competitive: they are very likely to have spare capacity

Agarwal and Somaini 2018

- Use data from the Immediate Acceptance algorithm used in Cambridge
- There are two sets of schools:
  - Competitive: they are very likely to clear in first round
  - Non-competitive: they are very likely to have spare capacity
- Incentives to pick the top rank carefully

Agarwal and Somaini 2018

- Use data from the Immediate Acceptance algorithm used in Cambridge
- There are two sets of schools:
  - Competitive: they are very likely to clear in first round
  - Non-competitive: they are very likely to have spare capacity
- Incentives to pick the top rank carefully
- Provide evidence of strategic behavior

Agarwal and Somaini 2018

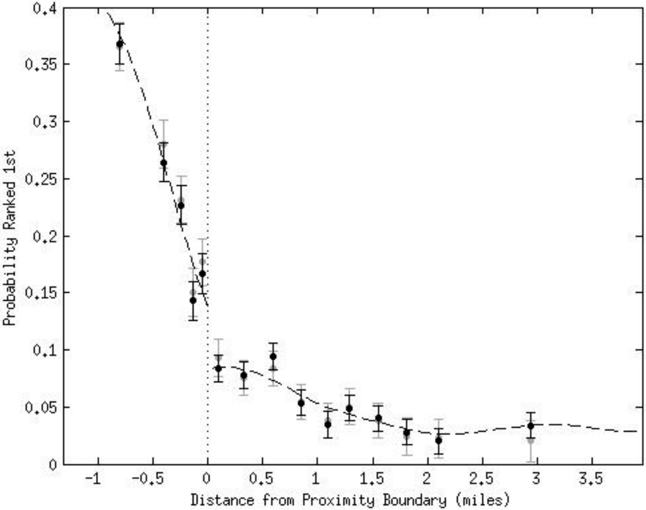
- Use data from the Immediate Acceptance algorithm used in Cambridge
- There are two sets of schools:
  - Competitive: they are very likely to clear in first round
  - Non-competitive: they are very likely to have spare capacity
- Incentives to pick the top rank carefully
- Provide evidence of strategic behavior
- Estimate preferences under alternative assumptions on beliefs

Agarwal and Somaini 2018

- Use data from the Immediate Acceptance algorithm used in Cambridge
- There are two sets of schools:
  - Competitive: they are very likely to clear in first round
  - Non-competitive: they are very likely to have spare capacity
- Incentives to pick the top rank carefully
- Provide evidence of strategic behavior
- Estimate preferences under alternative assumptions on beliefs
- Compare performance of DA vs IA

Elementary Schools and Students

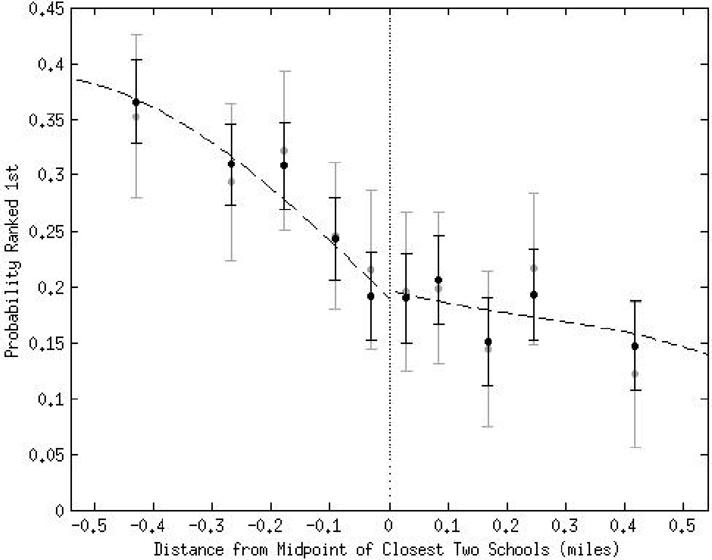
Year	2004	2005	2006	2007	2008	Average
			Panel A: District Characteristics			
Schools	13	13	13	13	13	13
Programs	24	25	25	27	27	25.6
Seats	473	456	476	508	438	470
Students	412	432	397	457	431	426
Free/Reduced Lunch	32%	38%	37%	29%	32%	34%
Paid Lunch	68%	62%	63%	71%	68%	66%
			Panel B: Student's Ethnicity			
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



Assignment Probabilities

- Individual faces two sources of uncertainty:
  - Own lottery draw $\nu_i \sim U[0,1]$

Assignment Probabilities

- Individual faces two sources of uncertainty:
  - Own lottery draw $\nu_i \sim U[0,1]$
  - Market clearing cutoff p^* depend on all agents' actions and lotteries

Assignment Probabilities

- Individual faces two sources of uncertainty:
  - Own lottery draw $\nu_i \sim U[0,1]$
  - Market clearing cutoff p^* depend on all agents' actions and lotteries

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

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

Assignment Probabilities

- Individual faces two sources of uncertainty:
  - Own lottery draw $\nu_i \sim U\left[0,1\right]$
  - Market clearing cutoff p^* depend on all agents' actions and lotteries

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

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

  - Idea: Resampling approximation to beliefs about assignment probabilities

Assignment Probabilities

- Individual faces two sources of uncertainty:
  - Own lottery draw $\nu_i \sim U[0,1]$
  - Market clearing cutoff p^* depend on all agents' actions and lotteries

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

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

  - Idea: Resampling approximation to beliefs about assignment probabilities

✓ 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

Methods Recap

- Estimating preferences in school choice context

Methods Recap

- Estimating preferences in school choice context
- General model of student's preferences

Methods Recap

- Estimating preferences in school choice context
- General model of student's preferences
- Approach depends on the mechanism and the available data:

Methods Recap

- Estimating preferences in school choice context
- General model of student's preferences
- Approach depends on the mechanism and the available data:
  - Data on final stable allocation

Methods Recap

- Estimating preferences in school choice context
- General model of student's preferences
- Approach depends on the mechanism and the available data:
  - Data on final stable allocation
  - Data on truthful rank ordered lists

Methods Recap

- Estimating preferences in school choice context
- General model of student's preferences
- Approach depends on the mechanism and the available data:
  - Data on final stable allocation
  - Data on truthful rank ordered lists
  - Data on strategic rank ordered lists

Findings

- Free tuition may have regressive effects

Findings

- Free tuition may have regressive effects
- Big welfare effects of centralized mechanisms

Findings

- Free tuition may have regressive effects
- Big welfare effects of centralized mechanisms
- IA can increase our measure of welfare if students strategize correctly

Findings

- Free tuition may have regressive effects
- 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

Findings

- Free tuition may have regressive effects
- 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]

Findings

- Free tuition may have regressive effects
- 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]

Exciting avenues for research

- School choice and educational outcomes [Abdulkadiroglu, Angrist, Narita, Pathak 2017 & 2019, Abdulkadiroglu, Pathak, Schellenberg, and Walters, 2020]
- Effect of affirmative action policies [Otero, Barahona and Dobbin, 2022]

Exciting avenues for research

- School choice and educational outcomes [Abdulkadiroglu, Angrist, Narita, Pathak 2017 & 2019, Abdulkadiroglu, Pathak, Schellenberg, and Walters, 2020]
- Effect of affirmative action policies [Otero, Barahona and Dobbin, 2022]
- Informing students about schools and programs [Allende, Gallego and Neilson, 2019]

Exciting avenues for research

- School choice and educational outcomes [Abdulkadiroglu, Angrist, Narita, Pathak 2017 & 2019, Abdulkadiroglu, Pathak, Schellenberg, and Walters, 2020]
- Effect of affirmative action policies [Otero, Barahona and Dobbin, 2022]
- Informing students about schools and programs [Allende, Gallego and Neilson, 2019]
- Augment with supply models: school entry and investment decisions