A Dynamic Framework of School Choice: Effects of Middle Schools on High School Choice

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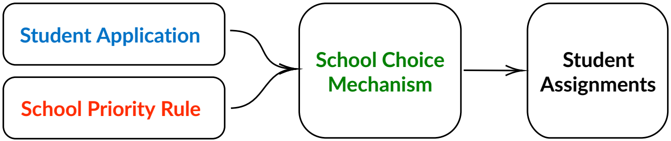

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- Prespecified school priority rules: intrinsic priority groups + single tie-breaking

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3. Counterfactual analysis: concurrent admissions reforms in NYC
   - Effects of admission reforms on segregation, **when implemented at alternative educational stages**

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Policy implication:

Dynamics of school choice can be used to design more effective policies

Related Literature

Effects of schools on future outcomes

- Academic performance (Jackson 2010; Pop-Eleches and Urquiola 2013; Abdulkadiroğlu, Angrist, and Pathak 2014; Deming, Hastings, Kane, and Staiger 2014; Dobbie and Fryer 2014), labor market outcomes (Card and Krueger 1992a,b; Clark and Bono 2016)
- **This paper**: first to evaluate the impacts on students' future academic choices in a K-12 context

Quasi-experiments in student assignments

- Hoxby and Rockoff, 2004; Deming, Hastings, Kane, and Staiger, 2014; Pop-Eleches and Urquiola, 2013; Abdulkadiroğlu, Angrist, and Pathak, 2014; Dobbie and Fryer, 2014; **Abdulkadiroğlu, Angrist, Narita, and Pathak, 2017, 2021**

School choice

- Assignment mechanism (Abdulkadiroğlu, Che, and Yasuda 2015; Abdulkadiroğlu, Agarwal, and Pathak 2017; He 2017; Agarwal and Somaini 2018; Che and Tercieux 2019; Calsamiglia, Fu, and Güell 2020), information provision (Hastings and Weinstein 2008; Ajayi, Friedman, and Lucas 2017; Luflade 2017; Corcoran, Jennings, Cohodes, and Sattin-Bajaj 2018; Chen and He 2021a,b; Grenet, He, and Kübler 2021)
- **This paper**: first to incorporate a dynamic framework to study the relationship of school choices at different stages

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- To overcome selection issue, use the quasi-experimental feature built in DA (Abdulkadiroğlu, Angrist, Narita and Pathak (2017, 2021, AANP)) AANP Identification

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Full Table | Heterogeneity | Mediation | High Minority | Sensitivity

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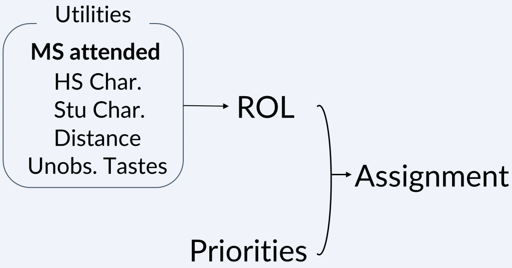

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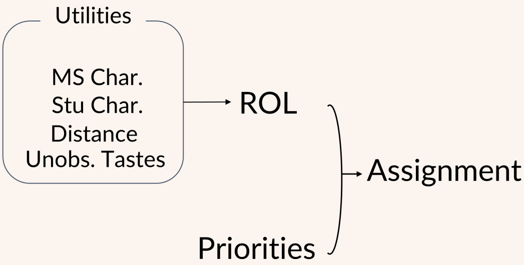
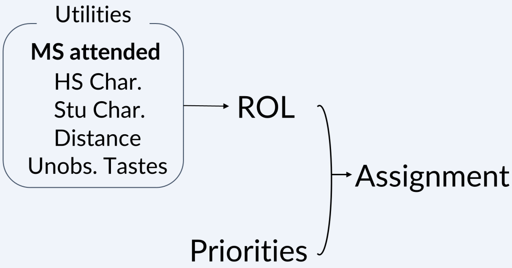


2nd Period: High School Choice



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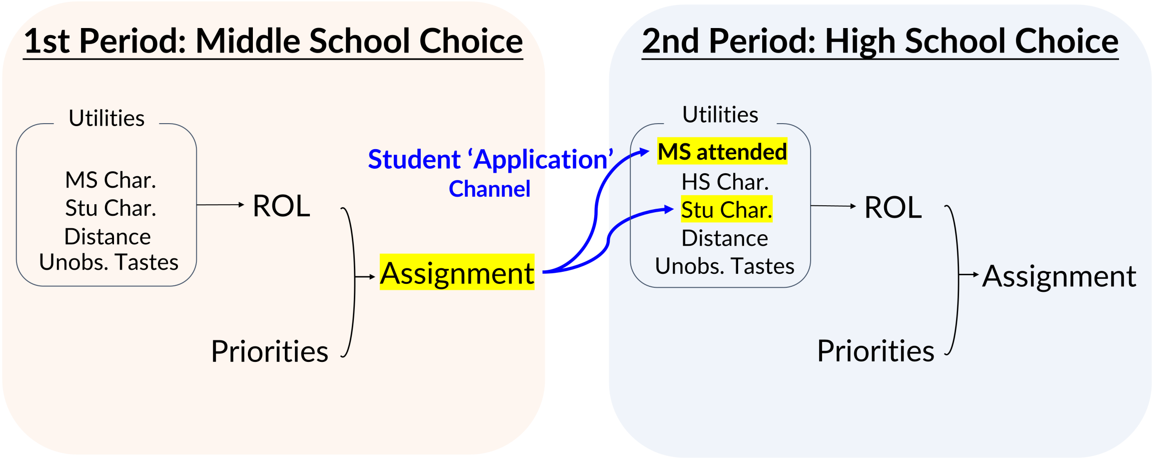

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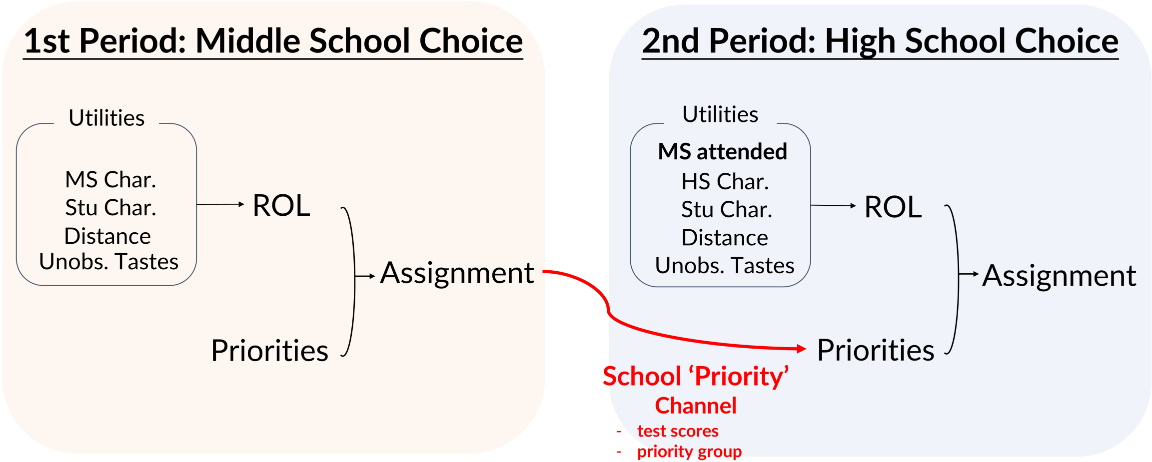

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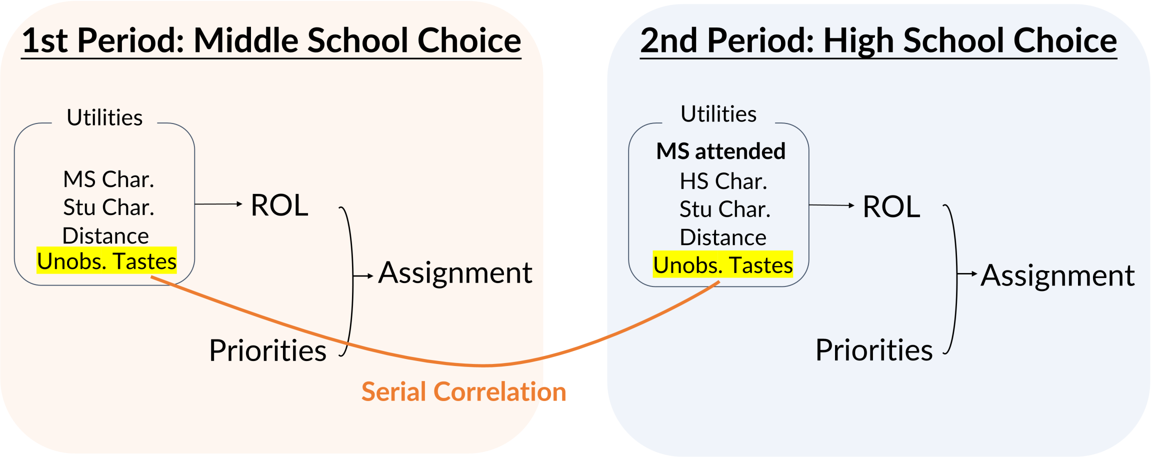

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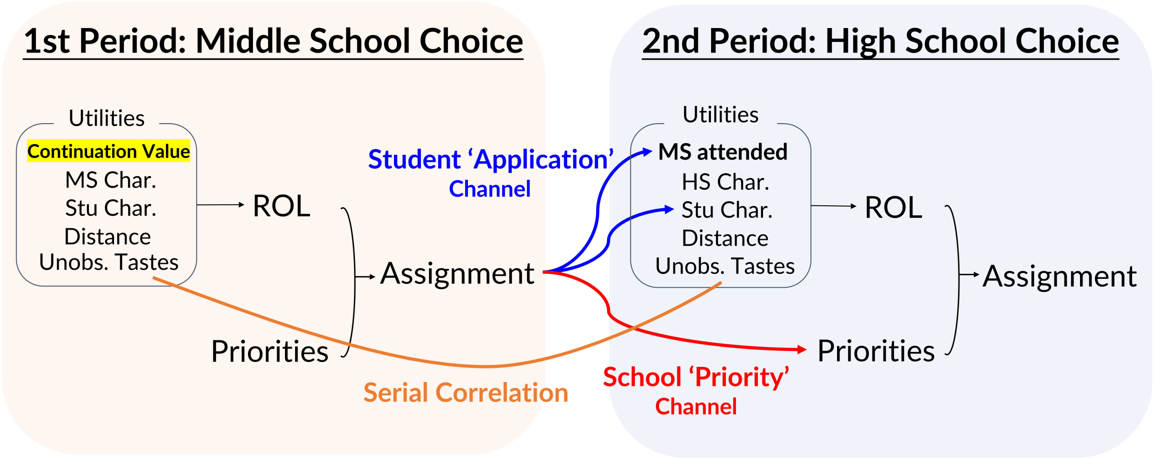

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- Agnostic about exact strategies, consistent with truth-telling or more robust assumptions

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Available Info

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Assumptions CV

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Full Estimates | By Race | Scatter Plot | Model Fit | Decomposition

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- We evaluate effects of **two actual policies combined**, implemented at different timings:
  1. **MS**: reform only middle school admissions
  2. **HS**: reform only high school admissions
  3. **MSHS**: reform both middle and high school admissions

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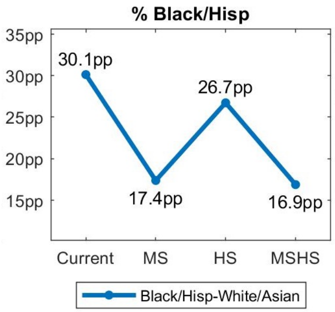

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1. MS can desegregate middle schools and high schools

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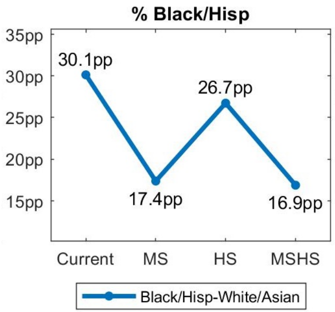

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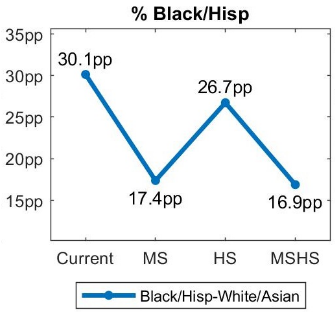

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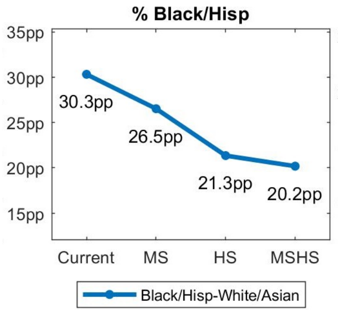

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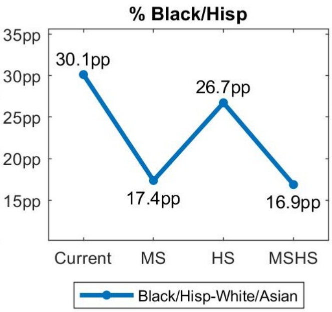

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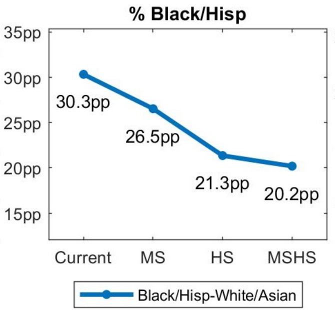
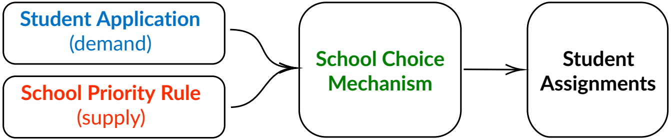


2. MSHS can improve on **HS** for desegregating high schools

Char Gap

Policy Implication



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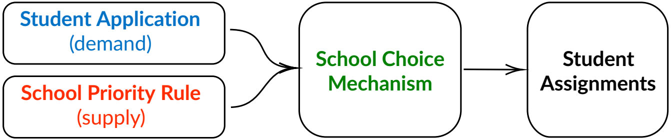

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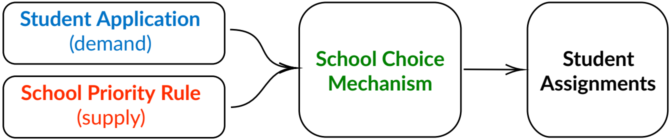

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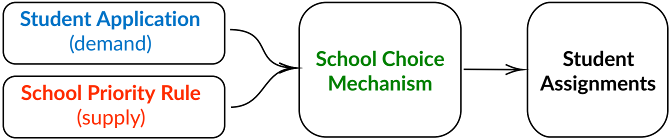

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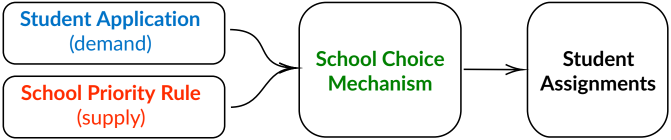

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- Most desegregation policies focused on reforming the supply side i.e., how schools select students
  - Little attention to how we can influence the demand side
- We suggest that:
  - ***Early*** intervention on the supply side can alter ***subsequent*** demand side behaviors
  - Such dynamic relationship can be used to design more effective policies

Conclusion

- The first to examine the **dynamic relationship** of school choices
  1. Empirical evidence of middle schools' effects on high school applications/assignments
  2. A novel dynamic framework of school choice
     - Middle schools' effects are mainly by changing student applications to high schools
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- We open a new avenue of research in the school choice literature by
  1. Bringing the dynamic aspect of school choice to the front
  2. Providing a new framework that is applicable to many other topics in school choice

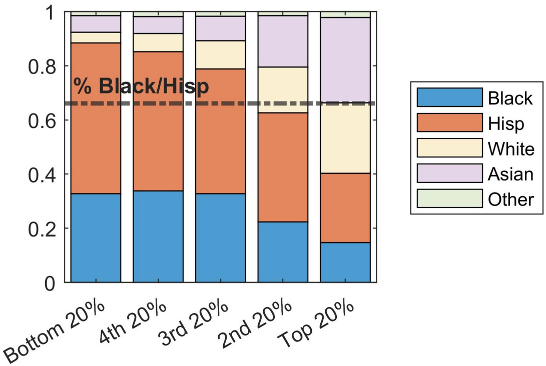
Thank you!

Comments or Suggestions?

dongwooh@usc.edu | mpark88@wisc.edu

Segregation in NYC High Schools CF

Black and Hispanic students are underrepresented in 'good' high schools



Note: Quintiles based on average performance at statewide exams.

Focusing on High School is Insufficient

e.g. NYC college enrollment 2016-17

	(1) Enrolled in College	(2) Enrolled in College	(3) Enrolled in College
Regents Score	0.141***	0.146***	0.139***
	(0.005)	(0.005)	(0.005)
HS Quality	0.028***		0.017***
	(0.007)		(0.006)
MS Quality		0.042***	0.034***
		(0.007)	(0.006)
N	51672	50942	50851
R2	0.160	0.162	0.163

Robust standard errors in parentheses. $* \; p < 0.1$, $** \; p < 0.05$, $* * * \; p < 0.01$

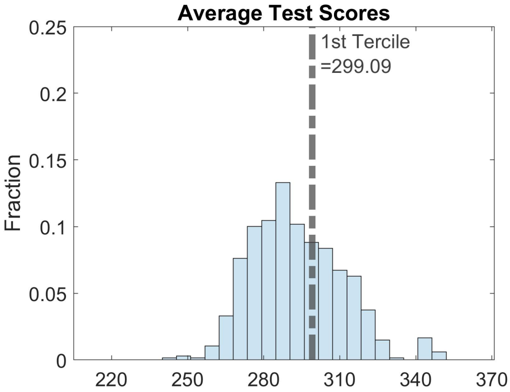
Middle school quality is more highly correlated with student's college outcome than high school quality!

Student Proposing Deferred Acceptance

- **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.
- **Step *k***
  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.
- The algorithm terminates either when there are no new proposals or equally when all rejected students have exhausted their preference lists.

Middle School Groups

High Achievement Middle Schools



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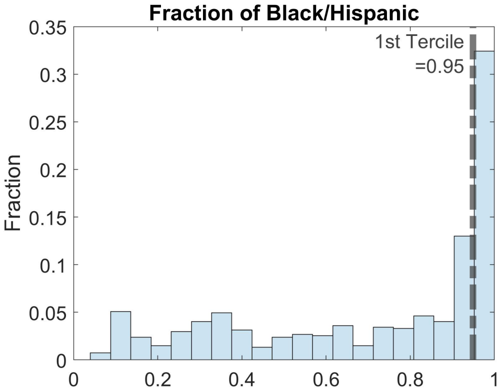

High School Groups

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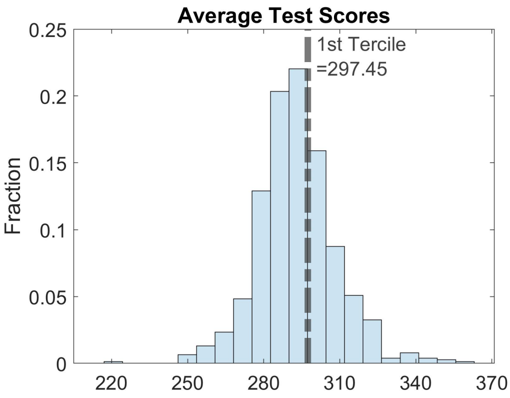

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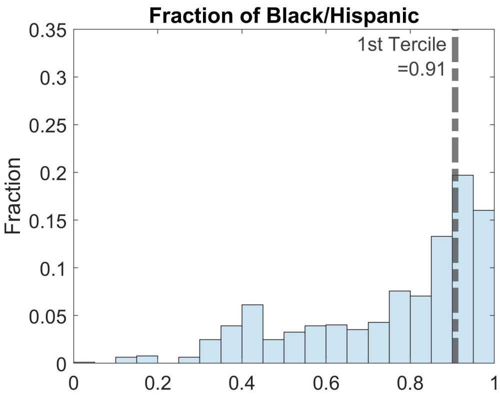

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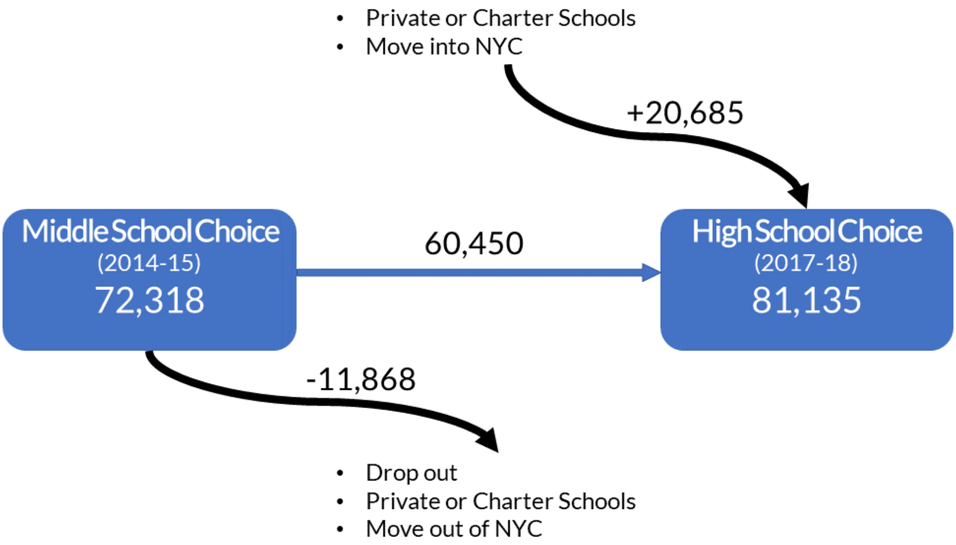

Private or Charter Schools
Move into NYC
+20,685
Middle School Choice
(2014-15)
72,318
60,450
High School Choice
(2017-18)
81,135
-11,868
Drop out
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Move out of NYC

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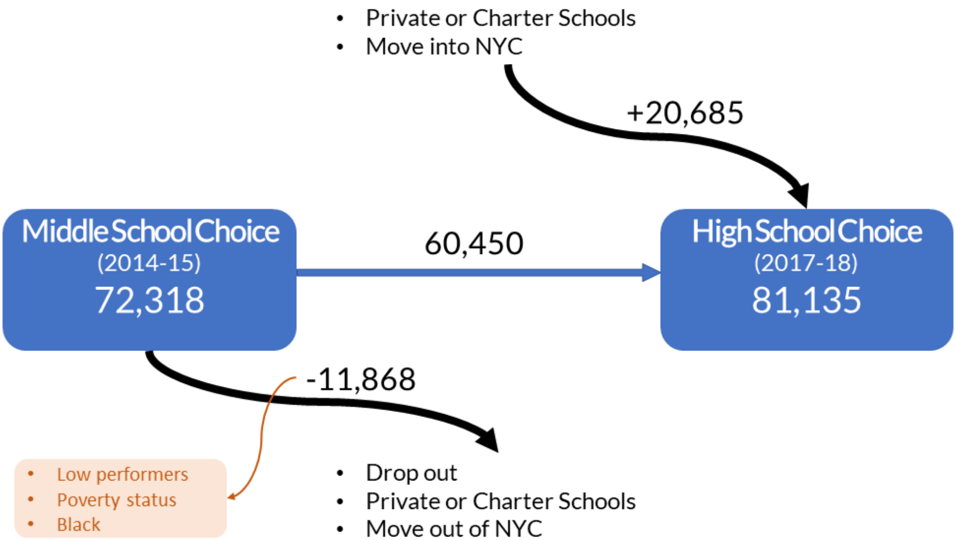

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Low performers
Poverty status
Black
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Summary Statistics: Students

Variables	N	Mean	Std
5th Grade Math Score	54,012	311.3	37.31
English Language Learner	54,012	0.12	0.32
Free or Reduced Lunch	54,012	0.73	0.45
Asian	54,012	0.19	0.39
Black	54,012	0.23	0.42
Hispanic	54,012	0.41	0.49
White	54,012	0.17	0.37

Note: The scale of 5th grade math score is from 125 to 402.

Quasi-experimental Variation in School Assignment

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  $\Longrightarrow$ **'stratified randomized trial'**

AANP Propensity Score

- Abdulkadiroğlu, Angrist, Narita and Pathak (2017,2021):
  1. Formally prove **Conditional Independence**
     $\Rightarrow$ eliminate OVB by conditioning on DA propensity score
  2. Provide a compact way of calculating DA propensity scores in a general framework with non-random tie-breaking, by combining RD and large-market matching model

Calculating Propensity Score

Two cases:

Calculating Propensity Score ◀

Two cases:

1. *Unscreened* programs: pure lottery tie-breaking

Calculating Propensity Score

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   - With lotteries, propensity score depends on only a few school-level cutoffs

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     - For those, **local conditional independence** holds

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	A	B	C
PG_{ij}	1	1	2
Cutoff	2.2	1.4	2.6
Admission Probability	0	1×0.6	$1 \times 0.4 \times (1 - F_i(0.6))$
Local Admission Probability	0	1×0.6	$1 \times 0.4 \times \mathbf{0.5}$

Identification Strategy

Identification Strategy ◂

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- Sample restriction: those with nondegenerate risk of being treated Marginal NDR-DR

Covariate Balance: Offered Students v.s. Non-offered Students

$$W_i = \alpha_0 + \gamma D_i + e_i$$

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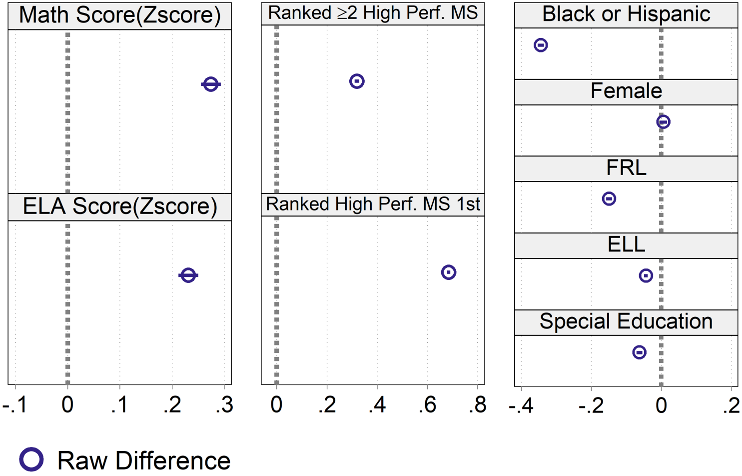
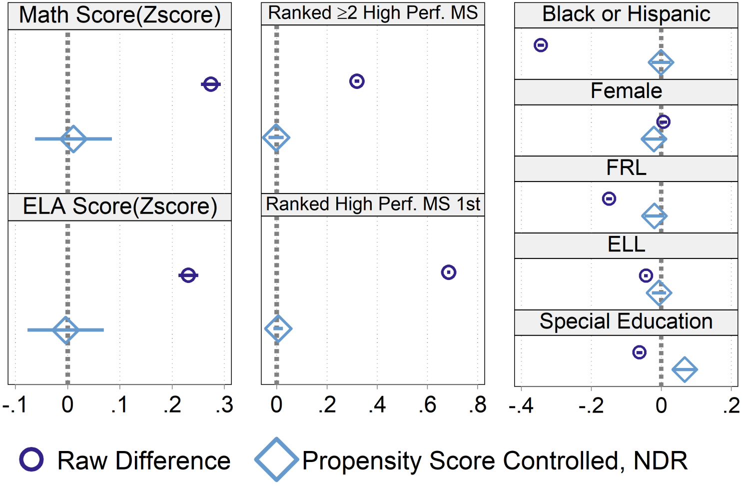


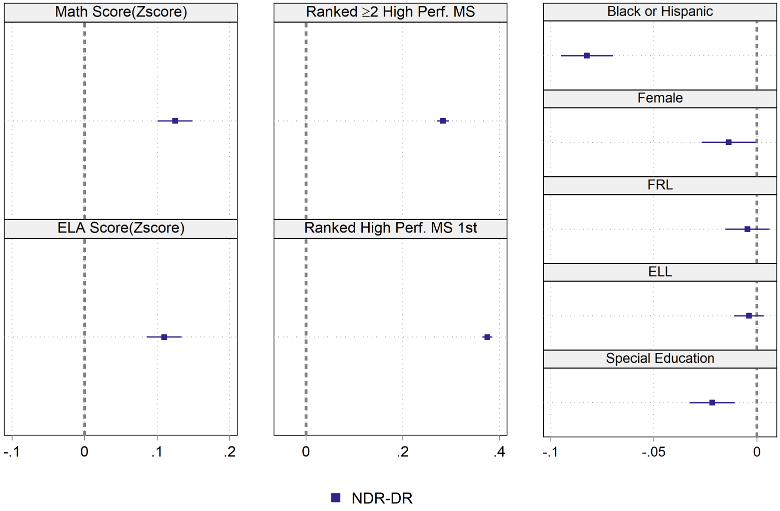
Covariate Balance: Offered Students v.s. Non-offered Students

$$W_i = \alpha_0 + \gamma D_i + \sum_x \alpha_1(x) d_i(x) + h(\mathcal{R}_i) + e_i$$



Nondegenerate v.s. Degenerate Risk Sample

Group mean difference of NDR and DR samples



Who Are Those Marginal Students?

Variables	All Mean	All Std	Marginal to High-achievement MS Mean	Marginal to High-achievement MS Std	Marginal to High-minority MS Mean	Marginal to High-minority MS Std
5th Grade Math Score	311.3	37.3	313.5	35.3	292.0	32.6
English Language Learner	0.12	0.32	0.07	0.25	0.12	0.32
Free or Reduced Lunch	0.73	0.45	0.76	0.43	0.90	0.30
Asian	0.19	0.39	0.22	0.42	0.02	0.15
Black	0.23	0.42	0.17	0.38	0.34	0.47
Hispanic	0.41	0.49	0.43	0.50	0.62	0.49
White	0.17	0.37	0.16	0.36	0.01	0.10

Note: The scale of 5th grade math score is from 125 to 402.

Main Result

Dependent Variable	Avg of Top 5 Ranked		Assigned	
Model	OLS	2SLS	OLS	2SLS
Sample	All	NDR	All	NDR
Panel A: College Enrollment Rate (%p)				
From High Achievement MS	2.854***	1.755*	4.530***	3.414**
	(0.516)	(1.011)	(0.669)	(1.566)
N	44158	7060	41546	6679
R2	0.367	0.459	0.244	0.310
$\bar{y}$	71.217	72.197	65.653	67.204
Panel B: % High Performing Students (%p)				
From High Achievement MS	5.188***	2.986*	6.886***	5.292**
	(0.840)	(1.805)	(0.825)	(2.105)
N	44237	7062	42180	6751
R2	0.450	0.502	0.388	0.400
$\bar{y}$	39.731	40.934	33.058	34.978
First Stage F-stat		135.2		135.2
Student Obs. Char.	✓	✓	✓	✓
Local Linear Control	✓	✓	✓	✓

Note: Standard errors clustered at attended middle school level.

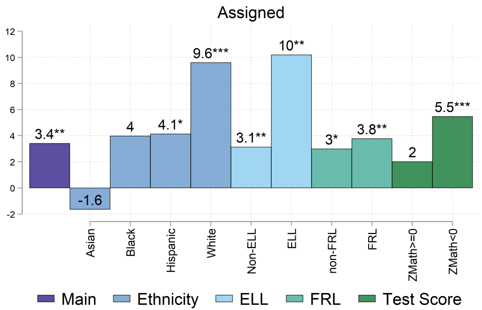
Main Result

Dependent Variable	Avg of Top 5 Ranked		Assigned	
Model	OLS	2SLS	OLS	2SLS
Sample	All	NDR	All	NDR
Panel C: % White (%p)				
From High Achievement MS	5.080***	0.311	5.755***	0.301
	(0.750)	(0.655)	(0.793)	(0.832)
N	44237	7062	42180	6751
R2	0.633	0.717	0.555	0.621
$\bar{y}$	18.627	20.334	15.097	16.761
Panel D: 1(STEM)				
From High Achievement MS	-0.053***	0.041	-0.057***	0.055
	(0.013)	(0.035)	(0.016)	(0.044)
N	44237	7062	42182	6751
R2	0.098	0.275	0.041	0.172
$\bar{y}$	0.324	0.318	0.314	0.322
First Stage F-stat		135.2		135.2
Student Obs. Char.	✓	✓	✓	✓
Local Linear Control	✓	✓	✓	✓

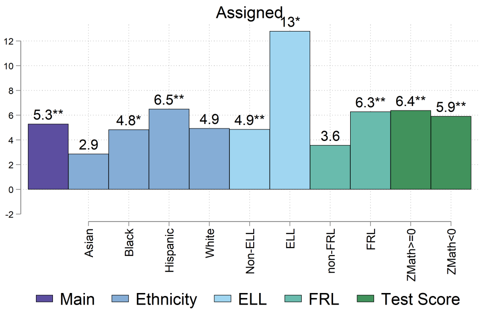
Note: Standard errors clustered at attended middle school level.

2SLS: Subgroup

College Enrollment Rate



% High Performing Students



- In general, more effective for groups with smaller baseline (with the exception for White)
  e.g. ELL, FRL, lower baseline math score

2SLS: Mediation Analysis

Is the effect mainly due to change in test scores? $\Rightarrow$ additionally include end-of-MS test scores

	Top 5 2SLS	Assigned 2SLS
Panel A: College Enrollment Rate (%p)		
From High Perf. MS	1.751*	3.301**
	(0.967)	(1.542)
8th Grade ELA Score (σ)	1.314***	2.070***
	(0.205)	(0.328)
8th Grade Math Score (σ)	0.910***	1.416***
	(0.231)	(0.374)
N	7060	6679
Panel B: % High Performing Students (%p)		
From High Perf. MS	2.913*	5.185**
	(1.748)	(2.061)
8th Grade ELA Score (σ)	2.114***	3.023***
	(0.351)	(0.409)
8th Grade Math Score (σ)	1.258***	1.315**
	(0.397)	(0.522)
N	7062	6751

While coefficients on 8th grade test scores are significantly positive, LATEs are largely unchanged

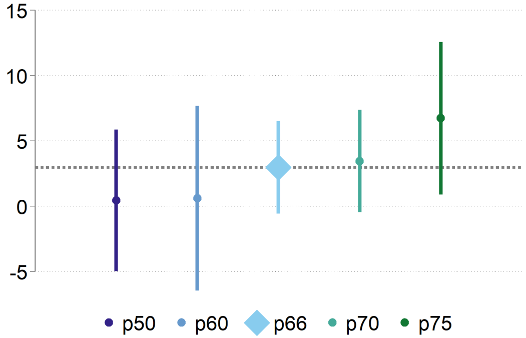
2SLS: Alternative Treatment: High Minority

	(1)	(2)	(3)	(4)
Dependent Variable	Top 5	Top 5	Assigned	Assigned
Model	OLS	2SLS	OLS	2SLS
Sample	All	NDR	All	NDR
Panel A: College Enrollment Rate (%p)				
From High Minority MS	-1.686***	0.248	-2.189***	-0.794
	(0.553)	(1.459)	(0.661)	(2.383)
N	46630	3307	43843	3091
R2	0.363	0.358	0.237	0.260
$\bar{y}$	71.371	66.679	65.829	60.183
Panel B: % High Performing Students (%p)				
From High Minority MS	-4.024***	3.188	-3.875***	3.957*
	(0.850)	(2.084)	(0.800)	(2.240)
N	46723	3317	44579	3163
R2	0.441	0.370	0.376	0.333
$\bar{y}$	39.839	28.252	33.146	21.158

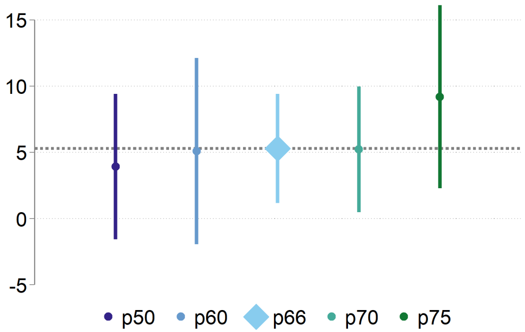
2SLS: Sensitivity to Other Definitions of Treatments

Are the identified LATEs sensitive to the choice of threshold (top 1/3)?

% High Performer (Top 5 Ranked)



% High Performer (Matched)



Value-added Estimation

- Let $y_{i,m}^{H}$: potential end-of-MS test score when i attends middle school m
- Estimate each m's production function based on selection on observables:

$$E\left[y_{i,m}^{H} \mid Z_i^M, m\right] = \alpha_m + Z_i^{M\prime}\beta_m$$

- OLS of $y_{i,m(i)}^{H}$ on school indicators interacted with Z_i^M where $m(i)$ is the actual middle school attendance in the data

Value-added Estimation

Mean and Standard Deviation of VA Coefficients Across Schools

	8th Grade Math		8th Grade ELA	
	Coefficient	SE	Coefficient	SE
Baseline Test Score	0.346	0.035	0.331	0.033
	(0.060)	(0.015)	(0.040)	(0.013)
Female	1.591	1.650	3.077	1.517
	(1.425)	(0.412)	(2.327)	(0.352)
Asian	6.002	3.993	6.029	3.402
	(4.892)	(2.108)	(4.617)	(1.547)
Black	-2.422	4.542	-2.502	4.642
	(6.194)	(2.527)	(3.826)	(3.216)
Hispanic	-2.309	2.708	-0.738	2.472
	(3.945)	(1.260)	(3.391)	(1.008)
English Language Learner	-2.862	5.691	1.239	6.066
	(7.230)	(2.669)	(6.273)	(3.045)
Student with Disability	-6.885	2.345	-5.571	2.212
	(3.192)	(0.690)	(2.122)	(0.663)
Free or Subsidized Lunch	-1.380	2.264	-1.501	2.013
	(2.124)	(1.190)	(1.974)	(0.863)

A Game of Incomplete Information

Che, Hahm and He (2022)

- Schools $\{c_1, ..., c_C\}$ with seats $S = (S_1, \cdots, S_C) \in \mathbb{N}^C$
- k students, each with an *ex-ante* type $\theta = (u, q) \in \Theta$ with distribution η
  - $u = (u_1, ..., u_C) \in [\underline{u}, \overline{u}]^C$: utility at each school
  - $q \in \mathcal{Q}$: "intrinsic" priorities at the schools — **e.g.** priority groups in NYC
  - ex-post scores $s \in [0, 1]^C$: distribution $G_q(s)$
    - schools rank students by ex-post scores in admissions
    - **e.g.** lottery tie-breaking: s **=** q **+ lottery**
- Private information: student type $\theta = (u, q)$; Common knowledge: DA, seats S, distributions η & $G_q(s)$
- A game of incomplete information: strategy is a measureable function $\sigma_i : \Theta \to \Delta(\mathcal{R})$
  - $\mathcal{R}$: set of all possible ROLs

Robust Equilibrium and Its Stability

Definition

An infinite profile σ is a **robust equilibrium** if, for any $\epsilon > 0$, there exists $K \in \mathbb{N}$ such that for $k > K$, its k-truncation σ^k is an interim ϵ-Bayes Nash equilibrium.

- Namely, for i, σ_i gives student i of each type θ a payoff within ϵ of the highest possible (i.e., supremum) payoff she can get by using any strategy when all the others employ σ^k_{-i}

Theorem (Stability Theorem)

Any regular robust equilibrium is asymptotically stable.

- **Asymptotic stability**: as $k \to \infty$ (the economy becomes large)

  The fraction of students assigned their most-preferred feasible schools $\xrightarrow{p} 1$

  - given any realized state of the world (e.g., realization of the tie-breaking lottery)

What is Known to the Student?

	Unobserved Taste on School Char. γ_i^M	γ_i^H	Idiosyncratic Preference Shock ϵ_{im}	η_{ij}	Program Characteristics $X_m, \tilde{X}_j$	Student's own Characteristics Z_i^M, Z_i^H	Uncertainty in High School Choice ω
1st Period (MSAP)	✓		✓		✓	✓	
2nd Period (HSAP)	✓	✓	✓	✓	✓	✓	

Distributional Assumptions

- Assumptions: let $\Psi_{1i} = (Z_i^M, \gamma_i^M, \epsilon_i, m)$

$$\eta_{ij} \perp \epsilon_{im} \Big| \gamma_i^M, \xi_i, \quad \forall i, j, m \tag{1}$$

$$\xi_i, \eta_i, \Psi_{1i} \text{ are mutually independent}, \quad \forall i \tag{2}$$

$$\omega \perp (\xi_i, \eta_{ij}) \Big| \Psi_{1i} \text{ and } \omega \perp \Psi_{1i}, \quad \forall i, j, m \tag{3}$$

- Idiosyncratic preferences:
  ϵ_{im} and η_{ij} both follow EVT1

- Unobservable tastes:
  $\gamma_i^M \perp \xi_i$, $\gamma_i^M \overset{iid}{\sim} \mathcal{N}(0, \Sigma_\gamma)$, $\xi_i \overset{iid}{\sim} \mathcal{N}(0, \Sigma_\xi)$

Continuation Value

Based on the assumptions on the unobservables,

$$
\begin{aligned}
&E_{\gamma_i^H,\omega,\boldsymbol{\eta}_i,Z_i^H}\left[\max_{j\in O_i(Z_i^H,m;\omega)} V_{ij}\middle| Z_i^M,\gamma_i^M,\boldsymbol{\epsilon}_i,m\right] \\
&= \int_\omega \int_{\xi_i} \left(\mu + \log\left(\sum_{j\in O_i(Z_i^H,m;\omega)} \exp(v_{ij}(\xi_i))\right)\right) d\Phi(\xi_i|\Sigma_\xi) dH(\omega)
\end{aligned}
$$

where

- $v_{ij} = V_{ij} - \eta_{ij}$
- $\Phi(\cdot|\Sigma)$: cdf of $\mathcal{N}(0,\Sigma)$
- $H(\cdot)$: cdf of ω

Source of Identification

1. Nonparametric identification of utilities:

$$(\gamma_i^M, \epsilon_{im}) \perp d_{im} \Big| X_m, Z_i^M$$

$$(\gamma_i^H, \eta_{ij}) \perp \tilde{d}_{ij} \Big| \tilde{X}_j, Z_i^H, m(i)$$

+ additive separability of distance (Agarwal and Somaini 2018)

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2. Popularity of schools with certain characteristics, for students with certain characteristics
   $\Rightarrow \beta_0^M, \beta_Z^M, \beta_0^H, \beta_Z^H$

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3. Persistent pattern on preference for some school characteristics $\Rightarrow$ $\boldsymbol{R_0}$

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3. Persistent pattern on preference for some school characteristics $\Rightarrow \boldsymbol{R_0}$
4. Common popularity of schools with certain characteristics among students attending same type of middle school + **quasi-random variation in MS assignments by tie-breaking** $\Rightarrow \rho_\tau$

Likelihood

For student i, conditional on γ_i^M, ξ_i,

$$
\begin{aligned}
P_i(\theta, \gamma_i^M, \xi_i) &= P(\text{observe } m_i, j_i | \gamma_i^M, \xi_i, \theta) \\
&= P\left(\begin{array}{rl} U_{im_i} = \max_{m \in O_i^m} U_{im} & \text{and} \\ V_{ij_i} = \max_{j \in O_i^h} V_{ij} & \text{given } m_i \end{array} \middle| \gamma_i^M, \xi_i, \theta \right) \\
&= \frac{\exp(u_{im_i}(\gamma_i^M, \theta))}{\sum_{m \in O_i^m} \exp(u_{im}(\gamma_i^M, \theta))} \frac{\exp(v_{ij_i}(\gamma_i^M, \xi_i, \theta; m_i))}{\sum_{j \in O_i^h} \exp(v_{ij}(\gamma_i^M, \xi_i, \theta; m_i))}
\end{aligned}
$$

Then,

$$
P_i(\theta) = \int_{\gamma_i^M} \int_{\xi_i} P_i(\theta, \gamma_i^M, \xi_i) \phi(\xi_i | \Sigma_\xi) \phi(\gamma_i^M | \Sigma_\gamma) d\xi_i d\gamma_i^M
$$

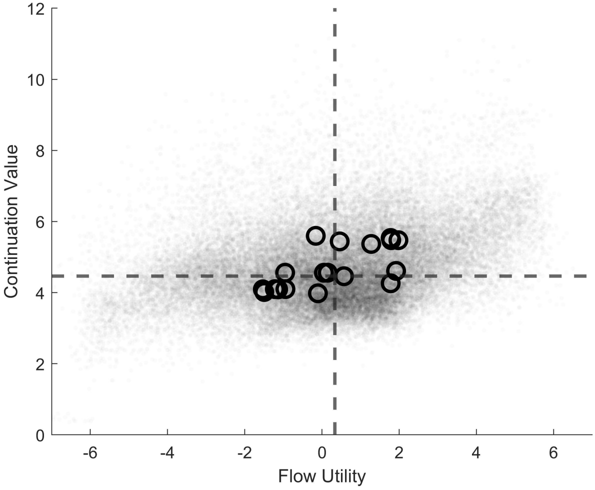
where $\phi(\cdot|\Sigma)$ is the pdf of a multivariate normal with mean zero and covariance matrix Σ, and hence

$$
\sum_i \log P_i(\theta)
$$

is the log-likelihood function

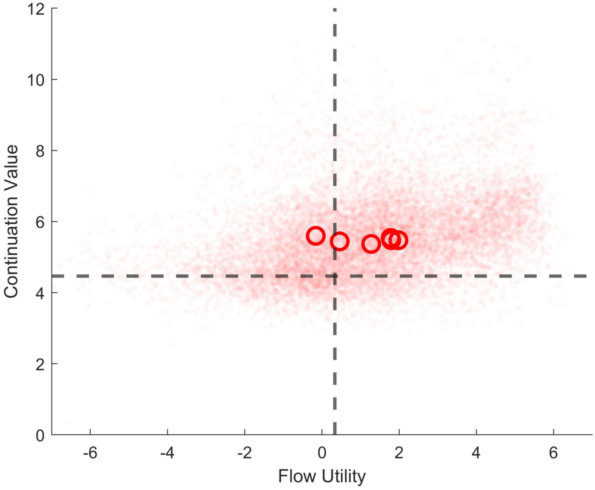
Flow Utility and Continuation Value

All Middle Schools



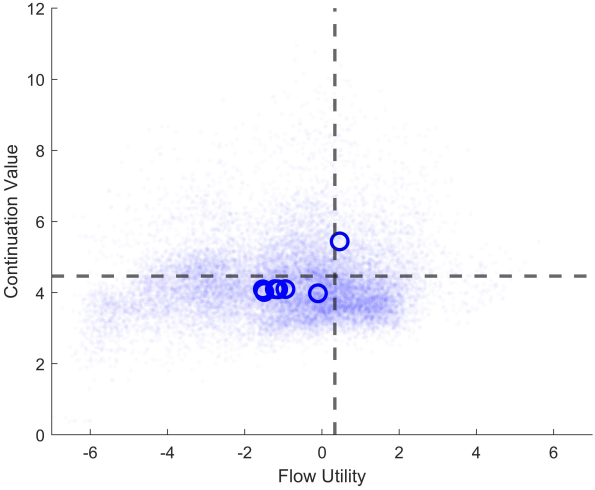
Flow Utility and Continuation Value

High Achievement Middle Schools



Flow Utility and Continuation Value

High Minority Middle Schools



Goodness-of-Fit

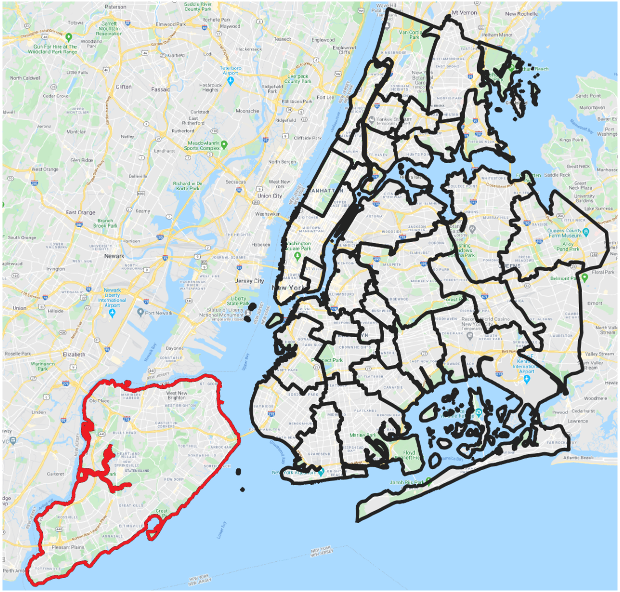
Goodness-of-Fit ◂

Characteristics of assigned schools by student type:

	Middle Schools				High Schools			
	% High Performer		% FRL		% High Performer		% FRL	
	Data	Model	Data	Model	Data	Model	Data	Model
Asian	36%	37%	62%	60%	33%	33%	58%	58%
Black	27%	32%	74%	69%	25%	24%	69%	70%
Hispanic	31%	34%	67%	65%	29%	27%	64%	66%
White	45%	45%	48%	49%	39%	37%	50%	52%
ELL	27%	30%	71%	67%	24%	24%	70%	69%
FRL	35%	37%	62%	61%	31%	30%	61%	62%

More

Staten Island



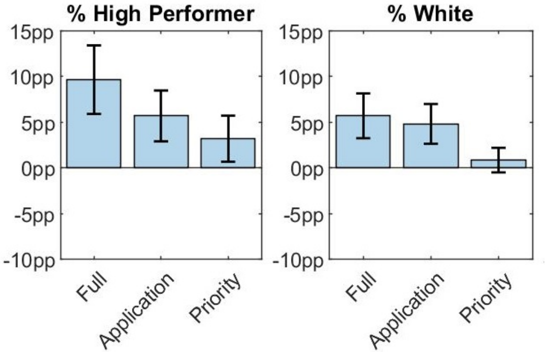
Staten Island

Affluent county with more White and better performing students compared to citywide average

	All NYC		Staten Island	
	Mean	Std	Mean	Std
5th Grade Math Score	311.26	(37.31)	315.49	(32.40)
5th Grade ELA Score	300.56	(34.96)	306.13	(31.10)
English Language Learner	0.12		0.05	
Disability	0.21		0.25	
Free or Reduced Lunch	0.73		0.54	
Asian	0.19		0.09	
Black	0.23		0.10	
Hispanic	0.41		0.24	
White	0.17		0.56	
N	54017		2626	

Decomposition of Middle School Effects

Change in Characteristics of Assigned High School (Lowest- $\to$ Highest Performing MS)



Full Estimates ◂

	Middle Schools est	Middle Schools se		High Schools est	High Schools se	
Panel A: Preference Estimates						
Fraction of High Performer	4.944	(1.144)	***	0.795	(0.272)	***
Asian	-1.267	(1.947)		0.827	(0.39)	**
Black	6.82	(1.961)	***	-0.199	(0.462)	
Hisp	1.781	(1.288)		-0.275	(0.33)	
Poverty	-0.881	(1.13)		-0.922	(0.271)	***
ELL	-1.804	(2.309)		0.342	(1.177)	
5th Gr Test Score	1.088	(0.581)	*	1.652	(0.141)	***
Fraction of White	3.056	(0.875)	***	4.931	(0.343)	***
Asian	0.976	(1.588)		-2.011	(0.599)	***
Black	-6.444	(1.721)	***	-1.52	(0.613)	**
Hisp	-1.666	(1.047)		-1.06	(0.421)	**
Poverty	-0.565	(0.886)		0.162	(0.346)	
ELL	0.752	(1.954)		-0.24	(1.202)	
5th Gr Test Score	-0.951	(0.468)	**	0.341	(0.126)	***
1(STEM)	0.281	(0.198)		-0.676	(0.123)	***
Asian	0.157	(0.324)		-0.174	(0.2)	
Black	-0.42	(0.269)		0.09	(0.196)	
Hisp	0.121	(0.213)		0.083	(0.144)	
Poverty	-0.122	(0.198)		0.257	(0.126)	**
ELL	0.062	(0.345)		1.005	(0.326)	***
5th Gr Test Score	-0.159	(0.096)	*	0.003	(0.044)	

Full Estimates ◀

	Middle Schools		High Schools		
	est	se	est	se	
Panel B: Middle School Type Effects					
Type 1 (High Achievement MS)					
Fraction of High Performer			0.546	(0.276)	**
Fraction of White			1.6	(0.318)	***
1(STEM)			-0.322	(0.137)	**
Type 2 (High Minority MS)					
Fraction of High Performer			0.875	(0.301)	***
Fraction of White			-1.447	(0.378)	***
1(STEM)			0.198	(0.136)	

Full Estimates ◀

	Middle Schools est	Middle Schools se		High Schools est	High Schools se	
Panel C: Unobservable Tastes						
ρ_0				0.074	(0.044)	*
				0.429	(0.127)	***
				-0.035	(0.118)	
(1,1) of Σ_γ	18.461	(10.853)	*			
(1,2)	-17.93	(9.653)	*			
(1,3)	-0.186	(1.626)				
(2,2)	23.168	(10.222)	**			
(2,3)	2.765	(2.018)				
(3,3)	1.163	(0.697)	*			
(1,1) of Σ_ξ				0.447	(0.316)	
(1,2)				-2.184	(0.95)	**
(1,3)				0.411	(0.163)	**
(2,2)				10.67	(2.877)	***
(2,3)				-2.006	(0.512)	***
(3,3)				0.377	(0.193)	*

Full Estimates ◂

	Middle Schools			High Schools		
	est	se		est	se	
Panel D: Other Parameters						
Outside option	2.698	(0.367)	***	-0.371	(0.175)	**
Distance	0.655	(0.038)	***	0.509	(0.018)	***
Discount Factor	0.877	(0.064)	***			

MS Effects by Race

White/Asian

High achievement MS makes students willing to travel $\begin{cases} +\ 0.12 \text{ miles} \\ +\ 0.41 \text{ miles} \end{cases}$ for 10pp increase of $\begin{cases} \%\text{ high performer} \\ \%\text{ White} \end{cases}$

High minority MS makes students willing to travel $\begin{cases} +\ 0.24 \text{ miles} \\ -\ 0.34 \text{ miles} \end{cases}$ for 10pp increase of $\begin{cases} \%\text{ high performer} \\ \%\text{ White} \end{cases}$

Black/Hispanic

High achievement MS makes students willing to travel $\begin{cases} +\ 0.12 \text{ miles} \\ +\ 0.08 \text{ miles} \end{cases}$ for 10pp increase of $\begin{cases} \%\text{ high performer} \\ \%\text{ White} \end{cases}$

High minority MS makes students willing to travel $\begin{cases} +\ 0.11 \text{ miles} \\ -\ 0.22 \text{ miles} \end{cases}$ for 10pp increase of $\begin{cases} \%\text{ high performer} \\ \%\text{ White} \end{cases}$

Goodness-of-Fit

Characteristics of assigned students by school type:

	Middle Schools				High Schools			
	High Achievement		High Minority		High Achievement		High Minority	
	Data	Model	Data	Model	Data	Model	Data	Model
Asian (%)	9%	9%	9%	9%	9%	9%	7%	8%
Black (%)	4%	3%	25%	24%	4%	4%	30%	23%
Hispanic (%)	12%	12%	41%	39%	18%	15%	42%	40%
White (%)	74%	75%	25%	27%	68%	71%	20%	28%
ELL (%)	2%	1%	10%	9%	3%	3%	11%	9%
FRL (%)	41%	40%	77%	73%	46%	44%	78%	74%
5th grade Math	322.6	322.6	304.2	307.5	320.0	322.3	301.9	303.7
From High Achievement MS (%)					57%	61%	10%	9%
From High Minority MS (%)					10%	10%	62%	49%

Note: The scale of 5th grade math score is from 125 to 402.

Goodness-of-Fit

Assignment and ROL prediction:

	Dynamic Model	
	MS Application	HS Application
Panel A. Simulated versus observed assignment (100 simulated samples)		
Mean predicted fraction of students assigned to observed assignments	0.5709	0.2022
	(0.0053)	(0.0049)
Panel B. Predicted versus observed partial preference order		
Mean predicted probability that a student's partial preference order among the programs in her ROL coincides with the submitted rank order	0.3848	0.1395

Benchmark for assignment prediction (Panel A):

- Lower bound (random assignment): 5.9% (MSAP), 2.3% (HSAP)

Decomposition Exercise

Specifically,

1. Assign students to *School A*, and **one student at a time**, change the assignment to *School B*
2. Keep track of how the student's high school assignment change in alternative scenarios
   i. Both channels are active
   ii. Turn off the priority channel i.e., priorities don't depend on middle schools
   iii. Turn off the application channel i.e., applications don't depend on middle schools

Racial Gap in Assigned High School Characteristics ◂