Exploring the Relationship between Information, Returns, and College Attendance Disparities

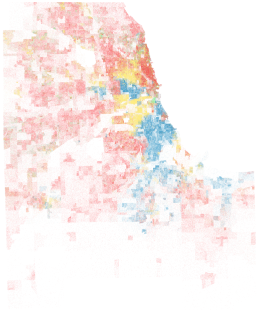
Nadav Kunievsky

May 19, 2023

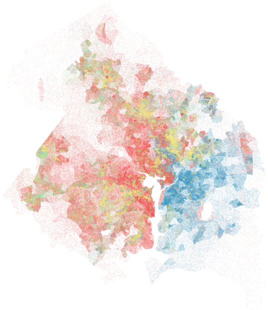
Introduction

- The environment in which a person is raised can significantly impact the decisions they make throughout their life
- We know that people from different social groups grow up in very different environments

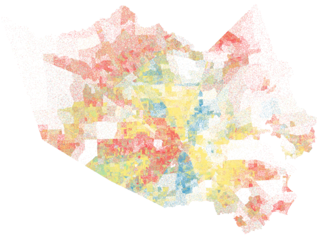
Introduction



Chicago



Washington



Houston

Source: Washington Post, data from ACS

Introduction

Heterogeneity in Upbringing Environment → Incentives, Resources, and Information → Disparities in Choices

- Neighborhoods
- Parental Backgrounds
- Crime
- Social Ties

- Credit Constraints
- Labor market outcomes
- Information

- Education
- Where to live
- Where to invest

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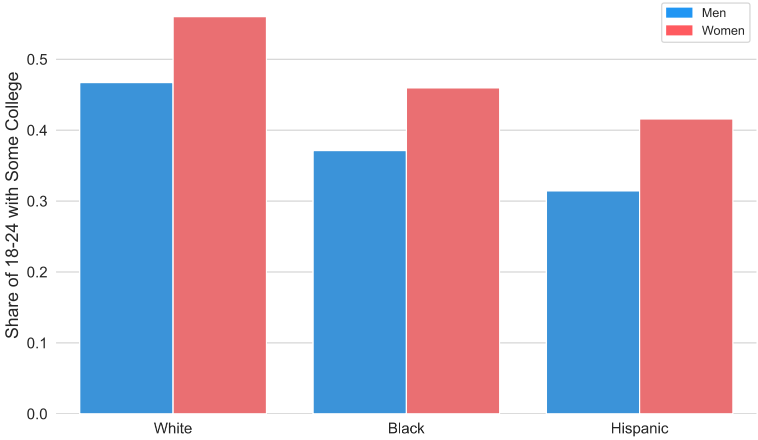
College Enrollment Gap



Source: CPS, 2000-2019 College Attendance over the years

Today - Exploring College Attendance Gap

- This study aims to use administrative data from Texas to investigate how variations in college returns and available information on these returns impact the college attendance gap among different social groups.
- By adopting a structural, non-parametric approach, we use the Roy Model to explore how the observed college attendance gap is affected by these factors.
- The decomposition technique seeks to address questions such as:

  What would the proportion of college attendees from one group be if they possessed the information/returns of another group?

- Given that high school graduates' information is typically unknown, we rely on the robust mechanism design literature to partially identify answers to these quantitative questions.

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Overview

A Guiding Framework

- $\mathcal{R}$ is the net returns from going to college, distributed with distribution $\pi(\mathcal{R})$
- $s \in S$ is an informative signal on the returns, drawn from the conditional distribution $P(s|\mathcal{R})$
- HG choose to go to college if
$$E[\mathcal{R}|s] \geq 0$$
- We call the distributions of $\mathcal{R}$ and the information structure $\mathcal{S} = (P(s|\mathcal{R}), S)$ the **Choice Environment**

Decomposition Approach

- Our objective is to understand the importance of each factor in choice environment shapes the disparities in college attendance
- We answer:

*If one group had the same **X** as the other group's choice environment, what would be the proportion of college attendees from the first group?*

What is the information structure $(P(s_i|\theta), S)$?

The informational structure encompasses all of the information that high school graduates might possess with respect to their future pursuits. These constituents include:

- Social environment
- Media exposure
- Academic assessments and school examinations
- Guidance from school counselors and educators
- Knowledge derived from parents
- Etc.

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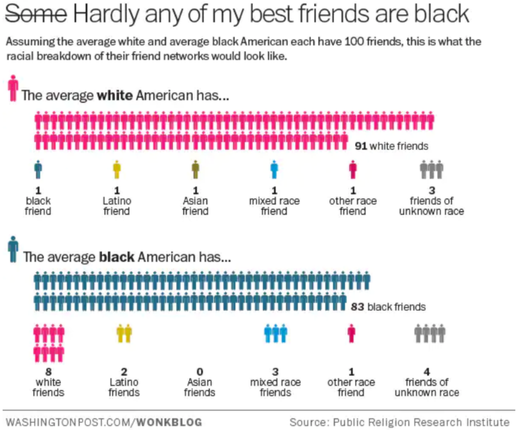
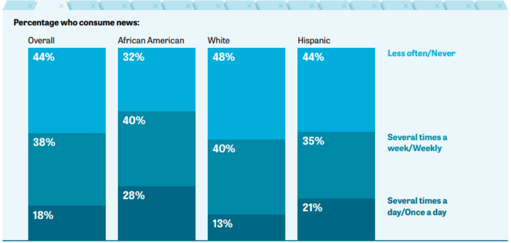


What is the information structure $(P(s_i|\theta), S)$?

Young African Americans share news at higher rates than other young adults.



QUESTION How often do you share news stories you've seen with other people, such as friends, family, or social media followers?

SOURCE Nationally representative survey of 1,660 adults age 18-34 conducted March 19–April 12 2018 by NORC at the University of Chicago with funding from The Knight Foundation

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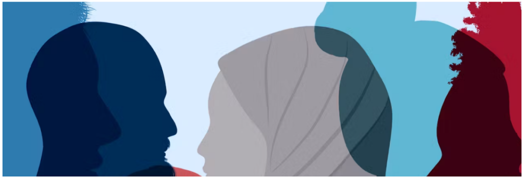
DIVERSITY AND EQUITY

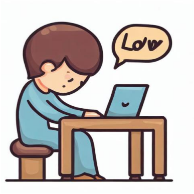
School Counselors Have Implicit Bias. Some Are Ready to Address It.

By Emily Tate Sullivan Apr 6, 2021



Practical Illustration of the Information Structure

ϕ_H



ϕ_L

Practical Illustration of the Information Structure

$R(\phi_H)$

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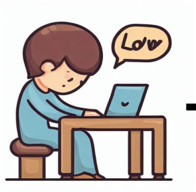

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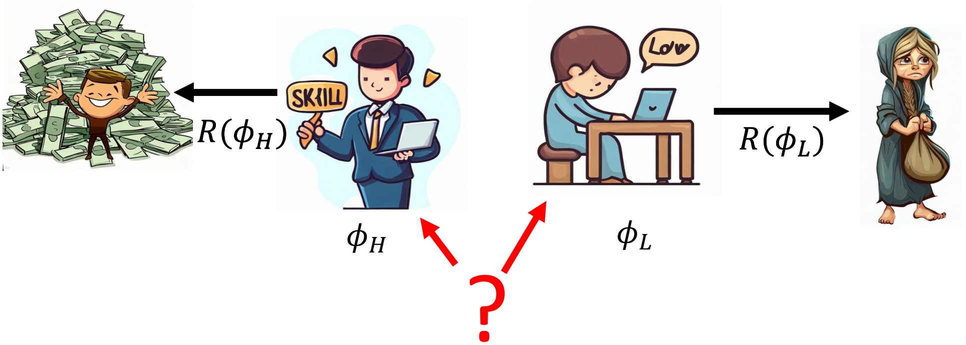

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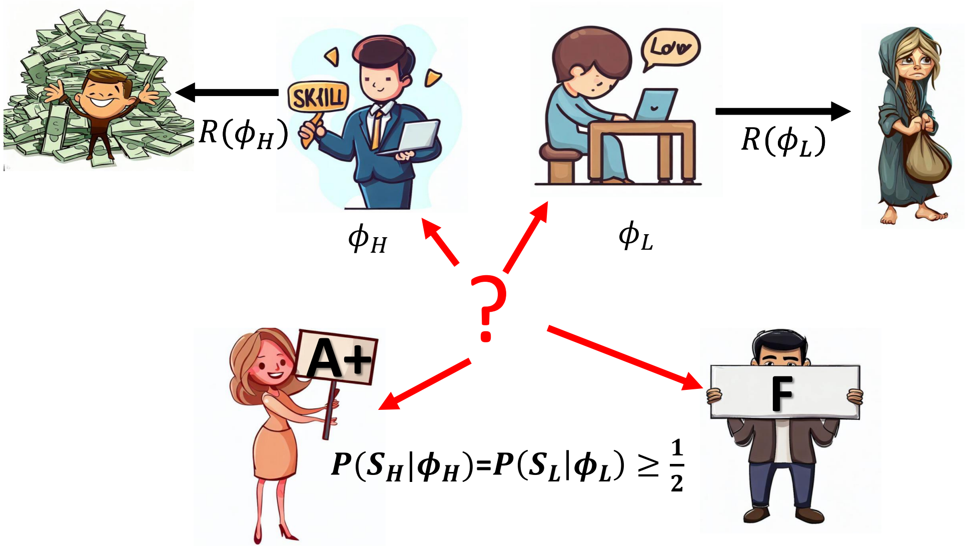

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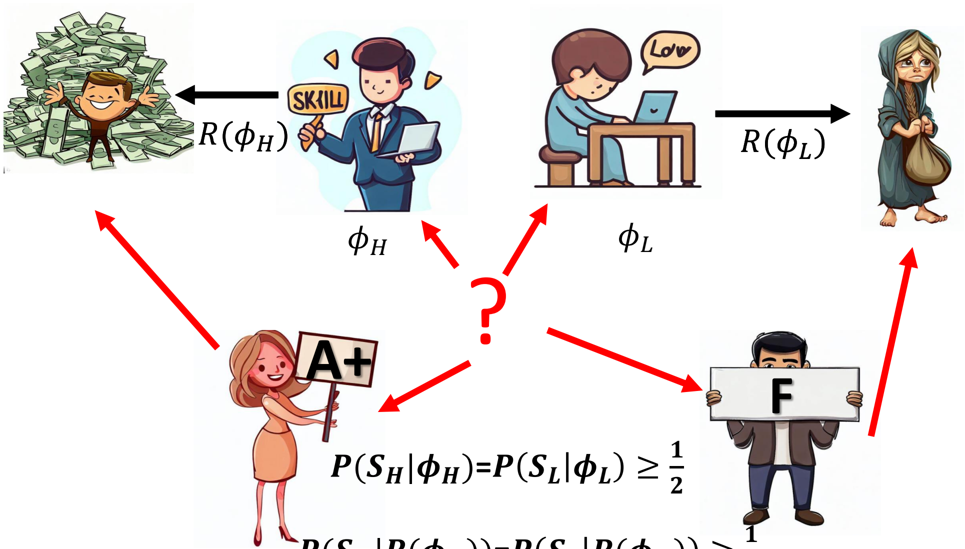

$$\boldsymbol{P(S_H|\phi_H)=P(S_L|\phi_L) \geq \frac{1}{2}}$$

$$\boldsymbol{P(S_H|R(\phi_H))=P(S_L|R(\phi_H)) \geq \frac{1}{2}}$$

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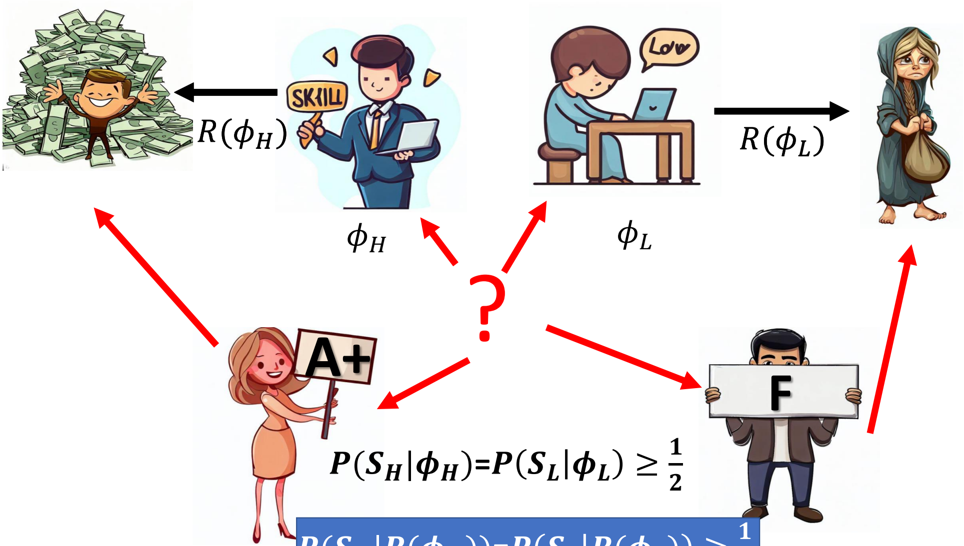

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Decomposition Approach - Counterfactual Posterior Mean

- What's shape the observed gaps in choices are the differences in distribution of beliefs
- Let there be two groups $\{a, b\}$
- Let

$$m_{\mathcal{R}}(s_a; \pi_b) = \int_{\tilde{\mathcal{R}}} \tilde{\mathcal{R}} \frac{\overbrace{P_a(s_a|\tilde{\mathcal{R}})}^{\text{Information}} \overbrace{\pi_b(\tilde{\mathcal{R}})}^{\text{Returns}}}{\int P_a(s_a|\tilde{\mathcal{R}})\pi_b(\tilde{\mathcal{R}})d\tilde{\mathcal{R}}} d\tilde{\mathcal{R}}$$

Decomposition Approach - Distribution of posterior means

- Let
$$\mathcal{P}_{a,b}(m_{\mathcal{R}}(s_a;\pi_b)|\mathcal{R})$$
be the conditional distribution of posterior means induced by the information structure of group a and the returns of group b

- This is a random variable, with respect to s, we and we can define it's conditional probability, conditioned on the returns as

$$\mathcal{P}_{a,b}\left(m_{\mathcal{R}}(s_a;\pi_b)=t\middle|\mathcal{R}\right)=P_a\left(\left\{s\in\mathcal{S}\middle|t=\int_{\tilde{\mathcal{R}}}\tilde{\mathcal{R}}\frac{P_a(s|\tilde{\mathcal{R}})\pi_b(\tilde{\mathcal{R}})}{\int P_a(s|\tilde{\mathcal{R}})\pi_b(\tilde{\mathcal{R}})d\tilde{\mathcal{R}}}d\tilde{\mathcal{R}}\right\}\middle|\mathcal{R}\right)$$
$$\equiv\mathcal{P}_{a,b}(m_{\mathcal{R}}(s)|\mathcal{R})$$

Decomposition Approach - Distribution of posterior means

- Finally the counterfactual beliefs would have the following distribution

$$\mathcal{P}_{a,b}(m_{\mathcal{R}}(s_a;\pi_b)) = \int_{\mathcal{R}} \mathcal{P}_{a,b}(m_{\mathcal{R}}(s_a;\pi_b)|\mathcal{R})\pi_b(\mathcal{R})d\mathcal{R}$$

Decomposition Approach - Distribution of posterior means - Example

- Again, assume that group a have binary returns and access to binary test results, which implies that high school graduates have two binary beliefs $m_{\mathcal{R}}(s_H)$ and $m_{\mathcal{R}}(s_L)$ distributed with the following conditional probability

$$\mathcal{P}_{a,a}(m_{\mathcal{R}}(s_H)|\mathcal{R}_i) = P(s_H|\mathcal{R}_i)$$

and

$$\mathcal{P}_{a,a}(m_{\mathcal{R}}(s_H)) = P(s_H|\mathcal{R}_H)\pi_a(\mathcal{R}_H) + P(s_H|\mathcal{R}_L)\pi_a(\mathcal{R}_L)$$

Decomposition Approach - Distribution of posterior means - Example

- Assume that we change the distribution of returns to π_b. This would induce two new beliefs $\tilde{m}_{\mathcal{R}}(s_H)$, and $\tilde{m}_{\mathcal{R}}(s_L)$ where

$$\tilde{m}_{\mathcal{R}}(s_H) = \frac{\mathcal{R}_H \times P_a(s_H|\mathcal{R}_i)\pi_b(\mathcal{R}_H) + \mathcal{R}_L \times P_a(s_H|\mathcal{R}_L)\pi_b(\mathcal{R}_L)}{P_a(s_H|\mathcal{R}_H)\pi_b(\mathcal{R}_H) + P_a(s_H|\mathcal{R}_L)\pi_b(\mathcal{R}_L)}$$

  and similarly for $\tilde{m}_{\mathcal{R}}(s_L)$

- With conditional probility

$$\mathcal{P}_{a,b}(\tilde{m}_{\mathcal{R}}(s_H)|\mathcal{R}_H) = \mathcal{P}_{a,a}(m_{\mathcal{R}}(s_H)|\mathcal{R}_H)$$

  and

$$\mathcal{P}_{a,b}(\tilde{m}_{\mathcal{R}}(s_H)) = \mathcal{P}_{a,b}(\tilde{m}_{\mathcal{R}}(s_H)|\mathcal{R}_H)\pi_b(\mathcal{R}_H) + \mathcal{P}_{a,b}(\tilde{m}_{\mathcal{R}}(s_H)|\mathcal{R}_L)\pi_b(\mathcal{R}_L)$$

Parameter of interest

- Our objective is to understand the importance of each component of the choice environment in making decision

Parameter 1

What the share of HG from group a who would go to college, assuming:

- The Returns to College distribution of HG from group a are the same as the RC distribution of HG from group b
- The information structure for HG from group a does not change

$$\tilde{\mathrm{P}}_{RC}(D=1) = \int_{\mathcal{R}} \underbrace{\mathcal{P}_{a,b}(m_{\mathcal{R}}(s) \geq 0 | \mathcal{R})}_{Information} \underbrace{\pi_b(\mathcal{R})} d\mathcal{R}$$

Parameter of interest

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Parameter 2

The share of HG from group a who would go to college, assuming:

- The information structure of HG from group a is the same as the information structure of HG from group b.
- The RC distribution and cost distribution for HG from group a do not change.

$$\widetilde{\mathrm{P}}_I(D=1) = \int_{\mathcal{R}} \underbrace{\mathcal{P}_{b,a}(m_{\mathcal{R}}(s) \geq 0|\mathcal{R})}_{\text{Information}} \underbrace{\pi_a(\mathcal{R})}_{\text{RC}} \, d\mathcal{R}$$

Related Literature

- Information Experiments and Belief Elicitation
  Ingar Haaland et al (2023), Jensen (2010), Bleemer and Zafar (2018), Conlon (2021), Chetty and Saez (2013), Bursztyn et. al. (2014), Dominitz and Manski (1996), Wiswall and Zafar (2015)
  - Individuals typically possess incomplete information and tend to update their beliefs upon receiving new information. Does not capture how much of observed gaps are due to information
  - Belief elicitation captures the distribution of beliefs. Simple difference in the belief distribution does not tell us how it contributes to the observed gaps

- Structural Papers on the role of information
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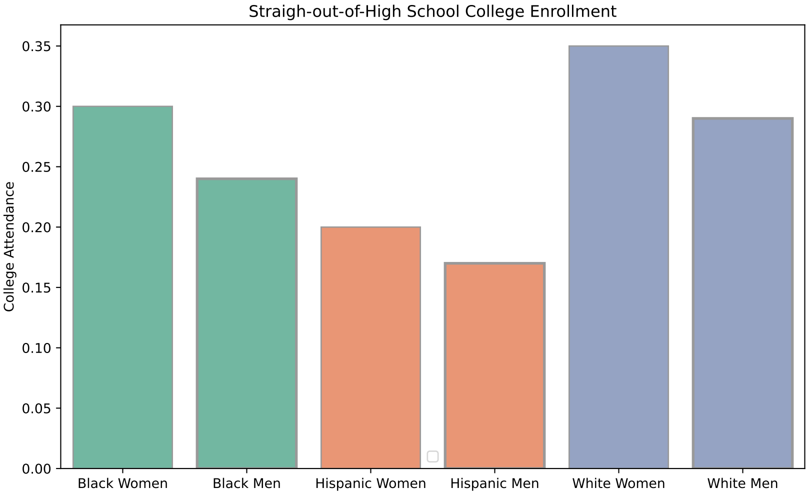
Overview

- A Guiding Framework and Decomposition Approach
  - Framework
  - Defining the Counterfactual Distribution of Posterior Means
  - Parameters of Interest
- Data
  - Differences In the Choice Environment
  - Differences in Choice Environment - Information
- Partial Identification
- Conclusions

Data

- Texas administrative data for the population high school graduates from 2000-2020 Descriptives
- The data includes information on
  - (THECB) College enrollment and performances
  - (FAD) Financial Assistance
  - (TEA) High-school Courses, Academic Readiness Test Score, Graduation
  - (TWC) Employed workers wages

Straight-out-High-School College Enrollment



Differences in the Choice Environment - Returns and Costs

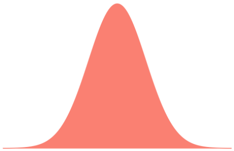
	Net College Costs		College Grad (6 Yrs)		Test Factor Percentile		Wage 12-14		Wage 1-14		Wage 1-14 (Missing)	
	NC	College	NC	College	NC	College	NC	College	NC	College	NC	College
All	4698	48973	0.0	0.62	44.29	67.52	8119	11266	5494	6890	4493	5364
	(13691)	(30808)	(0.0)	(0.49)	(26.76)	(23.71)	(5453)	(6568)	(3545)	(4236)	(3181)	(3460)
	931580	336739	931580	336739	742801	317839	425456	175476	531366	219265	476050	204863
Black Women	3683	38604	0.0	0.48	33.21	49.38	5853	8517	4187	5548	3444	4489
	(11700)	(26985)	(0.0)	(0.5)	(23.46)	(24.65)	(3866)	(4843)	(2498)	(2910)	(2259)	(2594)
	64413	27902	64413	27902	49577	25852	31877	15878	37157	18133	34140	17454
Black Men	3184	37957	0.0	0.36	33.22	47.85	6825	9042	4700	5660	3799	4481
	(11122)	(28871)	(0.0)	(0.48)	(23.83)	(25.25)	(4764)	(5749)	(3108)	(3477)	(2810)	(3042)
	62937	19625	62937	19625	42915	17828	28881	10385	35856	12613	31084	11724
Hispanic Women	3248	37942	0.0	0.58	36.58	60.81	6263	9265	4469	5982	3693	4791
	(10509)	(27219)	(0.0)	(0.49)	(24.59)	(23.93)	(3825)	(5029)	(2417)	(3213)	(2361)	(2800)
	185492	46682	185492	46682	149536	43845	81500	24775	98689	29466	90215	27998
Hispanic Men	2442	37682	0.0	0.47	38.88	63.74	8972	11102	6245	6807	5262	5427
	(9542)	(27984)	(0.0)	(0.5)	(25.68)	(24.07)	(5345)	(6226)	(3531)	(4016)	(3348)	(3394)
	182716	37327	182716	37327	138873	35142	81085	19272	96281	23157	88094	21660
White Women	7214	55449	0.0	0.74	51.72	72.88	7353	10923	4845	6682	3896	5164
	(16734)	(29681)	(0.0)	(0.44)	(26.09)	(20.57)	(4936)	(6161)	(3074)	(3905)	(2753)	(3270)
	207734	110680	207734	110680	175752	104899	93682	55721	125915	73590	111666	69145
White Men	6097	56647	0.0	0.65	53.01	75.11	10547	14068	6859	8237	5556	6318
	(16134)	(31803)	(0.0)	(0.48)	(26.46)	(19.87)	(6430)	(7389)	(4332)	(5125)	(3774)	(4048)
	228288	94523	228288	94523	186148	90273	108431	49445	137468	62306	120851	56882

Differences in the Choice Environment - Information

- School Informativeness is different for Black High School Students
- The proportion of previous cohorts students who attended college, conditional upon school and year, is positively correlated with college attendance Peer Effects
  - This has greater effect if the share is higher from you own ethnic group

Overview

So what are we doing?



$\pi(R)$

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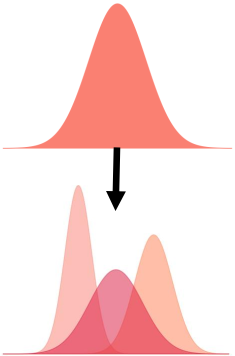

$\pi(R)$

$P(S|R)$

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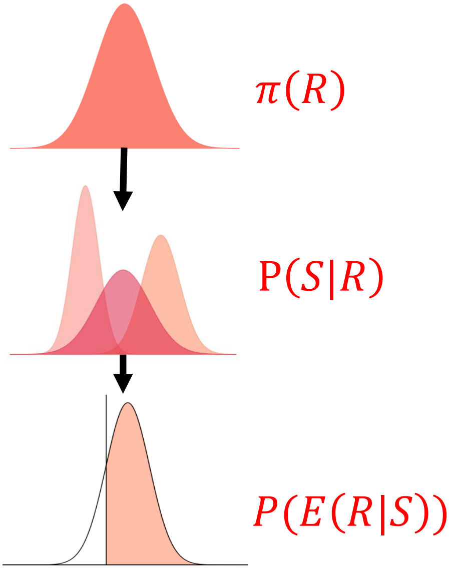

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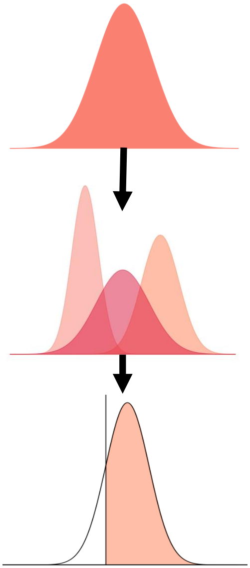

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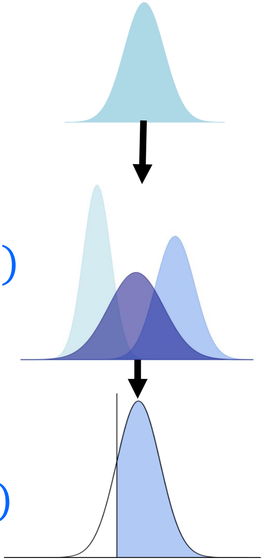
$P(E(R|S))$



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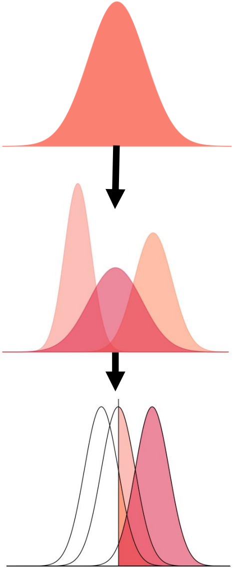
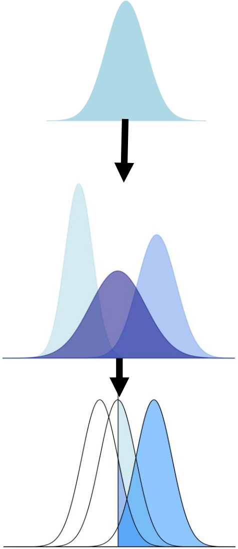


$$\pi(R) \longleftrightarrow \pi(R)$$

$$\mathrm{P}(S|R) \longleftrightarrow \mathrm{P}(S|R)$$

? ?



Partial Identification

- There are two parts for identification:

  1. Identify the distributions of beliefs and returns
     - Identification of the Roy Model and the Marginal Treatment Effects
  2. Given this distribution, construct the identified set of the parameters of interest
     - A tractable characterization of the set of identified parameters of interest

Identification of the parameters of interest

- Assume we observe the joint distribution of returns and beliefs for group b: $\phi_b(\mathcal{R}, m_{\mathcal{R}}(s))$

- To identify $\tilde{P}_I^c$, Let

$$\mathcal{C}(\phi_b(\mathcal{R}, m_{\mathcal{R}}), \pi_a) = \left\{ \tilde{\phi}(\mathcal{R}, m_{\mathcal{R}}) \in \Delta(\mathcal{R}, cl(\mathcal{R})) \middle| \exists \mathcal{S} \text{ s.t} \right. \\ \pi_b(\mathcal{R})\mathcal{P}_{\mathcal{S},\pi_b}(m_{\mathcal{R}}|\mathcal{R}) = \phi_b(\mathcal{R}, m_{\mathcal{R}}), \\ \left. \pi_a(\mathcal{R})\mathcal{P}_{\mathcal{S},\pi_a}(m_{\mathcal{R}}|\mathcal{R}) = \tilde{\phi}(\mathcal{R}, m_{\mathcal{R}}) \right\}$$

- which is the the set of joint distributions, $\tilde{\phi}(\mathcal{R}, m_{\mathcal{R}})$, that can be induced by an information structure $\mathcal{S}$, where π_a, and $\mathcal{S}$ is restricted to be an information structure that can induce $\phi_b(\mathcal{R}, m_{\mathcal{R}})$ with π_b

Identification of the parameters of interest

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\begin{aligned}
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& \pi_b(\mathcal{R}) \mathcal{P}_{\mathcal{S}, \pi_b}(m_{\mathcal{R}} | \mathcal{R}) = \phi_b(\mathcal{R}, m_{\mathcal{R}}), \\
& \pi_a(\mathcal{R}) \mathcal{P}_{\mathcal{S}, \pi_a}(m_{\mathcal{R}} | \mathcal{R}) = \tilde{\phi}(\mathcal{R}, m_{\mathcal{R}}) \Big\}
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$$\boxed{\pi_b(\mathcal{R})\mathcal{P}_{\mathcal{S},\pi_b}(m_\mathcal{R}|\mathcal{R}) = \phi_b(\mathcal{R}, m_\mathcal{R})},$$
$$\left. \pi_a(\mathcal{R})\mathcal{P}_{\mathcal{S},\pi_a}(m_\mathcal{R}|\mathcal{R}) = \tilde{\phi}(\mathcal{R}, m_\mathcal{R}) \right\}$$

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Partial Identification of the parameters of interest

- We can show that the set is equal to the set

$$\mathcal{M}(\phi_b(\mathcal{R}, m_\mathcal{R}), \pi_a) = \Bigg\{ \tilde{\phi}(\mathcal{R}, m_\mathcal{R}) \in \Delta(\mathcal{R}, cl(\mathcal{R})) \Bigg| \; \tilde{\phi}(\mathcal{R}, m_\mathcal{R}) = \int_{m_{\mathcal{R},b}} \frac{\pi_a(\mathcal{R})}{\pi_b(\mathcal{R})} \mathcal{Q}(\mathcal{R}, m_{\mathcal{R},b}, m_R) dm_{\mathcal{R},b}, \; \mathcal{Q} \text{ satisfies } (1), (2), (3) \Bigg\}$$

1. $\int_{m_\mathcal{R}} \mathcal{Q}(\mathcal{R}, m_{\mathcal{R},b}, m_\mathcal{R}) dm_\mathcal{R} = \phi(\mathcal{R}, m_{\mathcal{R},b})$ (Data Match)
2. $\forall m_{\mathcal{R},b}, m_\mathcal{R} \quad m_{\mathcal{R},b} = arg \min_m \int_\mathcal{R} (\mathcal{R} - m)^2 \mathcal{Q}(\mathcal{R}, m_{\mathcal{R},b}, m_\mathcal{R}) d\mathcal{R}$ (BC b)
3. $\forall m_{\mathcal{R},b}, m_\mathcal{R} \quad m_\mathcal{R} = arg \min_m \int_\mathcal{R} (\mathcal{R} - m)^2 \frac{\pi_a(\mathcal{R})}{\pi_b(\mathcal{R})} \mathcal{Q}(\mathcal{R}, m_{\mathcal{R},b}, m_R) d\mathcal{R}$ (BC a)

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Identification of $\phi(\mathcal{R}, m_{\mathcal{R}})$

- We assume that High School Graduates want to maximize income
- In general we can't observe the joint distribution of potential outcomes, we therefore we impose restrictions on the information high school graduates have and the labor market structure

Identification of $\phi(\mathcal{R}, m_{\mathcal{R}})$

- Let $D = \mathbb{1}\{E[\mathcal{R}|s] \geq 0\}$

- Assumptions on the labor market structure
  - Workers are be characterised by a continuum of types $t \in \mathcal{T}$
  - Wages are set by

$$w_{i,a} = D(\alpha_1(t) + \epsilon^1_{i,a}) + (1 - D)(\alpha_0(t) + \epsilon^0_{i,a})$$

  - We impose the additional assumptions on the labor market structure
    1. Types are invariant to treatment
    2. α_1 and α_0 are increasing functions (might be relaxed if types are discrete)
    3. There exists a and a' such that $\epsilon_{i,a}$, $\epsilon_{i,a'}$ and t are mutually independent (might be relaxed to conditional independence)

- Assumptions on the information structure
  - for all a we have

$$s \perp\!\!\!\perp \epsilon^1_{i,a}, \epsilon^0_{i,a}$$

Identification of $\phi(\mathcal{R}, m_{\mathcal{R}})$

- Let Z be the school distance to college we assume:
  1. $H_{i,t}, \epsilon_1, \epsilon_1, t \perp\!\!\!\perp Z|X$
  2. $S \perp\!\!\!\perp Z|t, X$
  3. Z is continuously distributed on $\mathcal{Z} \subseteq \mathbb{R}$ with density $h(Z)$
  4. $E[\mathcal{R}(t, \epsilon_1, \epsilon_0)|s]$ continuously distributed
  5. $C(z)$ is differentiable and covers the support of $E[\mathcal{R}(t, \epsilon_1, \epsilon_0)|s]$

Identification of $\phi(\mathcal{R}, m_{\mathcal{R}})$

- Main Argument:
  1. $\mathrm{P}(E[\mathcal{R}|s]$ is identified using the usual arguments of the identification of seprable discrete choice models
  2. Restrictions on the labor market allows us to identify

     $$\Pr(\alpha_1|D=1, P(z)), \quad \Pr(\alpha_0|D=0, P(z))$$

     using Kotlarski's Lemma (1967)
  3. Carneiro and Lee (2009) allows us to identify

     $$\Pr(\alpha_1|E[\mathcal{R}|s]), \quad \Pr(\alpha_0|E[\mathcal{R}|s])$$

  4. Using the fact that α_1 and α_0 are increasing we can identify

     $$\Pr(\alpha_1 - \alpha_0|E[\mathcal{R}|s])$$

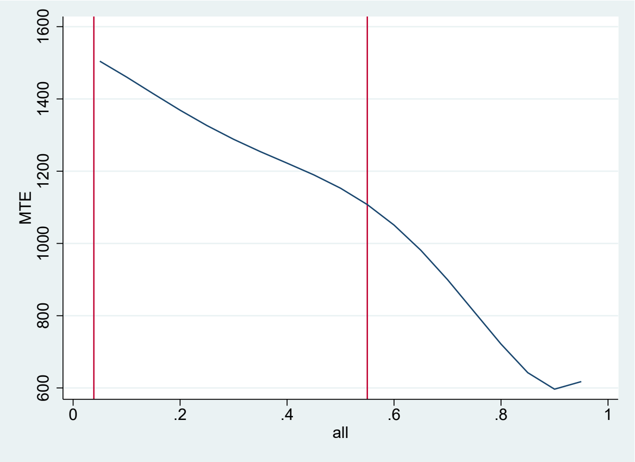
Instrument Validity

	Test Factor	Math	Reading
All	-0.00042	0.00022	-0.00041
	(0.00171)	(0.00184)	(0.00107)
Black Women	-0.0005	0.00169	-0.00156
	(0.00262)	(0.00283)	(0.00191)
Black Men	-0.00076	0.00316	-0.00331
	(0.00265)	(0.00269)	(0.00208)
Hispanic Women	-0.00182	-0.00083	-0.00102
	(0.0024)	(0.0027)	(0.00172)
Hispanic Men	0.00231	0.00434	-0.00147
	(0.00248)	(0.00258)	(0.00177)
White Women	-0.00232	-0.00173	-0.00034
	(0.00231)	(0.00238)	(0.00157)
White Men	-0.00107	-0.00155	0.0011
	(0.00232)	(0.00226)	(0.00164)
School Chars	V	V	V
Neigborhood Chars	V	V	V
Individual Chars	V	V	V

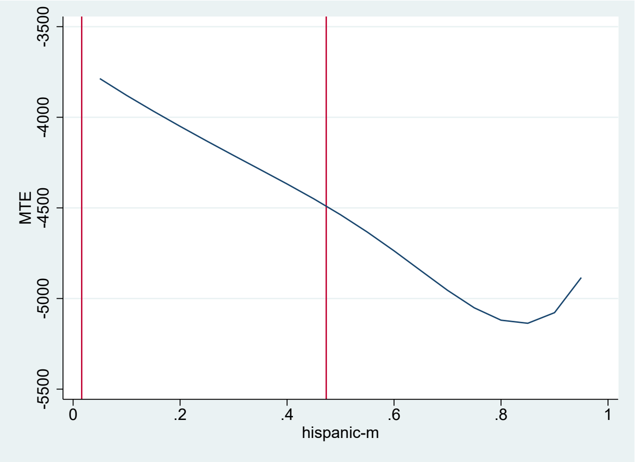
First Stage and Reduced Form

	All	Black Women	Black Men	Hispanic Women	Hispanic Men	White Women	White Men
College	-0.00154	-0.00042	1e-05	-0.00231	-0.00232	-0.00112	-0.00088
	(0.00018)	(0.00052)	(0.00052)	(0.00031)	(0.00029)	(0.00026)	(0.00023)
Avg. Wage 12-14	-2.11	-5.36	-0.66	-7.98	6.71	-6.43	0.97
	(2.02)	(4.61)	(6.8)	(2.88)	(4.53)	(2.84)	(3.98)
Avg. Wage 1-14	-0.95	-5.09	0.73	-4.9	3.15	-3.37	2.65
	(1.17)	(2.7)	(3.82)	(1.65)	(2.78)	(1.65)	(2.3)
Avg. Wage 1-14 (with Missing)	-0.42	-5.9	1.45	-4.96	1.0	-1.33	4.55
	(1.06)	(2.52)	(3.71)	(1.63)	(2.69)	(1.43)	(2.15)

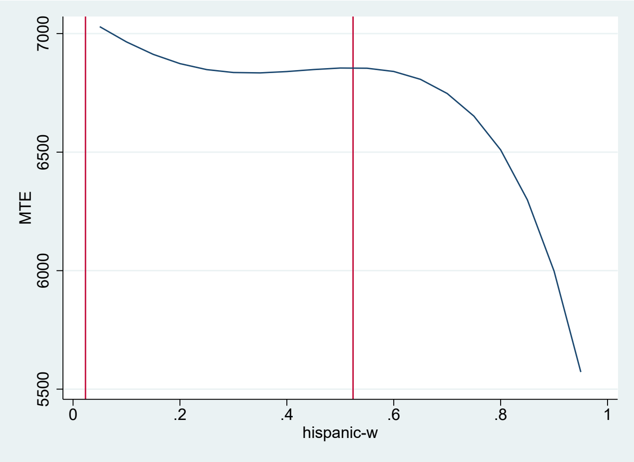
Nonparametric MTEs



Nonparametric MTEs



Nonparametric MTEs



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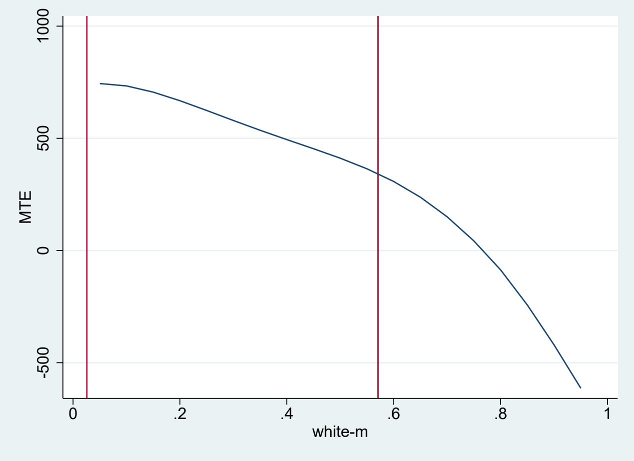

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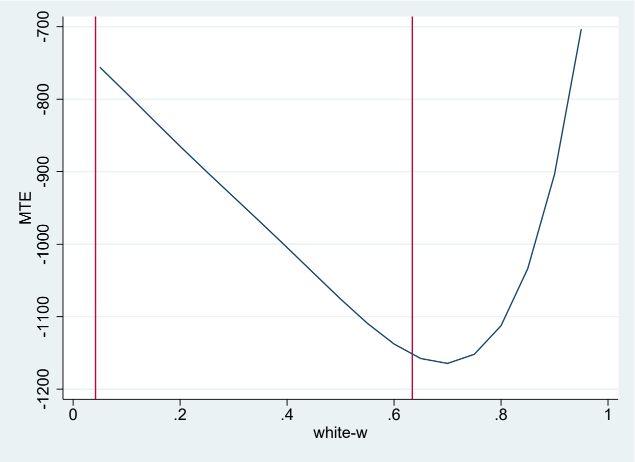
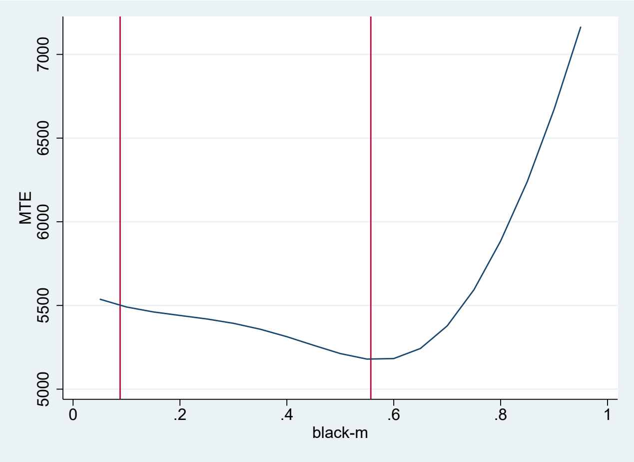


Nonparametric MTEs



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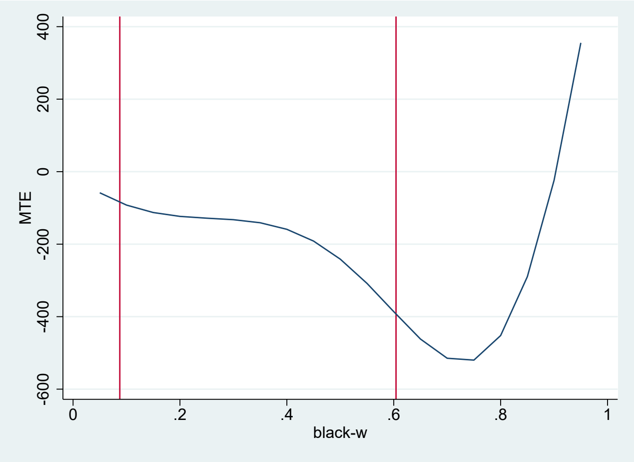


Conclusions

- In this project I introduced a new decomposition methods that decomposes the observed gaps in college attendance to
  - Differences in Returns Distribution
  - Differences in the Information on these returns
  - Differences in known costs
- Next Step:
  - Finish estimating the model
  - Provide more reduce form evidence on differences in the informative of signals

thx.

appendix

Carneiro and Lee (2009)

- Following Carneiro and Lee (2009) we can identify $Y_1|\eta$

$$
\begin{aligned}
E[\mathbb{1}\{Y_1 \leq t\}|E[Y_1 - Y_0|s] = c(Z)] &= E[\mathbb{1}\{Y \leq t\}|P(Z) = p, D = 1] \\
&\quad + p\frac{\partial E[\mathbb{1}\{Y \leq t\}|P(Z) = p, D = 1]}{\partial p}
\end{aligned}
$$

- Similarly, we can identify $Y_0|\eta$
- We therefore can identify $\mathrm{P}(y_1, \eta)$ and $\mathrm{P}(y_0, \eta)$
- Under these assumptions, we can construct $P(Y_1 - Y_0|\eta)$

Differences in the Choice Environment - School informativeness

	2003-2007		2007-2011	
	High School	College	High School	College
All	0.104	0.057	0.117	0.067
Men	0.068	0.059	0.081	0.068
Women	0.061	0.051	0.065	0.056
Black	0.041	0.041	0.038	0.033
Hispanic	0.112	0.039	0.127	0.046
Whites	0.102	0.056	0.111	0.061

Table: Out of sample $R_g^2 = 1 - \frac{E[(wage - E[wage|x,g,D])^2|D,g]}{E[(wage - E[y|g])^2|D,g]}$

with school fixed effect

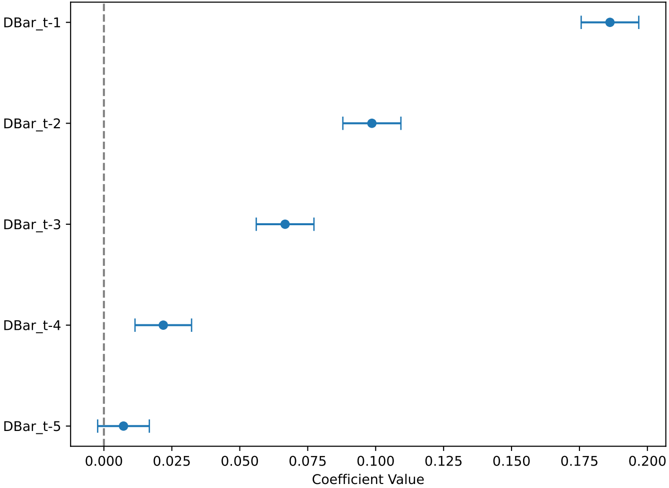
Differences in the Choice Environment - Peer Effects

- We explore how informative are previous cohort on college attendance decisions
- To do so we estimate the following TWFE regression

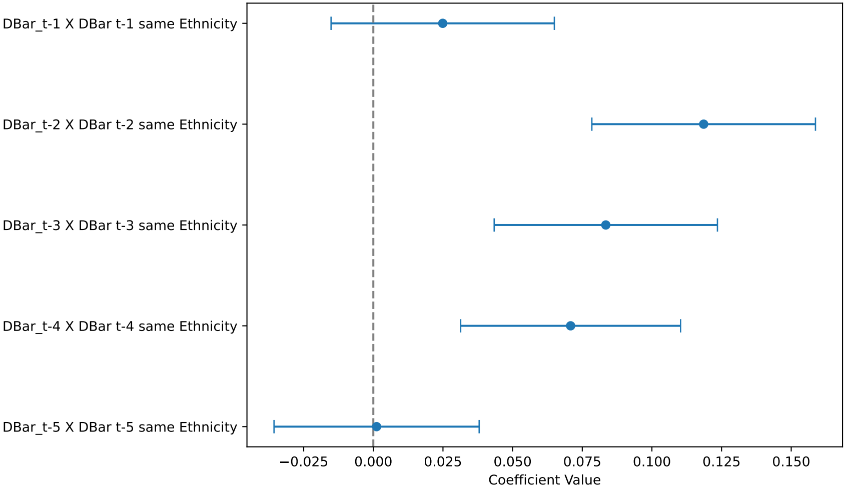
$$D_i = \alpha_t + \gamma_s + \sum_{j=1}^{j=5} \beta_{t-j} \bar{D}_{s,t-j} + X_i \gamma + \epsilon_i$$

  - D_i - Decision whether to attend college
  - α_t γ_s are school and cohort fixed effects
  - $\bar{D}_{s,t-j}$ the share of people who went to college from school s at year $t-j$

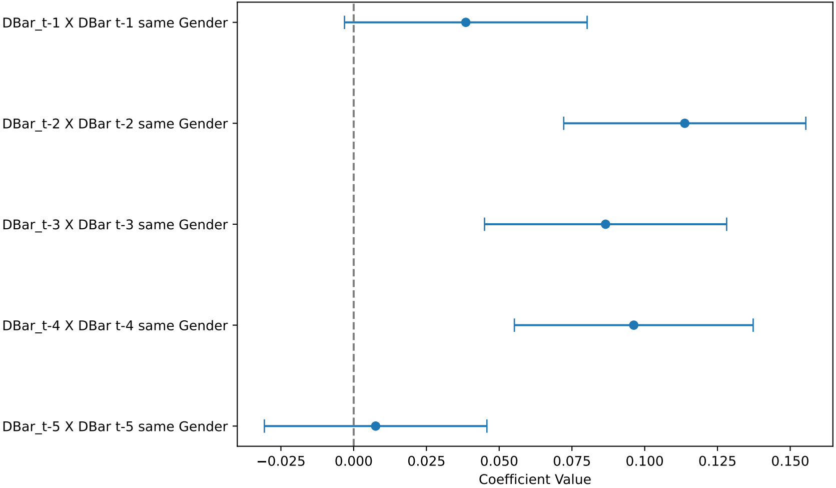
Changing Environment - Peer Effects



Changing Environment - Peer Effects



Changing Environment - Peer Effects



Descriptive Statistics

	College	No College
Men	0.45	0.51
	(0.5)	(0.5)
Black	0.14	0.14
	(0.35)	(0.34)
Hispanic	0.23	0.38
	(0.42)	(0.49)
White	0.63	0.48
	(0.48)	(0.5)
Avg. Wage 1-2 Years After HG	1698.0	2548.0
	(1289.0)	(1771.0)
Avg. Wage 3-4 Years After HG	2933.0	3681.0
	(2217.0)	(2579.0)
Avg. Wage 5-7 Years After HG	6023.0	4891.0
	(3922.0)	(3308.0)
Avg. Wage 8-10 Years After HG	8446.0	6197.0
	(5200.0)	(4380.0)
Avg. Wage 1-10 Years After HG	5414.0	4522.0
	(3400.0)	(2943.0)
Avg. Wage 1-10 Years After HG (Including Unemployment)	4187.0	3681.0

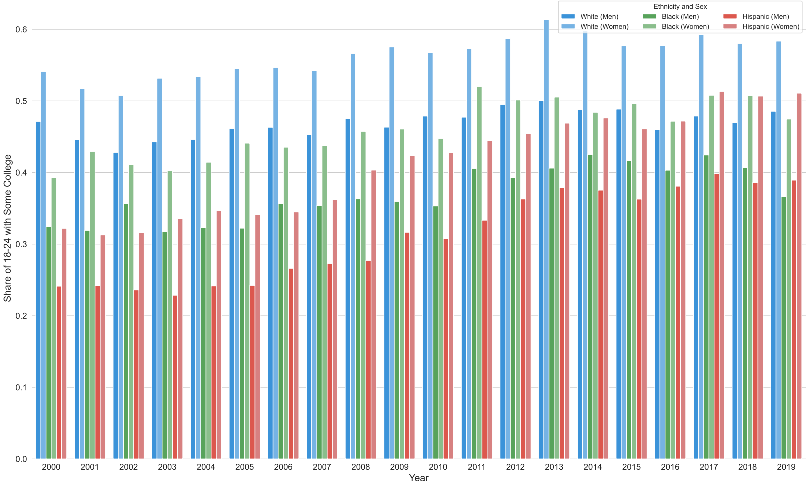
Descriptive Statistics

	College	No College
Distance to College	11.58	12.59
	(15.17)	(16.32)
High School Graduate	1.0	0.9
	(0.06)	(0.3)
Std. Reading Score	68.3	46.36
	(25.23)	(29.4)
Std. Math Score	66.66	44.07
	(25.27)	(27.98)
Std. Writing Score	68.46	46.15
	(25.47)	(28.92)
Total Cost	62402.0	5287.0
	(34958.0)	(16067.0)
Grants	14105.0	1048.0
	(19975.0)	(5026.0)

Out of sample with school Fixed Effects

	2003-2007		2007-2011	
	High School	College	High School	College
All	0.097	0.054	0.109	0.068
Men	0.061	0.05	0.078	0.073
Women	0.058	0.052	0.066	0.065
Black	0.043	0.038	0.04	0.027
Hispanic	0.109	0.04	0.119	0.044
white	0.096	0.05	0.108	0.061

Share of College Attenders over the years



Cost of College Decomposition