Discrimination

Urban Economics

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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.
  - Housing/neighborhood preferences that also affect residential sorting behavior (Depro et al., 2015, Banzhaf and Walsh, 2013).
  - 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
  - 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).

Measuring Discrimination in the Field

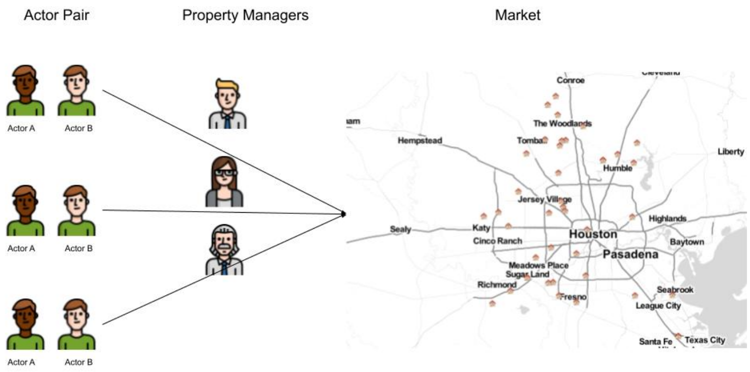
- Earlier research on discrimination focused on individual-level outcome regressions, with discrimination estimated from the "minority" differential that remains unexplained after including as many proxies as possible.
- The limitations of this approach are well-known. The interpretation of the estimated "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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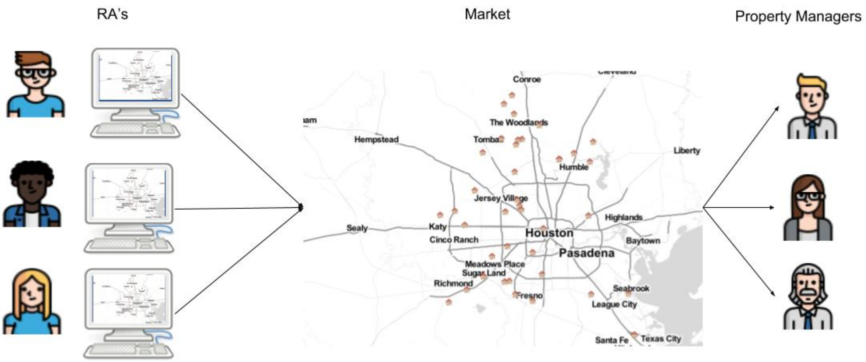
1. Paired-tester: Blind-matched actors trained to be identical in every respect except for characteristic of interest (e.g., race)
2. Send teams of actors (white & minority) to real estate offices and rental management companies and record differential treatment
3. Strong evidence of discrimination in 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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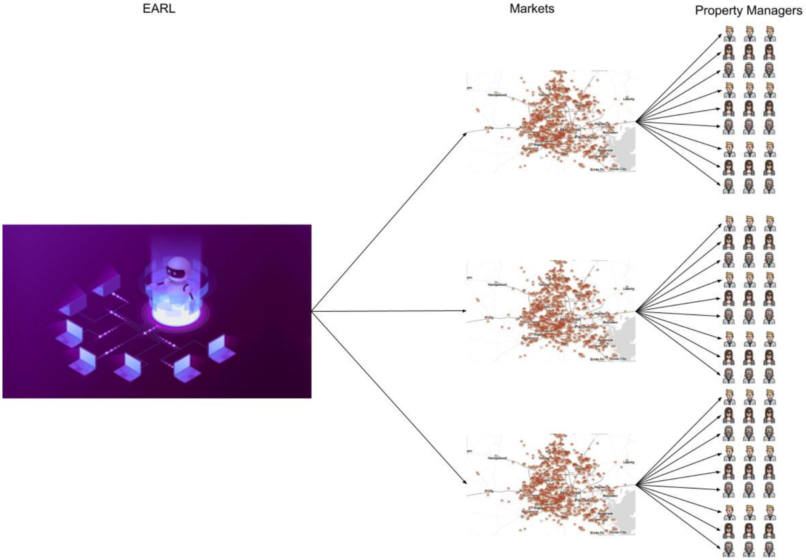
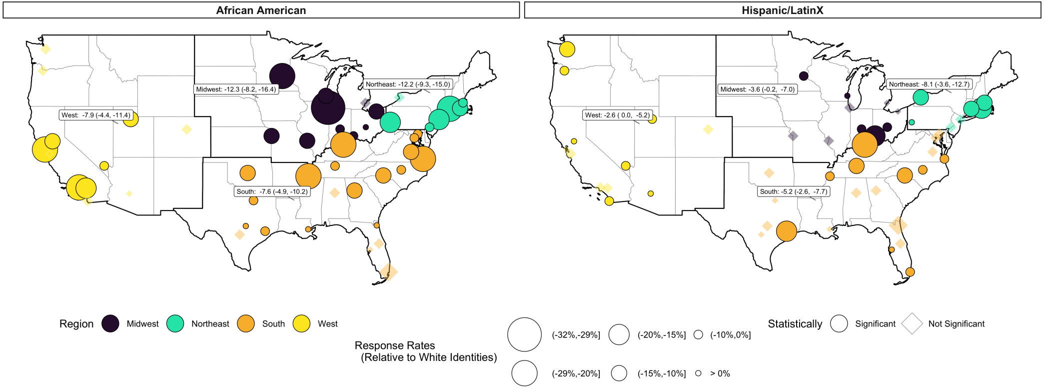
  1. Create fictitious identities
  2. Interact with retailers, employers, or housing brokers
  3. Randomly vary racial trait
- Advantages of Correspondence Studies (vs Audit Designs)
  1. Correspondence studies give more control to the analyst (Bertrand and Duflo, 2017)
  2. Hard to control for all differences between paired testers (Siegelman and Heckman, 1993, Heckman, 1998)
  3. Less expensive (large, geographically targeted samples)

(Aside) What we do: EARL

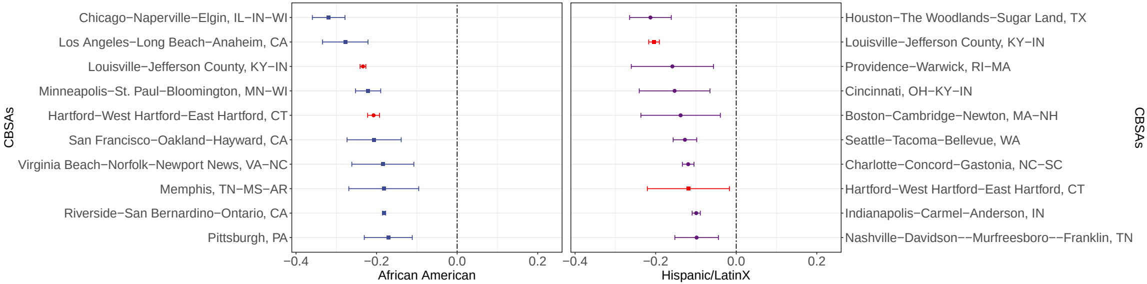


The Geography of Discriminatory Behavior in the US

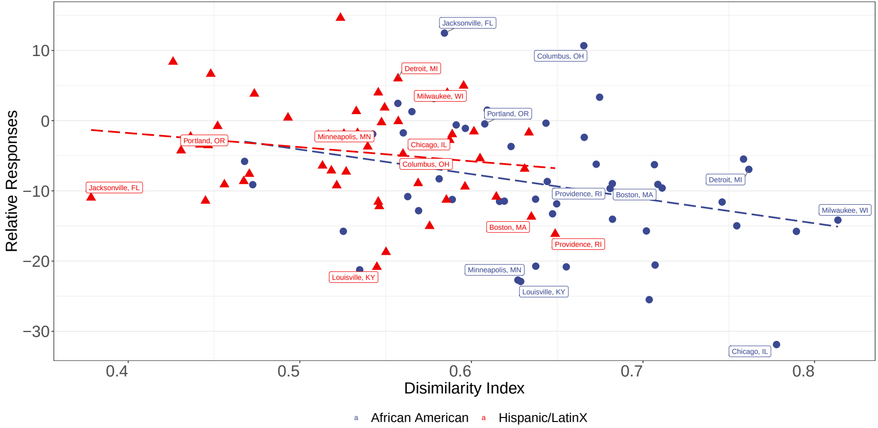
Figure 1: Response Rates CBSAs



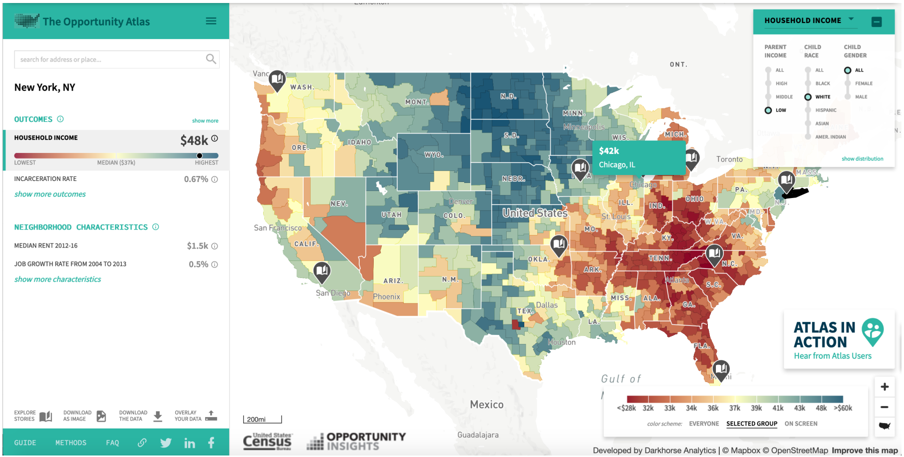
The Geography of Discriminatory Behavior in the US: The "Not" Top Ten



Discriminatory Behavior and Segregation



Discriminatory Behavior and the Income Mobility Gap



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

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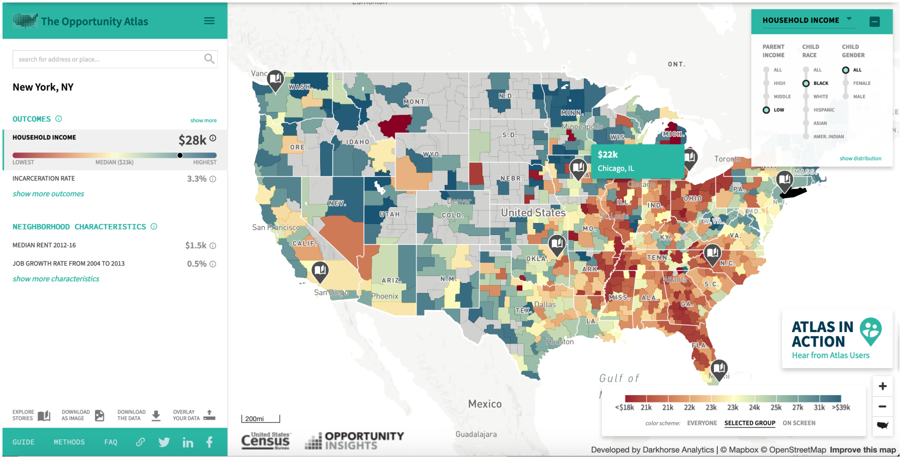

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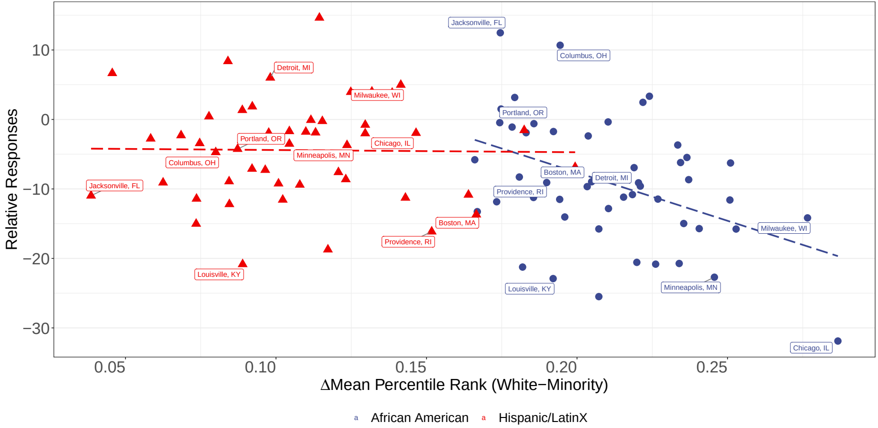


Discriminatory Behavior and Housing Outcomes

- 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

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

  - $Same\ Race_{ij}$ (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

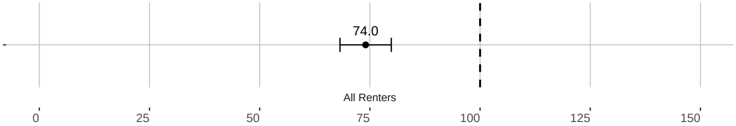
Tests of Differential Treatment and Housing Outcomes

- 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.

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

- 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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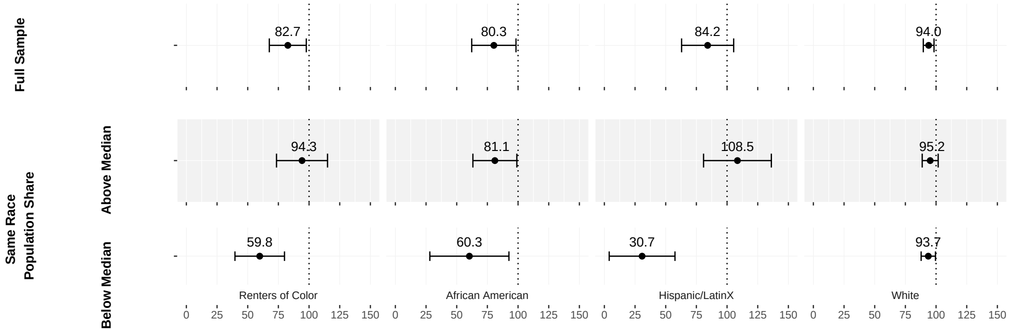

Discrimination and Toxics: Experimental Design

Christensen, Sarmiento-Barbieri, Timmins (2022) *RESTAT*

Sample of Markets

1. Markets: Zip codes with a high-emitting TRI plant within 1 mile of a residential neighborhood
   - High-emitting $\rightarrow$ above $80th$ percentile of airborne emissions
   - More than 150 active listings

Discrimination and Toxics: Experimental Design

Zip Codes With TRI Toxic Plants within one mile

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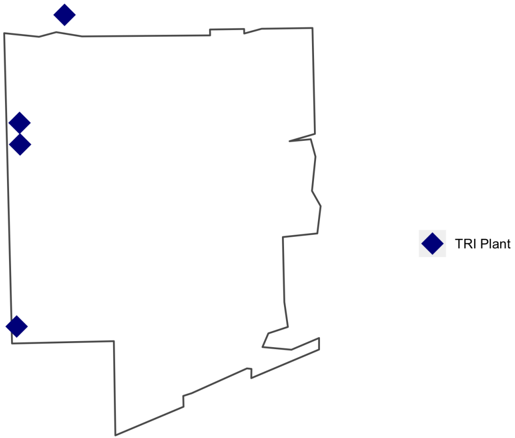

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   - Balanced sample of listings near and far TRI plants ($\approx$ 30%)

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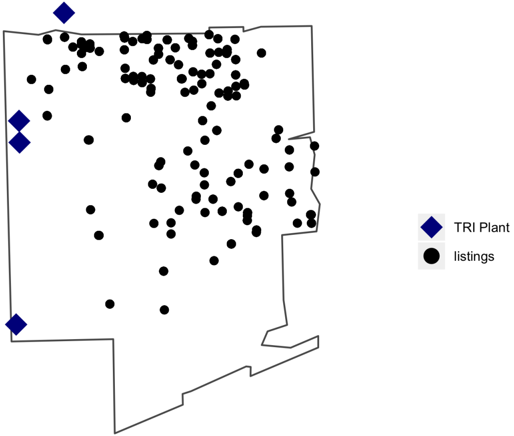

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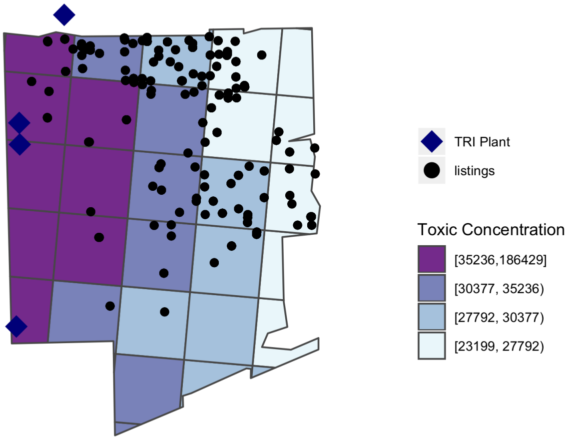

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4. Distinguish between 3 areas in the zip code
    - Lowest quartile (0-25)
    - The interquartile range (25-75)
    - Highest quartile of ambient emissions (75-100)

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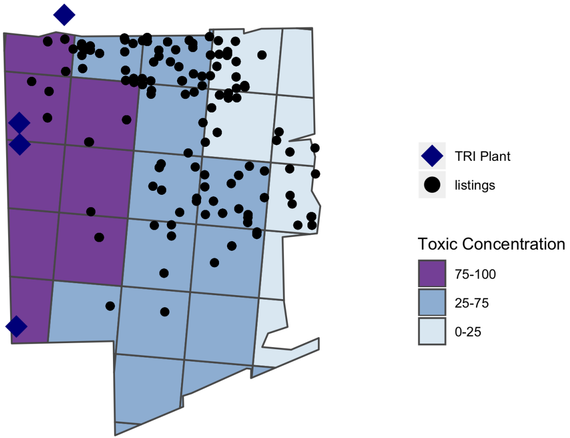

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4. Distinguish between 3 areas in the zip code
   - Lowest quartile (0-25)
   - The interquartile range (25-75)
   - Highest quartile of ambient emissions (75-100)
5. We also distinguish between those listings within/more than 1 mile of a TRI plant

Discrimination and Toxics: Experimental Design

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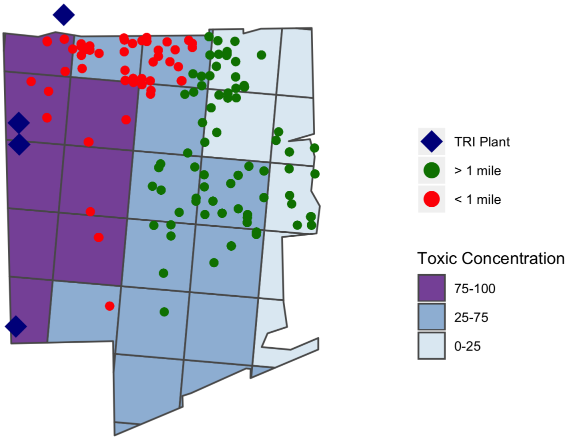

Estimation

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- Each rental apartment receives an inquiry from each of the racial groups in three separate days.
    1. The manager of the unit could receive an inquiry from the White identity,
    2. then from an African American identity,
    3. and from a Hispanic/LatinX identity .

Estimation

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Based on this design, we observe a sequence of binomial decisions, where the landlord-listing i decides whether to respond ($y_{ij} = 1, j = 1, 2, 3$) or not if her underlying utility is positive:

$$\begin{aligned} u^*_{i1} &= \sum_k (\psi_k + \beta_{k1} Minority_1) Z_{i\in k} + \theta X_1 + \delta_i + \epsilon_{i1} \\ u^*_{i2} &= \sum_k (\psi_k + \beta_{k2} Minority_2) Z_{i\in k} + \theta X_2 + \delta_i + \epsilon_{i2} \\ u^*_{i3} &= \sum_k (\psi_k + \beta_{k3} Minority_3) Z_{i\in k} + \theta X_3 + \delta_i + \epsilon_{i3} \end{aligned} \tag{3}$$

Where ϵ_{ij} follows a logistic distribution. Where we assume that ϵ_{ij} are independent across j but may be correlated across ZIP codes

Estimation

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Therefore:

$$P(y_{ij}=1|X,Z,\delta)=F(\sum_k(\psi_k+\beta_{kj}Minority_j)Z_{i\in k}+\theta X_j+\delta_i) \tag{4}$$

- F is the logistic cumulative distribution function.
- $Minority_j$ is an indicator that takes the value one if the race group associated with the identity is either African American or Hispanic/LatinX; and is zero if it is the White identity.
- X_j is a vector of renter-specific control variables: gender, education level and the order in which the inquiry was sent.
- Assuming that names are drawn randomly and balanced across gender, education level, and inquiry order, estimates of β_{kj} should be robust to the inclusion/omission of X_j.
- δ_i is a landlord-property specific fixed effect.
- $Z_{i\in k}$ are indicators denoting the bin (k) of within-ZIP code percentile of pollution exposure of the listing.

Results: Discrimination by RSEI Concentration

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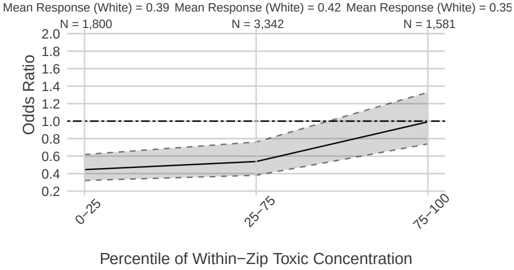
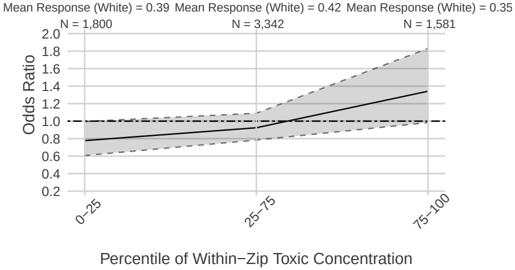
Figure 2: Odds Ratio by Within-ZIP Toxic Concentration



(a) African American



(b) Hispanic/LatinX

Results: Discrimination by Distance to Emissions Source

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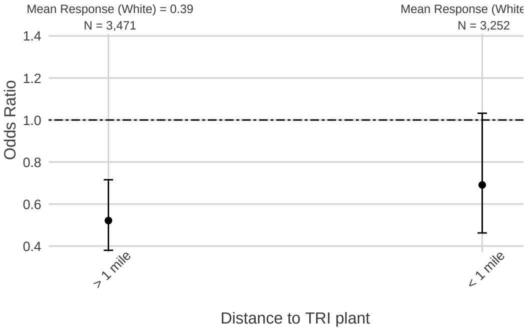
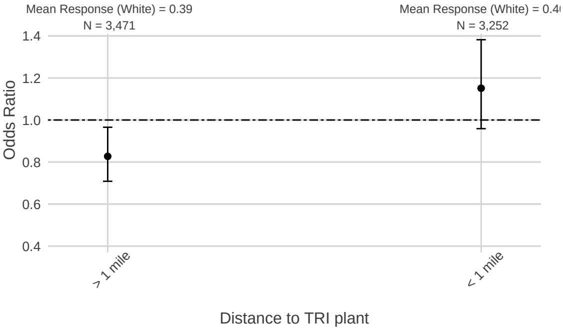
Figure 4: Odds Ratio by Proximity to Closest TRI Plant

Panel B: African American vs Hispanic/LatinX



(a) African American



(b) Hispanic/LatinX

Heterogeneity in Discriminatory Constraints

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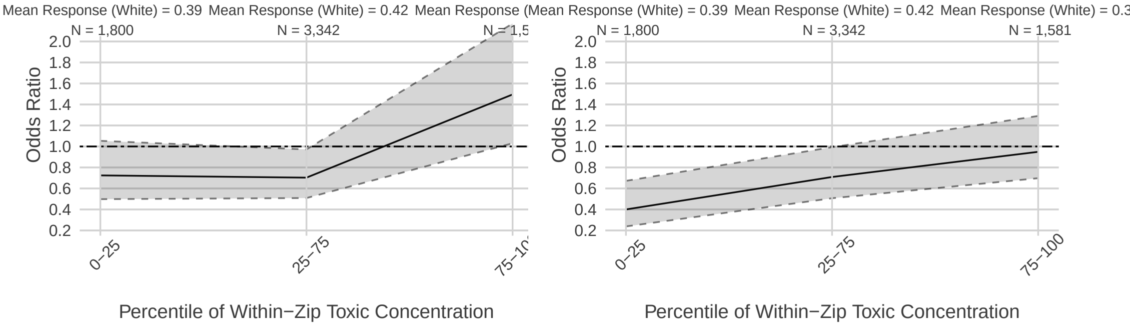
Figure 6: Odds Ratio by Within-ZIP Toxic Concentration

Panel A: Demographic Composition, Above vs Below Minority Shares



(A.1) Above Median Minority Share

(A.2) Below Median Minority Share

Heterogeneity in Discriminatory Constraints

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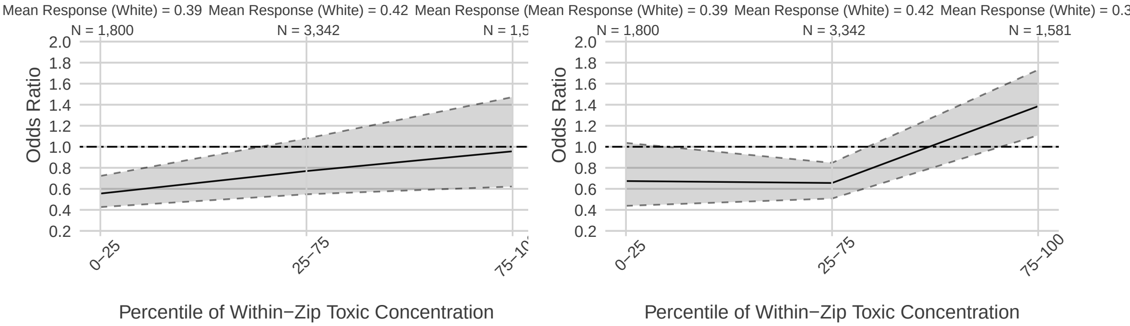
Figure 8: Odds Ratio by Within-ZIP Toxic Concentration

Panel B: Above vs Below Median Rent



(B.1) Above Median Rent

(B.2) Below Median Rent

Heterogeneity in Discriminatory Constraints

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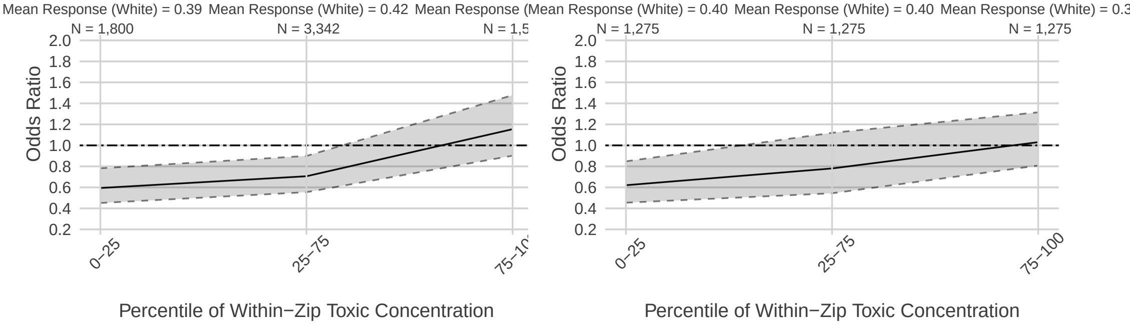
Figure 10: Odds Ratio by Within-ZIP Toxic Concentration

Panel C: Full vs Matched Sample



(C.1) Full Sample (C.2) Matched Sample

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