Discrimination

Urban Economics

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Residential Location Patterns

- Recent research has shown that the neighborhood where people live has important implications for short-run, long-run and even intergenerational outcomes.
- Residential choice can be driven by multiple factors:
  - Neighborhood/Housing/Amenities preferences
  - Disparities in income
  - Racial discrimination
  - Others: Information, Taxes/subsidies, Labor market opportunities, etc...

Discrimination

- Black people are less likely to find a house, be employed, more likely to be arrested by the police, and more likely to be incarcerated.
- Women are very scarce at the top echelon of the corporate, academic and political ladders despite the fact that (in rich countries at least) they get better grades in school and are more likely to graduate from college.
- While many in the media and public opinion circles argue that discrimination is a key force in driving these patterns, showing that it is actually the case is not simple.
- Indeed, it has proven elusive to produce convincing evidence of discrimination using standard regression analysis methods and observational data, in the sense in which we define discrimination: members of a minority group (women, Blacks, Muslims, immigrants, etc.) are treated differentially (less favorably) than members of a majority group with otherwise identical characteristics in similar circumstances.

Measuring Discrimination in the Field

- Earlier research on discrimination focused on individual-level outcome regressions, with discrimination estimated from the "minority" differential that remains unexplained after including as many proxies as possible.
- The limitations of this approach are well-known. The interpretation of the estimated "minority" coefficient is problematic due to OVB.
- The traditional answer has been to saturate the regression with as many relevant variables as are available.

Measuring Discrimination in the Field

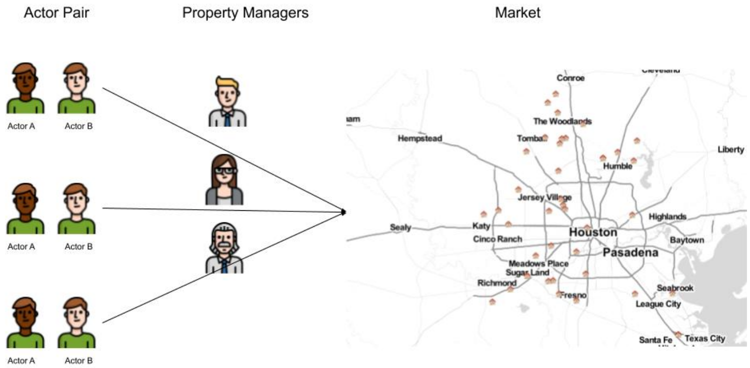
- But, of course, ensuring that the researcher observes all that the decision-maker observes is a hopeless task.
- Saturating also changes the interpretation and may introduce “bad controls” (Guryan and Charles, 2013)
- Audit and correspondence methodologies were developed to address these core limitations of the regression approach to measuring discrimination.

Experiment Set up: Identifying Housing Discrimination

Audit Studies – HDS 1977, 1989, 2000, 2012

1. Paired-tester: Blind-matched actors trained to be identical in every respect except for characteristic of interest (e.g., race)
2. Send teams of actors (white & minority) to real estate offices and rental management companies and record differential treatment

Traditional Way: Audit



Experiment Set up: Identifying Housing Discrimination

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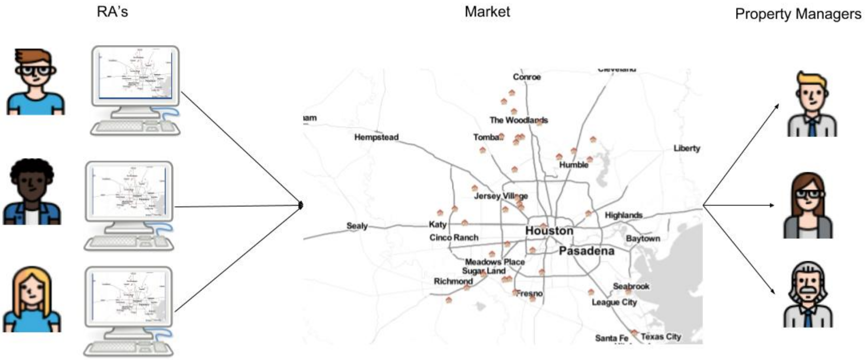
1. Paired-tester: Blind-matched actors trained to be identical in every respect except for characteristic of interest (e.g., race)
2. Send teams of actors (white & minority) to real estate offices and rental management companies and record differential treatment
3. Strong evidence of discrimination in previous reports (Turner et al 2002, 2012)
    1. Most blatant forms (e.g., refusal to show a property) to have declined over time
    2. Most persistent form: Steering (Ondrich et al 1998, 2003, 2005, Galster and Godfrey 2005)
        - Minority buyers are steered into neighborhoods with higher exposures to emissions from TRI facilities and Superfund sites (Christensen and Timmins, 2018)
4. Largest sample in 2012, 28 cities, 4,838 properties

Would a “Rose” by any other name get fewer callbacks?

- Correspondence Research Design (Bertrand and Mullainathan, 2004)
  1. Create fictitious identities
  2. Interact with retailers, employers, or housing brokers
  3. Randomly vary racial trait

Traditional Way: Correspondence



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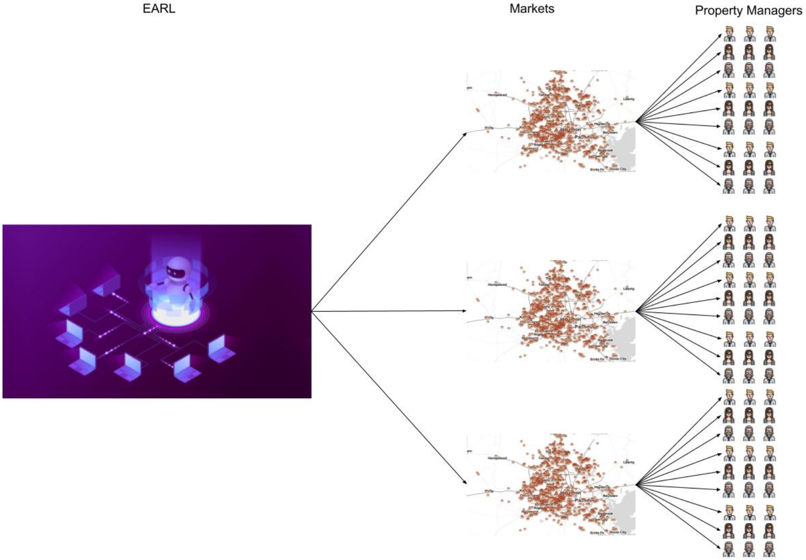
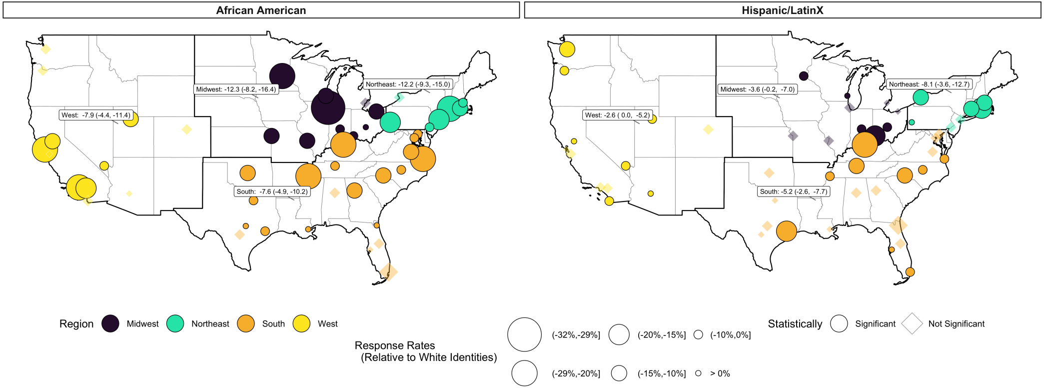
- Correspondence Research Design (Bertrand and Mullainathan, 2004)
  1. Create fictitious identities
  2. Interact with retailers, employers, or housing brokers
  3. Randomly vary racial trait
- Advantages of Correspondence Studies (vs Audit Designs)
  1. Correspondence studies give more control to the analyst (Bertrand, 2017)
  2. Hard to control for all differences between paired testers (Siegelman, 1993; Heckman, 1998)
  3. Less expensive (large, geographically targeted samples)

(Aside) What we do: EARL

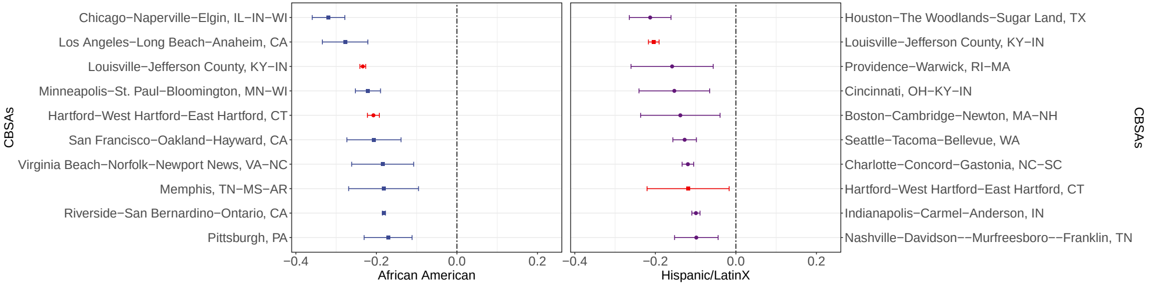


The Geography of Discriminatory Behavior in the US

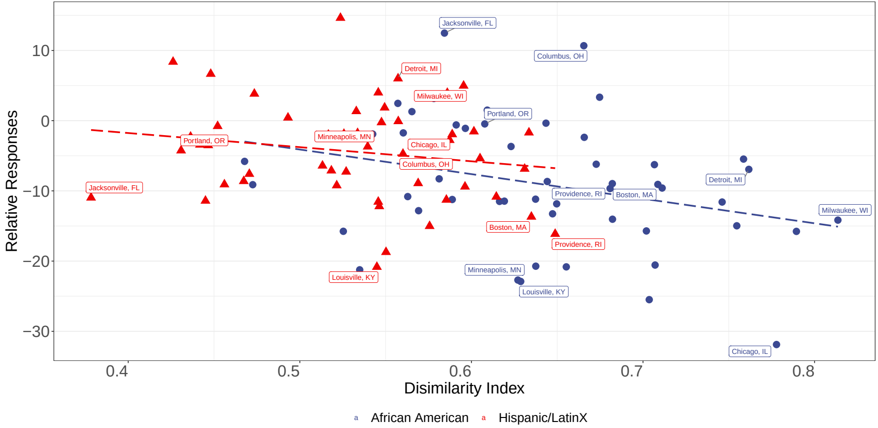
Figure 1: Response Rates CBSAs



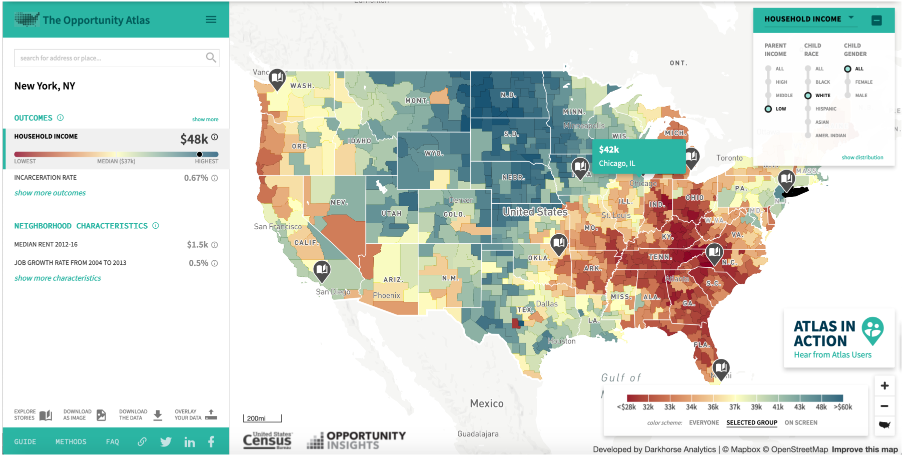
The Geography of Discriminatory Behavior in the US: The "Not" Top Ten



Discriminatory Behavior and Segregation



Discriminatory Behavior and the Income Mobility Gap



Source: https://www.opportunityatlas.org/

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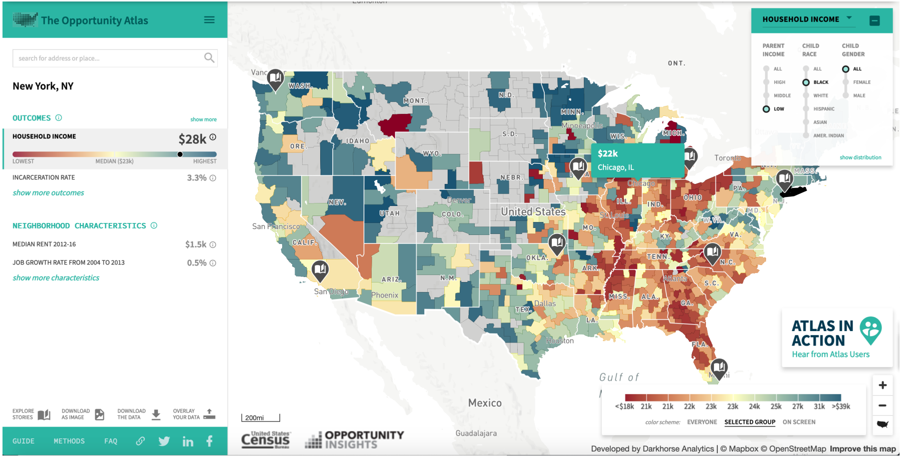

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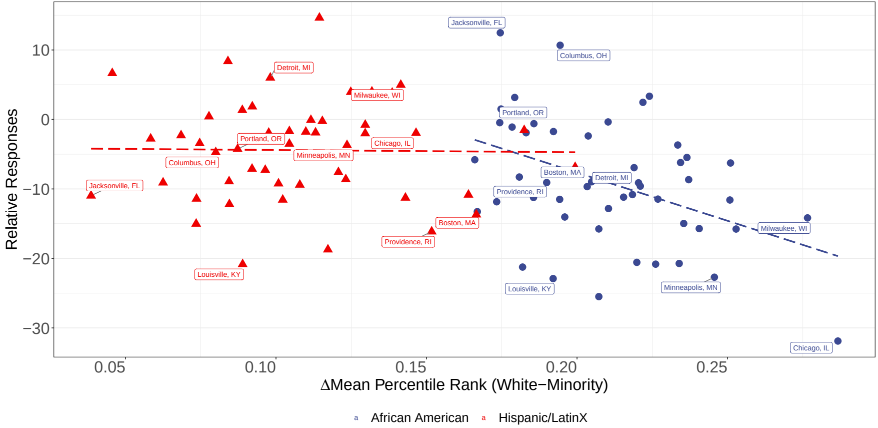


Discrimination: Two theories

- The two workhorse models of discrimination in the economics literature give drastically different answers, particularly with respect to the societal consequences.
  1. Taste based
  2. Statistical Discrimination

Ewens et al. paper

- Test: taste based vs statistical discrimination
- Use vacancy listings on Craigslist.org, across 34 U.S. cities,
- They send inquiry e-mails to 14,000 landlords.
- E-mails have information about the applicants: positive, negative, and no signals beyond race.
  - In the no-signal inquiry, landlords receive e-mails with racial-sounding names as the only signal.
  - In the positive information inquiry, the fictional applicant informs the landlord that she is a nonsmoker with a respectable job.
  - In the negative information inquiry, the applicant tells the landlord she has a below-average credit rating and smokes.

Ewens et al. model set up

- A landlord seeks to maximize the expected utility
- The expected utility derived from each applicant depends on the stream of future rental income (tenant quality) from renting the apartment successfully. Summarized by θ
- Although the rent is preannounced, θ may still vary as a result of default, lease renewal, and so on.
- Hence, the landlord forms a predicted quality $\hat{\theta}_i$ (a random variable) for each applicant and maximizes the expected utility $E[U(\hat{\theta}_i)]$

Ewens et al. model set up

- Four-stage process of matching potential tenants to apartments:
  1. **Inquiry**: An applicant with quality θ selects publicly posted rental units to send cost less inquiries with signal x to landlords.
  2. **Screening**: Given signals $X_T = \{x_1, \ldots, x_T\}$ received from T independent applicants, the landlord forms a set of predicted qualities $\Theta_T = \{\hat{\theta}_1, \ldots, \hat{\theta}_T\}$ and responds to n applicants.
  3. **Interview**: Interviews, which include credit and reference checking, reveal the true quality θ and these have costs.
  4. **Decision**: The candidate with the highest true quality θ is offered the apartment.

Ewens et al. model Statistical Discrimination

- Statistical Discrimination: Utility is **not** race dependent, but is (forecasted) quality dependent

$$E[U(\hat{\theta}_r)] = E[U(\hat{\theta}_{-r})] \tag{1}$$

- when

$$\tilde{\theta}_r = \tilde{\theta}_{-r} \tag{2}$$

Ewens et al. model Statistical Discrimination

- Statistical Discrimination:

$$x_r = \theta_r + \epsilon_r \tag{3}$$

  - $\theta_r \sim N(\mu_r, \sigma_\theta^2)$
  - $E(\theta_r) = \mu_r$
  - $V(\theta_r) = \sigma_\theta^2$
  - $E(\epsilon_r|\theta_r) = 0$
  - $V(\epsilon_r|\theta_r) = \sigma_{\epsilon,r}^2$

Ewens et al. Statistical Discrimination

- Landlord forecasted $\hat{\theta}$ for each race r:

$$\hat{\theta}_r = \hat{\mu}_r^L + \hat{\gamma}_r x_r \tag{4}$$

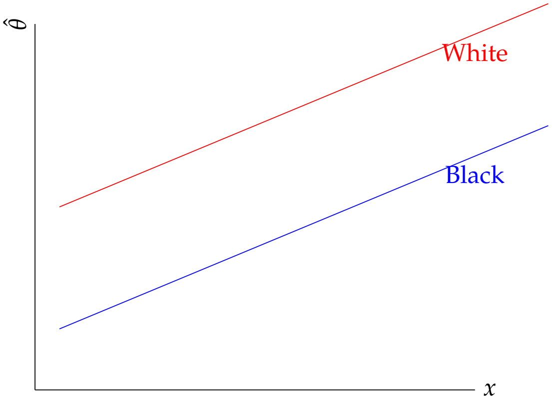
- were

$$\hat{\gamma}_r = \frac{cov(\theta_r, x_r)}{var(x_r)} \tag{5}$$

$$\hat{\mu}_r^L = \bar{\theta}_r - \hat{\gamma}_r \bar{x}_r \tag{6}$$

Ewens et al. Statistical Discrimination

- Landlord forecasting regression for each race r:



Ewens et al. Statistical Discrimination

- Two types of signals
  1. A negative signal $-\tilde{x}^{-} < 0$
  2. A positive signal $\tilde{x}^{+} > 0$
- The mean difference between black and white applicants sending
  - A positive signal is

$$E(\hat{\theta}_B|\tilde{x}^{+}) - E(\hat{\theta}_W|\tilde{x}^{+}) = \hat{\mu}_B^L - \hat{\mu}_W^L - (\hat{\gamma}_B - \hat{\gamma}_W)\,\tilde{x}^{+} \tag{7}$$

  - Negative signal

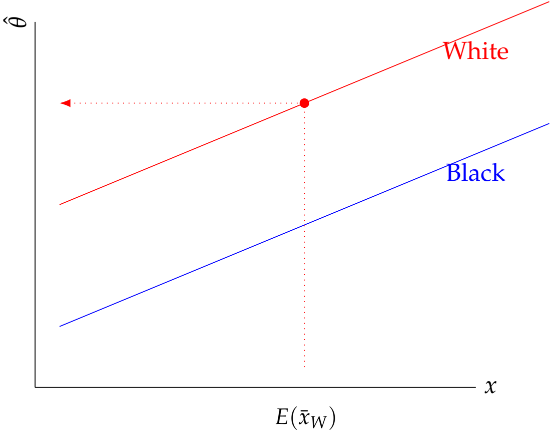
$$E(\hat{\theta}_B| - \tilde{x}^{-}) - E(\hat{\theta}_W| - \tilde{x}^{-}) = \hat{\mu}_B^L - \hat{\mu}_W^L + (\hat{\gamma}_W - \hat{\gamma}_B)\,\tilde{x}^{-} \tag{8}$$

  - The difference

$$E(\hat{\theta}_B - \hat{\theta}_W| - \tilde{x}^{-}) - E(\hat{\theta}_B - \hat{\theta}_W|\tilde{x}^{+}) = (\hat{\gamma}_W - \hat{\gamma}_B)\left(\tilde{x}^{+} + \tilde{x}^{-}\right) \tag{9}$$

Ewens et al. model Statistical Discrimination

- Suppose that $E(\bar{x}_W) > E(\bar{x}_B)$



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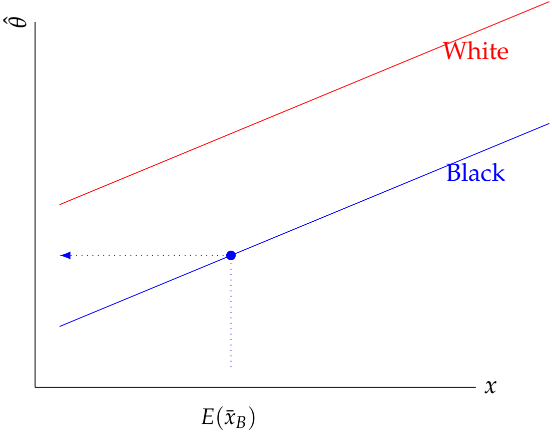

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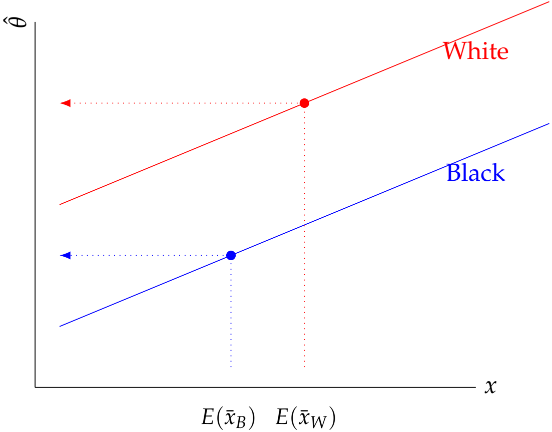
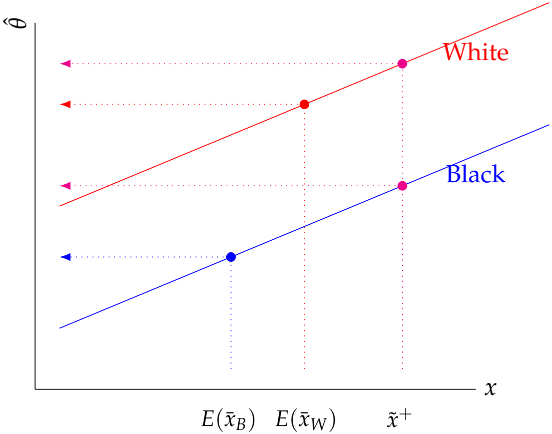


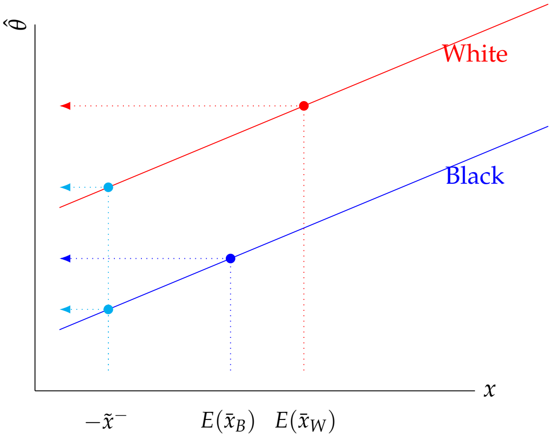
Ewens et al. model Statistical Discrimination

- Suppose that $E(\bar{x_W}) > E(\bar{x}_B)$ and a surprise positive signal $\tilde{x}^+ > E(\bar{x}_W)$



Ewens et al. model Statistical Discrimination

- Suppose that $E(\bar{x_W}) > E(\bar{x}_B)$ and a surprise negative signal $-\tilde{x}^- < E(\bar{x}_B)$



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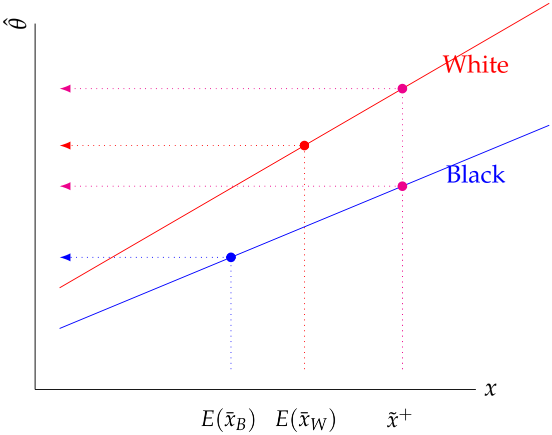

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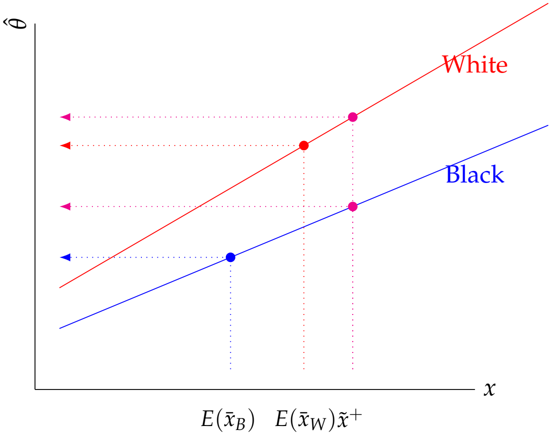

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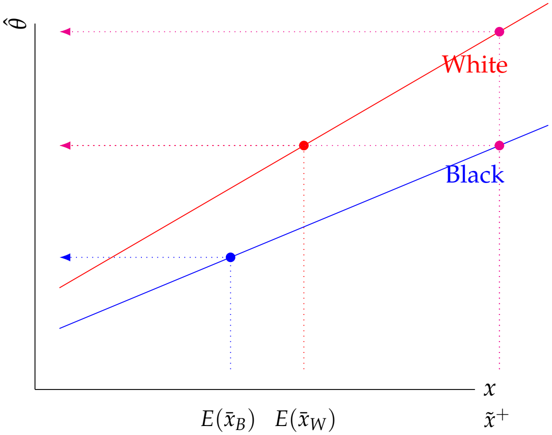

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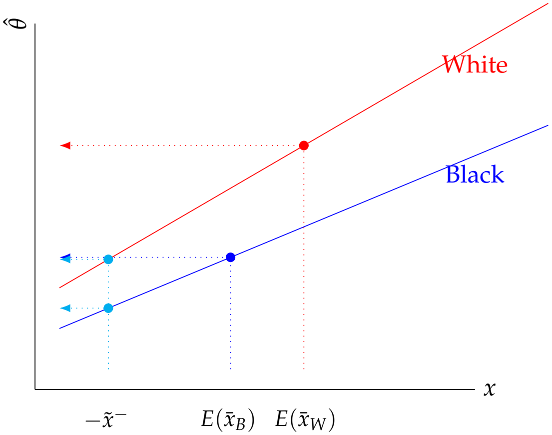

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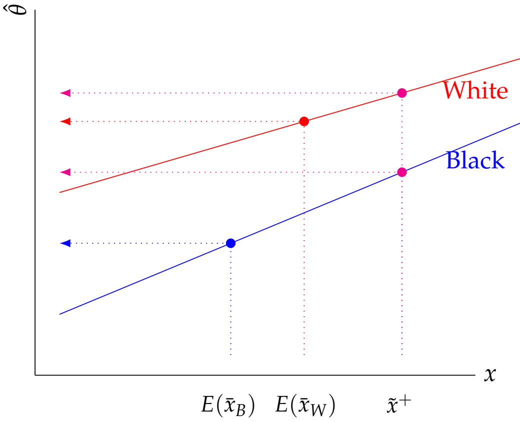

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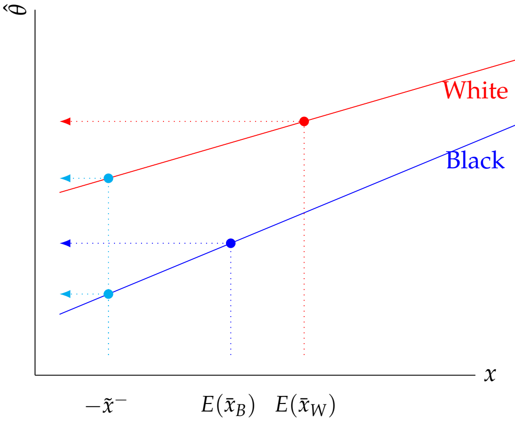


Ewens et al. model Taste Based Discrimination

- Taste Based Discrimination
  - Let a prejudiced landlord predict applicant quality based on a race-independent signal:

$$\hat{\theta}_i = \hat{\mu}^L + \hat{\gamma} x_i \tag{10}$$

  - Now their utility is race dependent.
    - Assume that the landlord exhibits out-group prejudice such that a prejudice parameter, k, discounts the utility derived from an out-group applicant so that

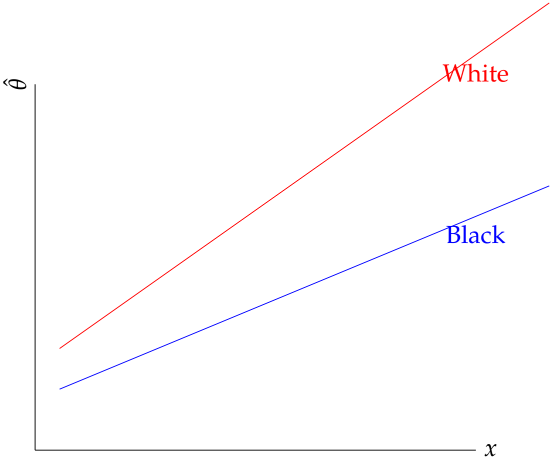
$$E[U(\tilde{\theta}_r)] > E[U(\tilde{\theta}_{-r})] \tag{11}$$

  - when

$$\tilde{\theta}_r = \tilde{\theta}_{-r} \tag{12}$$

Ewens et al. model Taste Based Discrimination

- For example $E[U(\tilde{\theta}_{-r})] = \left(\hat{\mu}^L + \hat{\gamma} x_i\right) k$



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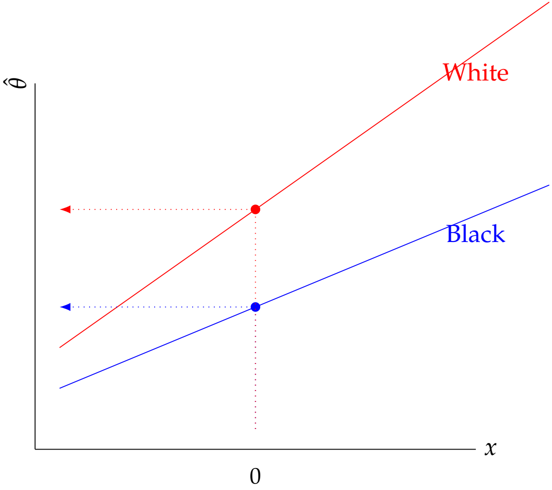

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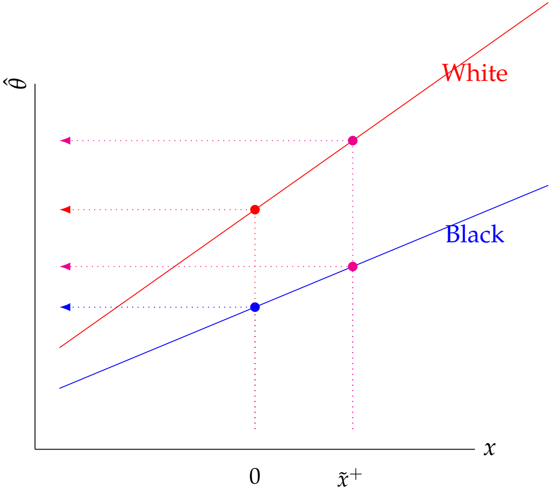

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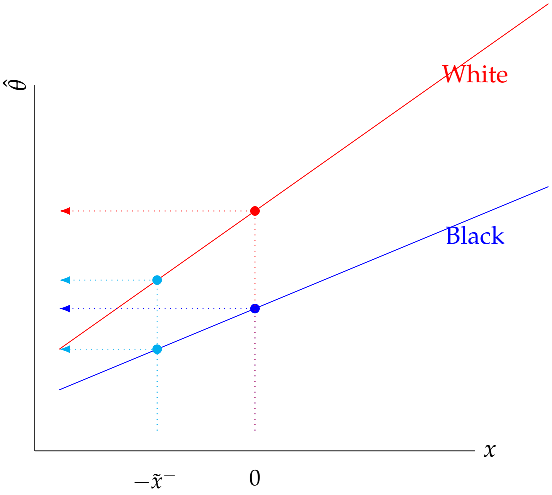

Ewens et al. results

- H1 Stat: On average, a white applicant is more likely to receive a positive response than a black applicant in the no-signal base case
- H1 Taste: On average, a white applicant is more likely to receive a positive response than a black applicant in the no-signal base case.

$$R_i = \alpha_W + \alpha_B B_i + u_i$$

Ewens et al. results

TABLE 6.—DIFFERENTIAL TREATMENT BY RACE AND INFORMATIONAL SIGNALS

	(1)	(2)	(3)	(4)
Black	−0.093***			
	(0.015)			
Positive Information				
Positive Information × Black				
Negative Information				
Negative Information × Black				
% Black				
Black × %Black				
Positive Information × %Black				
Positive Information × Black × %Black				
Negative Information × %Black				
Negative Information × Black × %Black				
Constant	0.581***			
	(0.012)			
Omitted category	White Baseline			
Observations	4,226			
R^2	0.009			

See definitions of variables in the notes to tables 2 and 3. Robust standard errors clustered by neighborhood reported in parentheses. Columns 1–4 correspond to hypotheses 1 and 1A, 2 and 2A, 3 and 3A, and 4 and 4A, respectively. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

Ewens et al. results

- H2 Stat: On average, the positive response gap between white and black applicants is larger with a positive signal sent than with a negative signal sent.
- H2 Taste: On average, the response gap between white and black applicants when a positive signal is sent is larger than the response gap between white and black applicants when a negative signal is sent.

$$R_i = \alpha_{PW} + \alpha_{PB} B_i + \alpha_{NW} N_i + \alpha_{NB} (N_i \times B_i) + u_i \tag{13}$$

Ewens et al. results

Table 6.—Differential Treatment by Race and Informational Signals

	(1)	(2)	(3)	(4)
Black	−0.093***	−0.092***		
	(0.015)	(0.012)		
Positive Information				
Positive Information × Black				
Negative Information		−0.377***		
		(0.013)		
Negative Information × Black		0.044**		
		(0.018)		
% Black				
Black × %Black				
Positive Information × %Black				
Positive Information × Black × %Black				
Negative Information × %Black				
Negative Information × Black × %Black				
Constant	0.581***	0.619***		
	(0.012)	(0.009)		
Omitted category	White	White		
	Baseline	Positive information		
Observations	4,226	10,011		
R^2	0.009	0.128		

See definitions of variables in the notes to tables 2 and 3. Robust standard errors clustered by neighborhood reported in parentheses. Columns 1–4 correspond to hypotheses 1 and 1A, 2 and 2A, 3 and 3A, and 4 and 4A, respectively. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Ewens et al. results

- H3 Stat: On average, negative information will shrink the racial gap observed in the base case, but positive information will have an ambiguous effect on the racial gap observed in the base case.
- H3 Taste: On average, negative information will unambiguously narrow the racial gap observed in the no-signal base case, but positive information will unambiguously widen the racial gap observed in the base case.

$$R_i = \beta_W + \beta_B B_i + \beta_P P_i + \beta_{PB}(P_i \times B_i) + \beta_{NW} N_i + \beta_{NB}(N_i \times B_i) + u_i \tag{14}$$

Ewens et al. results

TABLE 6.—DIFFERENTIAL TREATMENT BY RACE AND INFORMATIONAL SIGNALS

	(1)	(2)	(3)	(4)
Black	−0.093***	−0.092***	−0.093***	
	(0.015)	(0.012)	(0.015)	
Positive Information			0.039***	
			(0.013)	
Positive Information × Black			0.001	
			(0.019)	
Negative Information		−0.377***	−0.338***	
		(0.013)	(0.016)	
Negative Information × Black		0.044**	0.045**	
		(0.018)	(0.020)	
% Black				
Black × %Black				
Positive Information × %Black				
Positive Information × Black × %Black				
Negative Information × %Black				
Negative Information × Black × %Black				
Constant	0.581***	0.619***	0.581***	
	(0.012)	(0.009)	(0.012)	
Omitted category	White	White	White	
	Baseline	Positive information	Baseline	
Observations	4,226	10,011	14,237	
R^2	0.009	0.128	0.100	

See definitions of variables in the notes to tables 2 and 3. Robust standard errors clustered by neighborhood reported in parentheses. Columns 1–4 correspond to hypotheses 1 and 1A, 2 and 2A, 3 and 3A, and 4 and 4A, respectively. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

Ewens et al. results

- H4 Stat: Positive treatment should shrink the racial gap in positive responses relatively more in predominantly black neighborhoods. Conversely, negative treatment will shrink the racial gap in predominantly white neighborhoods, but not necessarily in predominantly black neighborhoods.
- H4 Taste: As the share of black residents in a neighborhood S_B increases, the response gap between white and black applicants in the base case decreases. In a majority black neighborhood, a surprising positive signal will unambiguously benefit a black applicant relatively more than a white applicant, while a surprising negative signal will unambiguously hurt a black applicant relatively more than a white applicant.

$$
\begin{aligned}
R_i = \beta_W + \beta_{SW} S_{Bi} + \beta_B B_i + \beta_{SB}(S_{Bi} \times B_i) + \beta_{PW} P_i & \quad (15) \\
+ \beta_{SPW}(S_{Bi} \times P_i) + \beta_{PB}(P_i \times B_i) & \quad (16) \\
+ \beta_{SPB}(S_{Bi} \times P_i \times B_i) + \beta_{NW} N_i + \beta_{SNW}(S_{Bi} \times N_i) & \quad (17) \\
+ \beta_{NB}(N_i \times B_i) + \beta_{SNB}(S_{Bi} \times N_i \times B_i) + u_i & \quad (18)
\end{aligned}
$$

Ewens et al. results

TABLE 6.—DIFFERENTIAL TREATMENT BY RACE AND INFORMATIONAL SIGNALS

	(1)	(2)	(3)	(4)
Black	−0.093***	−0.092***	−0.093***	−0.084***
	(0.015)	(0.012)	(0.015)	(0.019)
Positive Information			0.039***	0.053***
			(0.013)	(0.017)
Positive Information × Black			0.001	−0.032
			(0.019)	(0.025)
Negative Information		−0.377***	−0.338***	−0.347***
		(0.013)	(0.016)	(0.018)
Negative Information × Black		0.044**	0.045**	0.044*
		(0.018)	(0.020)	(0.026)
% Black				0.014
				(0.067)
Black × %Black				−0.077
				(0.099)
Positive Information × %Black				−0.118
				(0.082)
Positive Information × Black × %Black				0.267**
				(0.125)
Negative Information × %Black				0.078
				(0.093)
Negative Information × Black × %Black				0.009
				(0.130)
Constant	0.581***	0.619***	0.581***	0.579***
	(0.012)	(0.009)	(0.012)	(0.014)
Omitted category	White	White	White	White
	Baseline	Positive information	Baseline	Baseline
Observations	4,226	10,011	14,237	14,237
R^2	0.009	0.128	0.100	0.101

See definitions of variables in the notes to tables 2 and 3. Robust standard errors clustered by neighborhood reported in parentheses. Columns 1–4 correspond to hypotheses 1 and 1A, 2 and 2A, 3 and 3A, and 4 and 4A, respectively. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.