Discrimination

Urban Economics

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April 26, 2022

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.

Discrimination in Housing Markets

- Recent research has shown that the neighborhood where people live has important implications for short-run, long-run and even intergenerational outcomes.
- Observational data make it difficult to disentangle the multiple factors involved in the residential location choice.
  - Disparities in income, differences in information about neighborhood attributes (Banzhaf et al., 2019, Aliprantis et al., 2019, Logan, 2011),
  - Labor market opportunities (Hausman and Stolper, 2019, Currie and Walker, 2011), and
  - Housing/neighborhood preferences that also affect residential sorting behavior (Depro et al., 2015, Banzhaf and Walsh, 2013).
  - Racial discrimination (Ewens et al., 2014, Carlsson and Eriksson, 2014, Hanson and Hawley, 2011, Ahmed and Hammarstedt, 2008, Christensen and Timmins, 2018, Christensen et al., 2020).

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

Discrimination: Two theories

Taste based

- The first model, developed in Becker (1957) for the context of the labor market, some employers have a distaste for hiring members of the minority group. They may indulge this distaste by refusing to hire, say, Blacks or, if they do hire them, paying them less than other employees for the same level of productivity.
- If the fraction of discriminating employers in the economy is sufficiently large, a wage differential will emerge in equilibrium between otherwise identically productive minority and majority employees and this wage differential will be a reflection of the distaste parameter of the marginal employer for minority workers (Becker, 1957; Charles and Guryan, 2008).
- By electing to not hire minority workers, infra-margin racist employers will experience lower profits.
- In fact, if the conditions of perfect competition were satisfied, discriminating employers would be wiped away and taste-based discrimination would disappear.

Discrimination: Two theories

Statistical discrimination (Phelps, 1972; Arrow, 1973; Aigner and Cain, 1977)

- In a “statistical discrimination” model the differential treatment of members of the minority group is due to imperfect information, and discrimination is the result of a signal extraction problem.
- As a profit-maximizing prospective renter, employer, or car salesman, tries to infer the characteristics of a person that are relevant to the market transaction they are considering to complete with that person, they use all the information available to them.
- When the person-specific information is limited, group- specific membership may provide additional valuable information about expected behavior.

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.
- But, of course, ensuring that the re- searcher 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.

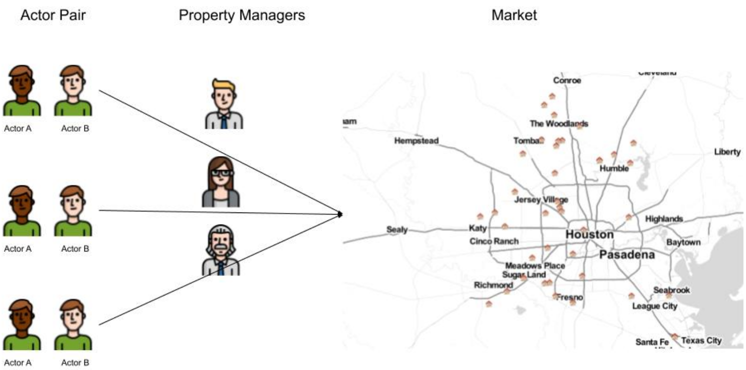
Experiment Set up: Identifying Housing Discrimination

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



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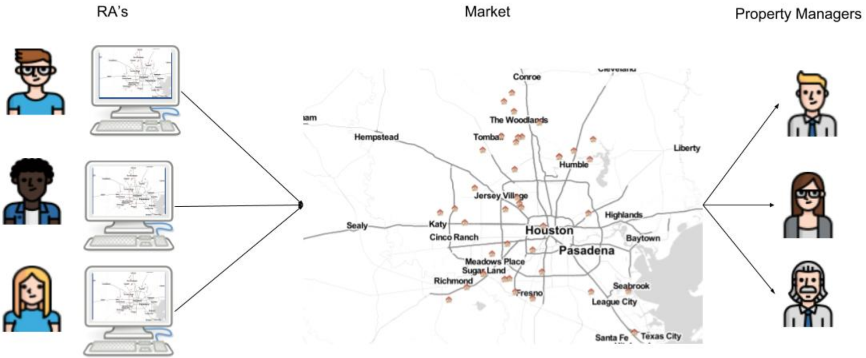
2. Send teams of actors (white & minority) to real estate offices and rental management companies and record differential treatment
3. Strong evidence of discrimination in previous reports (Turner et al 2002, 2012)
    1. Most blatant forms (e.g., refusal to show a property) to have declined over time
    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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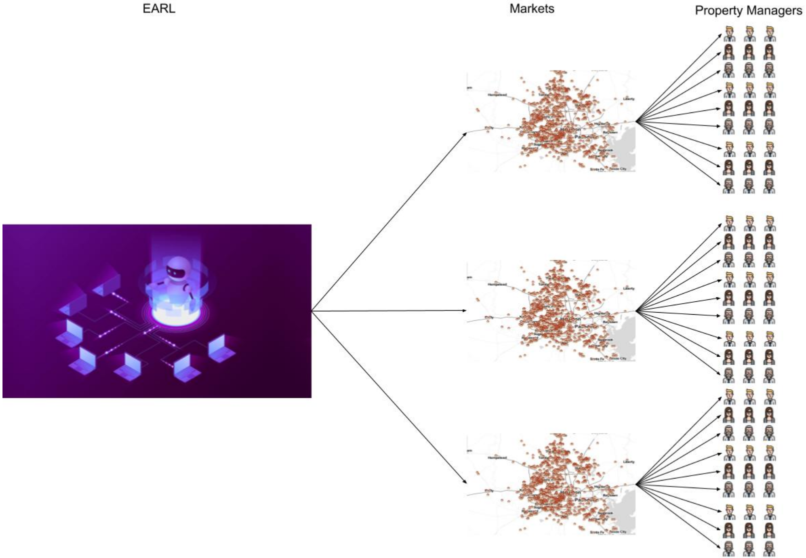
- Advantages of Correspondence Studies (vs Audit Designs)
  1. Correspondence studies give more control to the analyst (Bertrand and Duflo, 2017)
  2. Hard to control for all differences between paired testers (Siegelman and Heckman, 1993, Heckman, 1998)
  3. Less expensive (large, geographically targeted samples)

(Aside) What we do: EARL



Ewens et al. (2014) 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. (2014) model

Ewens et al. (2014) results

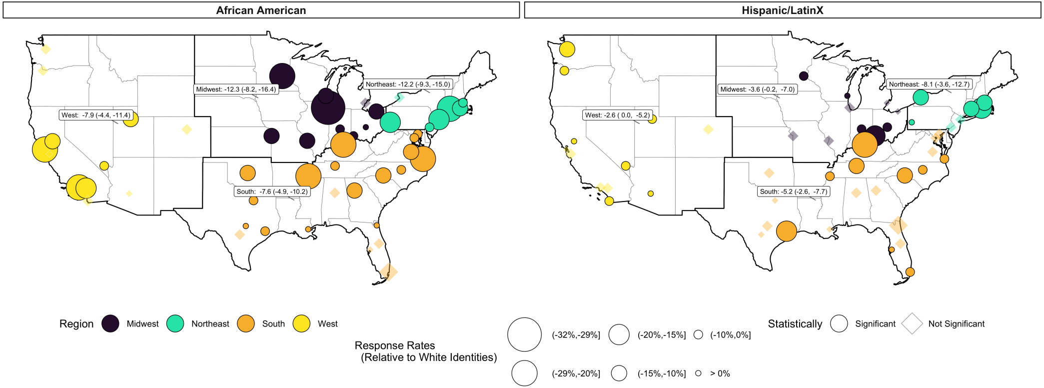
TABLE 6.—DIFFERENTIAL TREATMENT BY RACE AND INFORMATIONAL SIGNALS

	(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

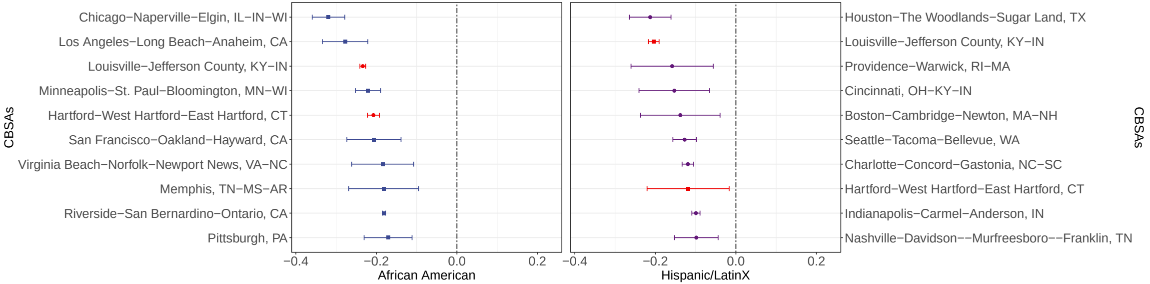
See definitions of variables in the notes to tables 2 and 3. Robust standard errors clustered by neighborhood reported in parentheses. Columns 1–4 correspond to hypotheses 1 and 1A, 2 and 2A, 3 and 3A, and 4 and 4A, respectively. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

The Geography of Discriminatory Behavior in the US

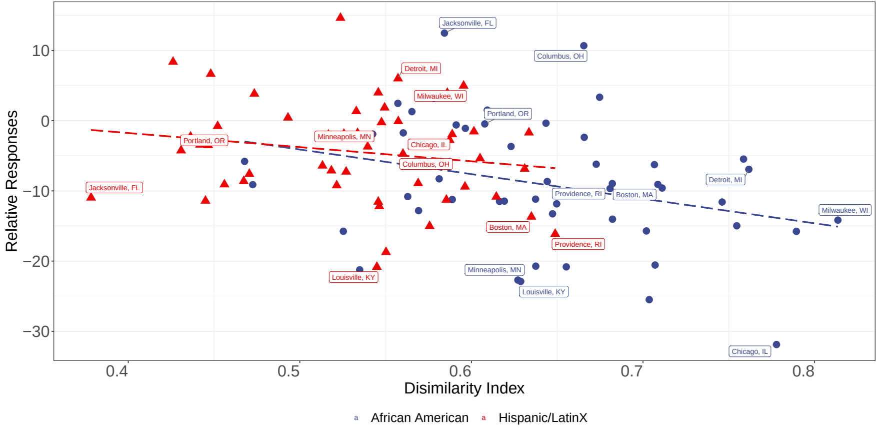
Figure 1: Response Rates CBSAs



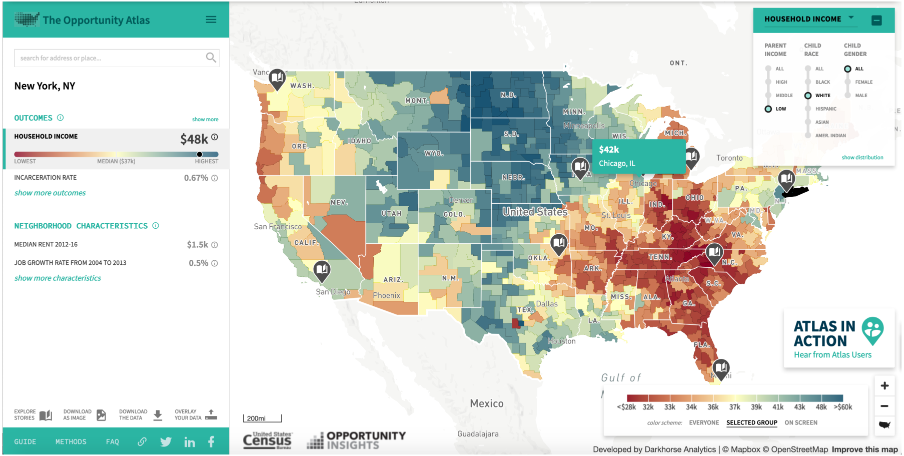
The Geography of Discriminatory Behavior in the US: The "Not" Top Ten



Discriminatory Behavior and Segregation



Discriminatory Behavior and the Income Mobility Gap



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

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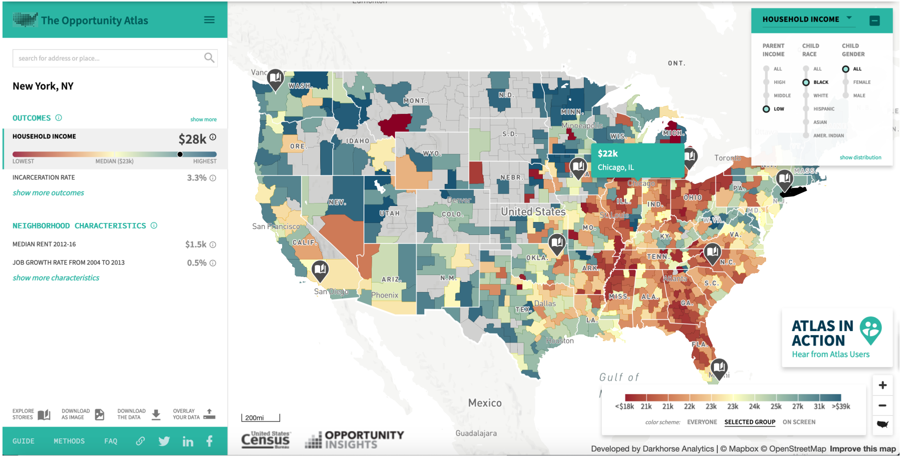

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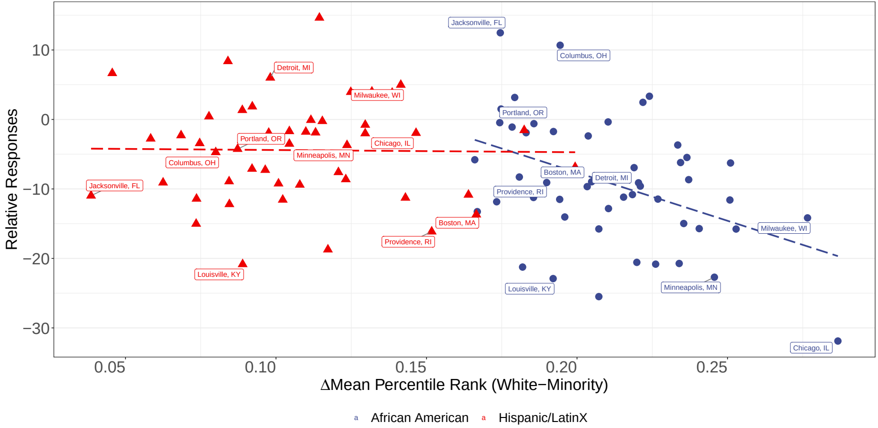


Discriminatory Behavior and Housing Outcomes

- A key limitation of the correspondence method is that the researcher never directly observes the effects of constraints faced by fictitious applicants on actual housing outcomes Heckman (1998).
- However, recently-available data on the renter housing location choices provide an opportunity to link the listed rental properties sampled for the experiment to the racial/ethnic identities of households that subsequently rented them in 2020
  - InfoUSA's consumer database tracks 120 million households and 292 million individuals between 2006-2019, and is maintained using 29 billion records from 100 sources including census statistics, billing statements, telephone directory listings and mail order buyers/magazine subscriptions.
  - Household-level identifiers provide information on the gender, race/ethnicity, age, address, renter/owner status and estimated household income of renters.
- Of the sample of properties in the correspondence experiment, 12% are ultimately rented by African American households, 11% by LatinX renters, 71% by white households, and the remaining 6% by households from other groups.

Discriminatory Behavior and Housing Outcomes

Tests of Differential Treatment and Housing Outcomes

- We estimate the following a series of within-listing linear probability models

$$Same\ Race_{ij} = \beta_R Response_j + \alpha + \theta X_j + \delta_i + \epsilon_{ij} \quad (1)$$

  - $Same\ Race_{ij}$ (SR) takes a value of one if the race/ethnicity of the renter observed to inhabit the property matches the race/ethnicity of experimental identity that sent the inquiry j to listing i; and zero otherwise.
  - $Response_j$ is an indicator that takes a value of one if the identity received a response.
  - X_j is a vector of identity-specific control variables: gender, education level, and the order in which the inquiry was sent.
  - δ_i is a listing-specific fixed effect that controls for any within listing time-invariant characteristics.

Discriminatory Behavior and Housing Outcomes

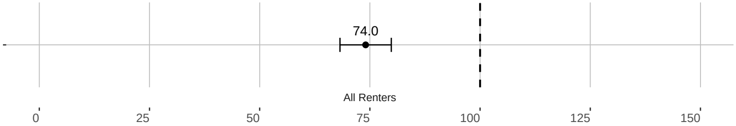
Tests of Differential Treatment and Housing Outcomes

- Using all groups and the full sample, we estimate the relative probability that the racial/ethnic identity of the renter that inhabits the property is the same as the identity that sends the inquiry:
- We use coefficients from Eq. 1 to compare these probabilities under the two experimental response conditions.

$$\frac{P(Same\ Race|Response = 0)}{P(Same\ Race|Response = 1)} = \frac{\alpha}{\beta_R + \alpha} \quad (2)$$

- It allows us to test the hypothesis that discriminatory constraints identified in the experiment also predict market outcomes outside the experiment.

Discriminatory Behavior and Housing Outcomes



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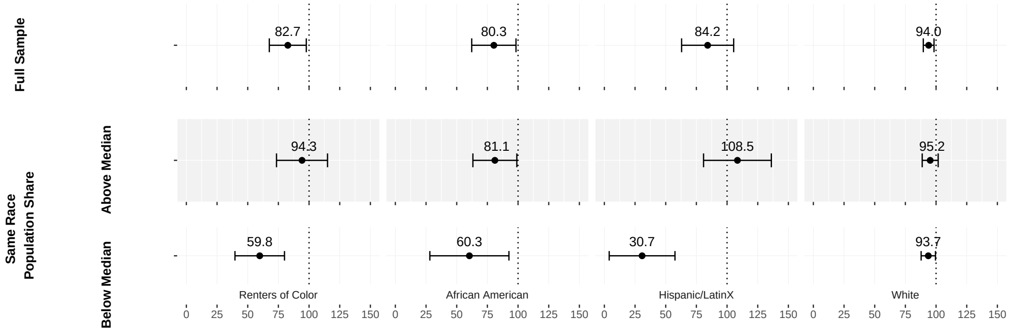

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