Static discrete choice models: application 1

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Application on school choice I

- Paper to be discussed: Abdulkadiroğlu, A., Agarwal, N., and Pathak, P. 2017. "The Welfare Effects of Coordinated Assignment: Evidence from the New York City High School Match". *American Economic Review* 107 (12): 3635–89.
- Uses RC logit model on data of rankings of students for different schools in NY
- Ranking obtained in strategy-proof mechanism, i.e. similar to choice data but richer
- Calculate welfare impact of different types of school assignment mechanisms
- Compare current mechanism to a hypothetical optimal mechanism and a neighborhood allocation

Application on school choice II

- Compare current mechanism to the previous, uncoordinated mechanism
- Paper finds that a coordinated mechanism can achieve most of a hypothetical optimal allocation where a social planners has perfect information about preferences
- Nice example of how economic theory can improve market design and how structural models can quantify that + what else is feasible

Background I

- In 2003, a coordinated mechanism was introduced in NY to allocate students to high schools
- The mechanism is the Gale-Shapley student-proposing deferred acceptance algorithm:
- Step 1: Each student proposes to her first choice. Each school tentatively assigns seats to its proposers one at a time, following their priority order. The student is rejected if no seats are available at the time of consideration.

Background II

- Step k>1: Each student who was rejected in the previous step proposes to her next best choice. Each school considers the students it has tentatively assigned together with its new proposers and tentatively assigns its seats to these students one at a time following the school's priority order. The student is rejected if no seats are available when she is considered.

- This mechanism has some nice properties, in particular it is strategy-proof

Data: students

TABLE 1—CHARACTERISTICS OF STUDENT SAMPLE

	Mechanism comparison		Demand estimation
	Uncoordinated mechanism (1)	Coordinated mechanism (2)	Coordinated mechanism (3)
Number of students	70,358	66,921	69,907
Female	49.4	49.0	49.0
Bronx	23.7	23.3	23.7
Brooklyn	31.9	34.1	33.3
Manhattan	12.5	11.8	12.0
Queens	25.0	24.8	24.7
Staten Island	6.9	6.0	6.3
Asian	10.6	10.9	10.6
Black	35.4	35.7	35.7
Hispanic	38.9	40.4	40.3
White	14.7	12.6	13.0
Other	0.4	0.4	0.4
Subsidized lunch	68.0	67.4	67.8
Neighborhood income ($)	38,360	37,855	37,920
Limited English proficient	13.1	12.6	12.6
Special education	8.2	7.9	7.5
SHSAT test-taker	22.4	24.3	23.9

Notes: Percents unless otherwise noted. Uncoordinated mechanism refers to the 2002–2003 mechanism and coordinated mechanism refers to the 2003–2004 mechanism based on deferred acceptance. Neighborhood income is the median census block group family income from the 2000 census. SHSAT stands for Specialized High School Achievement Test

Data: schools and programs

TABLE 2—DESCRIPTIVE STATISTICS FOR SCHOOLS AND PROGRAMS

	Uncoordinated mechanism (1)	Coordinated mechanism (2)
Panel A. Schools		
Number	215	235
High math achievement (%)	10.2	10.0
High English achievement (%)	19.1	19.3
Percent attending four-year college	47.8	47.2
Percent inexperienced teachers	54.7	55.6
Attendance rate (%)	85.5	85.7
Percent subsidized lunch	62.5	62.6
Size of ninth grade	465.7	451.3
Percent white	10.9	10.9
Percent Asian	8.7	8.6
Percent black	38.5	38.4
Percent Hispanic	41.9	42.1
Panel B. Programs		
Number	612	558
Screened	233	208
Unscreened	63	119
Education option	316	119
Spanish language	27	24
Asian language	10	9
Other language	6	7
Arts	80	80
Humanities	89	93
Math and science	53	60
Vocational	55	59
Other specialties	163	162

Notes: Panel A reports means and panel B reports counts, unless otherwise noted. Uncoordinated mechanism refers to the 2002–2003 mechanism and coordinated mechanism refers to the 2003–2004 mechanism based on deferred acceptance. The data Appendix presents information on the availability of school characteristics. High math and High English Achievement is the fraction of students who scored more than 85 percent on the Math A and English Regents tests,

Model I

- Rankings in DA mechanism of 69907 students
- x_j program characteristics
- z_i student characteristics
- ξ_j unobserved program characteristic
- γ_i taste vector for observed program characteristics
- α interactions between program and student characteristics
- d_{ij} distance
- Utility of a school-program pair

$$u_{ij} = \delta_j + \sum_l \alpha^l z_i^l x_j^l + \sum_k \gamma_i^k x_j^k - d_{ij} + \epsilon_{ij}$$

- with $\delta_j = x_j \beta + \xi_j$

Model II

- Normal distribution on γ_i,ξ_j and ϵ_{ij} with rich covariance matrix for γ_i
- Normalization not with respect to a specific school but by setting the mean of u_{ij} to 0 if all observables are 0
- Normalization not with respect to variance of ϵ_{ij} but by setting distance parameter $= 1$

Estimation results

Table 7—Select Preference Estimates for Different Demand Specifications

		School characteristics × Student characteristics		
			Models with random coefficients	
	No student interactions (1)	Without random coefficients (2)	All choices (3)	Choice among eligible programs (4)
High math achievement				
Main effect	0.016 (0.016)	0.027 (0.014)	−0.029 (0.018)	−0.058 (0.039)
Baseline math		0.031 (0.001)	0.039 (0.001)	0.050 (0.001)
Percent subsidized lunch				
Main effect	−0.085 (0.007)	−0.057 (0.004)	−0.069 (0.009)	−0.113 (0.058)
Size of ninth grade (in 100s)				
Main effect	−0.164 (0.036)	−0.092 (0.032)	−0.113 (0.048)	−0.153 (0.178)
Percent white				
Main effect	−0.002 (0.014)	0.070 (0.012)	0.062 (0.016)	0.093 (0.062)
Asian		−0.054 (0.002)	−0.075 (0.003)	−0.100 (0.004)
Black		−0.084 (0.002)	−0.124 (0.002)	−0.189 (0.003)
Hispanic		−0.047 (0.002)	−0.084 (0.002)	−0.119 (0.003)
Standard deviation of ε	7.226 (0.010)	7.385 (0.011)	7.858 (0.013)	10.059 (0.022)
Standard deviation of ξ	3.519 (0.121)	2.954 (0.100)	3.676 (0.129)	5.151 (0.650)
Random coefficients (covariances)				
Size of ninth grade (in 100s)			1.584 (0.009)	1.837 (0.012)
Percent white			−0.006 (0.001)	−0.009 (0.001)
Percent subsidized lunch			−0.002 (0.000)	−0.002 (0.000)
High math achievement			−0.011 (0.001)	−0.015 (0.001)
Percent white			0.008 (0.000)	0.013 (0.000)
Percent subsidized lunch			−0.001 (0.000)	−0.002 (0.000)
High math achievement			0.005 (0.000)	0.007 (0.000)
Percent subsidized lunch			0.002 (0.000)	0.003 (0.000)
High math achievement			0.000 (0.000)	−0.001 (0.000)
High math achievement			0.016 (0.000)	0.022 (0.000)
		X	X	X
		X	X	X
	69,907	69,907	69,907	69,907
	542,666	542,666	542,666	542,666

Interpretation

- Interpretation facilitated by using distance to scale utility
- Note that on p3656 the authors say: "we do not interpret the coefficients on school characteristics as measuring the causal effect of different school characteristics"
- When would this be important?
- Shows clearly that a structural model is never 100% structural and the modeling assumptions should depend on counterfactual considered
- Why is it okay to have a static model here? What if students (or their parents) choose for certain schools because they expect to gain from it on the labor market?

Welfare in alternative mechanisms I

- With these parameters, the authors can compare welfare (consumer surplus) in different mechanisms

- Welfare is estimated in a different way as we saw before, why?

$$\bar{W}(\mu) = \frac{1}{|\mathcal{I}|} \sum_{i \in \mathcal{I}} E\left[u_{i\mu(i)} | r_i\right]$$

Welfare in alternative mechanisms II

- Mechanisms considered
  - Utilitarian assignment
    - Social planner maximizes total student welfare
  - Neigborhood assignment
    - Run DA but with students rankings changed to geographic ordering
  - Coordinated mechanism
    - DA mechanism used in the data
  - Student-optimal matching
    - run stable improvements cycle algorithm
    - Pareto improvement but not strategy-proof
    - "cost of providing incentives"
  - Ordinal Pareto efficient matching
    - run top trading cycles algorithm
    - further Pareto improvement but not stable
    - "cost of providing incentives for school for participating in the system"

Welfare: results

TABLE 8—WELFARE COMPARISON OF ALTERNATIVE MECHANISMS COMPARED TO UTILITARIAN ASSIGNMENT

Assignment mechanism:	Neighborhood assignment (1)	School choice: Coordinated mechanism (2)	School choice: Student-optimal matching (3)	School choice: Ordinal Pareto efficient matching (4)
All	−18.96	−3.73	−3.62	−3.11
Female	−18.90	−3.71	−3.59	−3.07
Asian	−18.08	−3.53	−3.43	−3.01
Black	−19.43	−3.89	−3.79	−3.25
Hispanic	−19.37	−3.80	−3.67	−3.10
White	−17.07	−3.21	−3.11	−2.82
Bronx	−21.39	−4.63	−4.46	−3.72
Brooklyn	−18.48	−3.21	−3.14	−2.70
Manhattan	−20.07	−5.40	−5.25	−4.43
Queens	−18.02	−3.39	−3.29	−2.96
Staten Island	−13.82	−1.25	−1.10	−1.03
High baseline math	−18.53	−3.29	−3.18	−2.61
Low baseline math	−19.40	−4.28	−4.18	−3.63
Subsidized lunch	−19.16	−3.78	−3.66	−3.12
Bottom neighborhood income quartile	−19.89	−4.25	−4.12	−3.46
Top neighborhood income quartile	−17.44	−3.63	−3.51	−3.15
Special education	−19.41	−4.83	−4.73	−4.11
Limited English proficient	−19.81	−3.74	−3.64	−3.16
SHSAT test-takers	−19.13	−4.17	−4.05	−3.41

What about the uncoordinated system? I

- Before 2003, students could apply to five programs
- They could receive multiple offers and be placed on wait lists
- Students were allowed to accept only one school and one wait list offer
- Data is available for rankings and assignments in both coordinated and uncoordinated mechanisms
  - Utility parameters of coordinated mechanism are still used (reliable because strategy proof mechanism)
  - To compare welfare between both, we need to compare $E[u_i|r_i]$ in the two mechanisms

What about the uncoordinated system? II

- But since this mechanism is not strategy-proof, we need to make assumptions on how students rank to calculate this
  - Truthful reporting
    - Similar formula as before but now compare rankings and matches in both the coordinated and uncoordinated system
  - Optimal reporting (+- best case)
    - Using uncoordinated system data: obtain reduced form predictions of probability to be offered a spot, conditional on ranking
    - Same for probability to end up somewhere in administrative round
    - Calculate expected utility as a function of rank ordering and choose it optimally

Comparing mechanisms

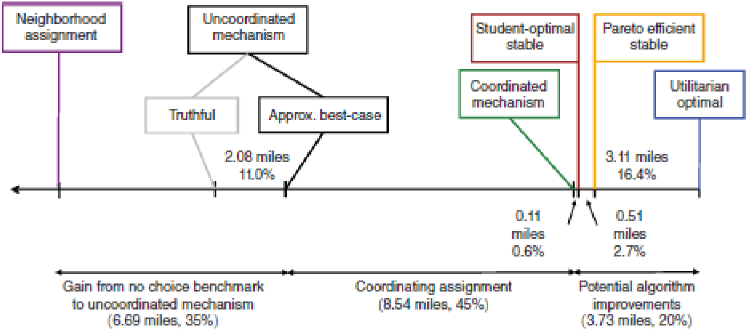

Figure 5. Coordinating Assignments versus Algorithm Improvements

Conclusion

- Welfare impact: 18.96 miles on average between neighbordhood assignment and utilitarian optimum
- Best-case uncoordinated mechanism achieves 35% of that
- Coordinated mechanism achieves 80%
- Potential (infeasible?) improvements only account for 20%
- Economics matters! And it doesn't have to be too fancy
    - Quote from paper: "In the context of auctions, Klemperer (2002, p. 170) argued that "most of the extensive auction literature is of second-order importance for practical auction design," and that "good auction design is mostly good elementary economics." Consistent with this point of view, for school matching market design, coordinating admissions produces much larger gains than algorithm refinements within the coordinated system."

Some related literature

- DA makes it easy to estimate preferences, other papers focus on identifying preferences when students are strategic
- A general approach using rankings: Agarwal and Somaini (2018)
- Approach for Boston mechanism using backwards induction: Calsamiglia, Fu and Güell (2020)
  - I'm working on something similar with Minyoung Rho using some of the dynamic methods you will see later (draft available)
- Making use of stability property and matches: Fack, Grenet and He (2019)

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References II

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