Racial Discrimination and Housing Outcomes in the United States Rental Market

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Motivation

- Recent research has shown that the neighborhood where people live has important implications for short-run, long-run and even intergenerational outcomes. (Akbar et al., 2019, Chetty et al., 2018, Currie, 2011, Currie and Neidell, 2005)
- 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).

Motivation

Housing Discrimination is Illegal

"We are here today because we are tired. We are tired of paying more for less. We are tired of living in rat-infested slums... We are tired of having to pay a median rent of $97 a month in Lawndale for four rooms while whites living in South Deering pay $73 a month for five rooms. Now is the time to make real the promises of democracy. Now is the time to open the doors of opportunity to all of God's children."
(Dr. King, 1966, Chicago Soldier Field Stadium as part of the Chicago Open Housing Movement)

Housing discrimination was made illegal under the Fair Housing Act (part of Civil Rights Act of 1968 and 1988 Amendments)

Research Question and Preview of Results

Does housing discrimination impose constraints to Renters of Colors?

- We conducted the largest (up to date) correspondence study on online rental housing markets
  1. 50 Largest U.S. housing markets where we test discrimination constrains in the housing choices available to minority households
  2. We elicit racial perceptions of African American, Hispanic/LatinX, and white social groups in the US through names
- Experimental Results
  - Lower response rates for RoC applicants in the majority of markets.
  - There are important differences across cities
  - Discriminatory constraints are systematically stronger in cities
    - with higher levels of residential segregation.
    - with persistent gaps in intergenerational income mobility.
  - Discriminatory constraints detected in a correspondence experiment predict population-level outcomes in the rental housing market.

Contributions

- We contribute to strands of the economics literature on racial discrimination and inequality in U.S. cities

  1. Measurement of discrimination in housising markets (Ewens et al., 2014, Hanson and Hawley, 2011, Ahmed et al., 2013, 2010, Ahmed and Hammarstedt, 2008, 2009)

     ★ This study provides the largest body of experimental evidence on housing market discrimination in the United States to date

  2. The nascent literature on the relationship between discrimination, segregation, and housing outcomes (Christensen et al., 2020, Christensen and Timmins, 2020, Li, 2019, Shertzer and Walsh, 2019, Boustan, 2012, 2010, Card et al., 2008, Chetty et al., 2018).

Limitations of Our Study

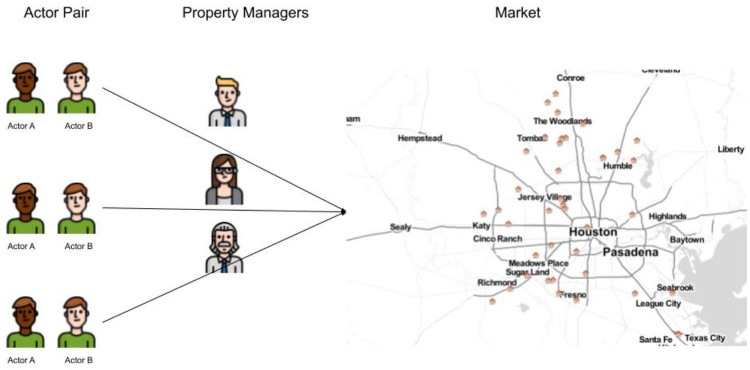
- We are restricted to listings advertised on a single rental housing website
- First Interaction
- Sampled Names: Not representative of the population
- Racial Prejudice vs. Statistical Discrimination (Ewens et al., 2014)
- Reduce form estimates (Christensen and Timmins, 2022)

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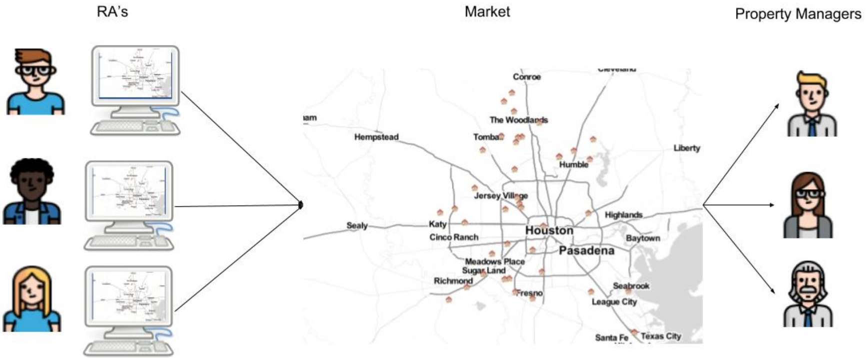
2. Send teams of actors (white & minority) to real estate offices and rental management companies and record differential treatment
3. Strong evidence of discrimination in previous reports (Turner et al 2002, 2012)
   1. Most blatant forms (e.g., refusal to show a property) have declined over time
 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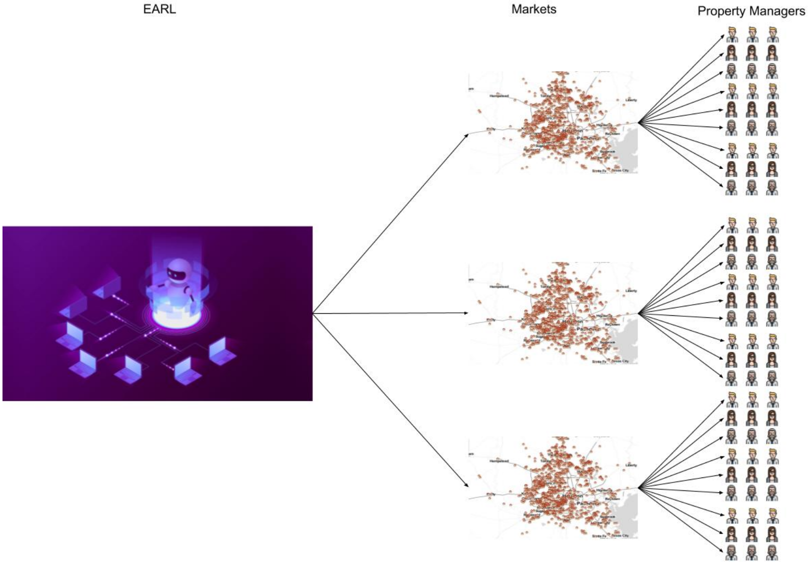
- Advantages of Correspondence Studies (vs Audit Designs)
  1. Correspondence studies give more control to the analyst (Bertrand and Duflo, 2017)
  2. Hard to control for all differences between paired testers (Siegelman and Heckman, 1993, Heckman, 1998)
  3. Less expensive (large, geographically targeted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

What we do: EARL



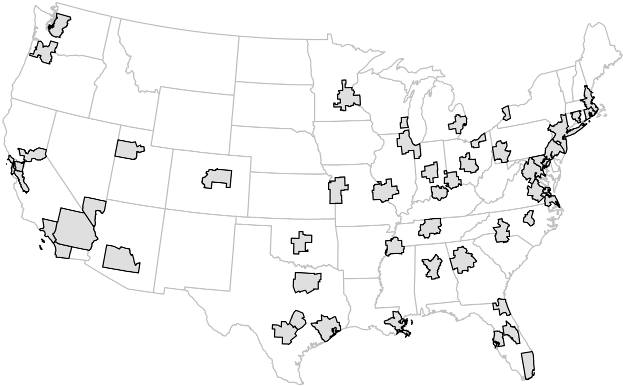
Experiment design

Sample of Markets

- 50 Largest CBSA's ($\sim$ 50% of US population)

Experiment design

Figure: CBSA's in Experiment



Experiment design

Sample of Markets

- 50 Largest CBSA's ($\sim$ 50% of US population)
- First day a listing is active we send an inquiry
  - Scrape all listing characteristics
  - Randomly assign one of 18 names that are associated with racialized perceptions of African American, Hispanic/LatinX, and white social groups in US (Gaddis, 2017a,b)

Experiment design

Race	First Name	No Last Name	Last Name Included	Quartile mother's education
Panel A. Identification Rates from Gaddis (2017a,b) (%)				
African American	Nia	41	65	High
African American	Jalen	63	71	High
African American	Ebony	91	95	Med
African American	Lamar	88	94	Med
African American	Shanice	93	92	Low
African American	DaQuan	91	96	Low
Hispanic/LatinX	Isabella	48	98	High
Hispanic/LatinX	Jorge	86	98	High
Hispanic/LatinX	Mariana	78	99	Med
Hispanic/LatinX	Pedro	98	99	Med
Hispanic/LatinX	Jimena	49	97	Low
Hispanic/LatinX	Luis	83	99	Low
White	Aubrey	90	93	High
White	Caleb	77	84	High
White	Erica	82	93	Med
White	Charlie	86	91	Med
White	Leslie	72	93	Low
White	Ronnie	71	89	Low

Experiment design

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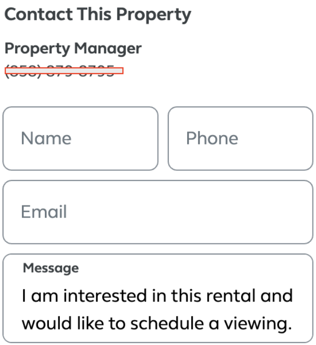
  - 3 male/female, 1 high/medium/low maternal educational attainment
  - Continue for the following 2 days with the remaining races

Experiment design



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  - 3 male/female, 1 high/medium/low maternal educational attainment
  - Continue for the following 2 days with the remaining races
- Record Responses (1 if responded with availability), 0 o.w.
  - email
  - phone
  - text sms
- Final sample: $25,428$ inquiries ($\sim 8,477$ properties)

Estimation

- The experimental design involves a sequence of binomial decisions ($j = 1, 2, 3$), the property manager of a given listing i decides whether
  - to respond ($Response_{ij} = 1$)
  - or not ($Response_{ij} = 0$) .
- The magnitude of discriminatory constraints are estimated using a within-listing linear probability model:

$$Response_{ij} = \beta_A African\ American_j + \beta_L Hispanic/LatinX_j + \theta X_j + \delta_i + \epsilon_{ij} \tag{1}$$

  - $African\ American_j$ and $Hispanic/LatinX_j$ are indicator variables for the respective race/ethnicity.
  - 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 the listing fixed effect

Estimation

- We then calculate Relative Response Rates

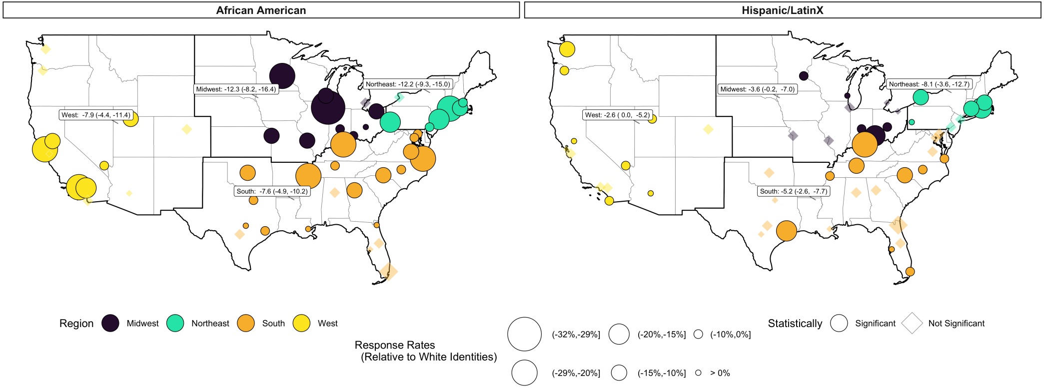
$$RR_A = \frac{P(Response|AfAm = 1)}{P(Response|W = 1)} = \frac{\beta_A}{\mu_W} \tag{2}$$

$$RR_L = \frac{P(Response|LatinX = 1)}{P(Response|W = 1)} = \frac{\beta_L}{\mu_W} \tag{3}$$

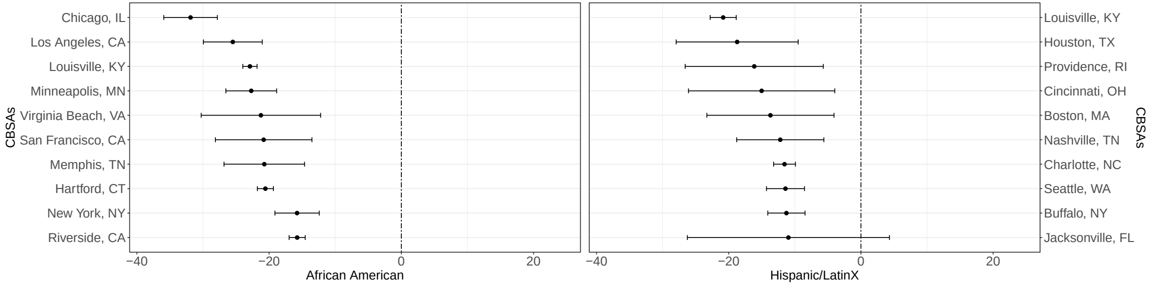
- where β_A and β_L are the coefficients from the previous regression
- μ_W is the average response for whites.

The Geography of Discriminatory Behavior in the US

Figure: Response Rates CBSAs

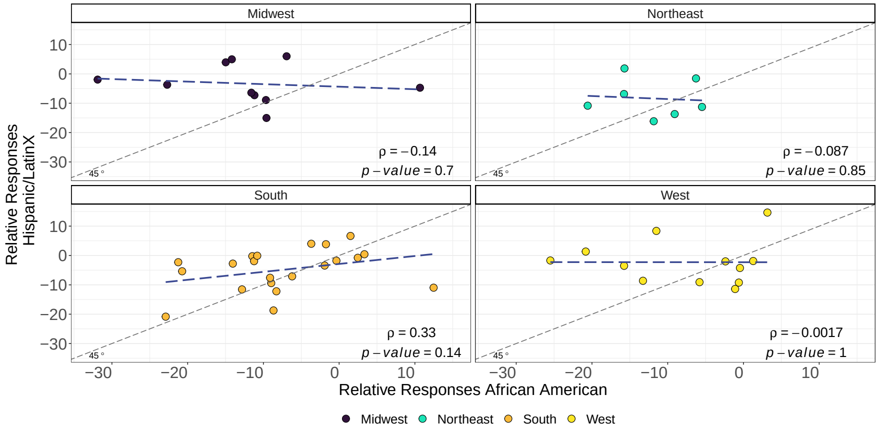


The Geography of Discriminatory Behavior in the US: The “Not” Top Ten

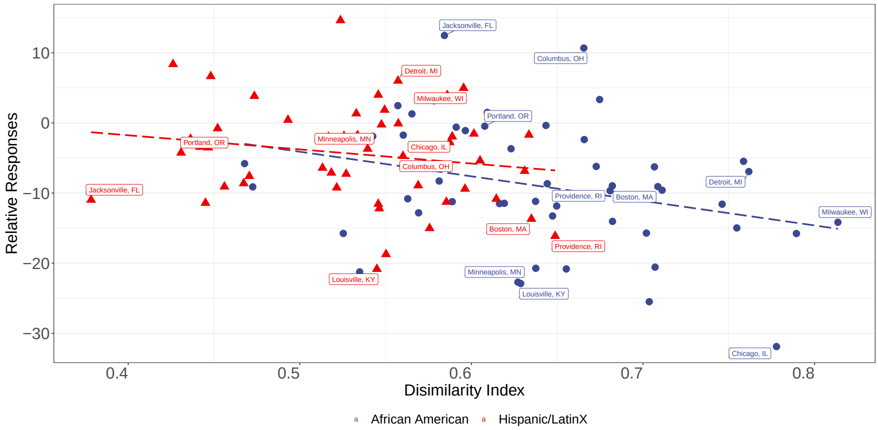


The Geography of Discriminatory Behavior in the US: Correlations across Regions

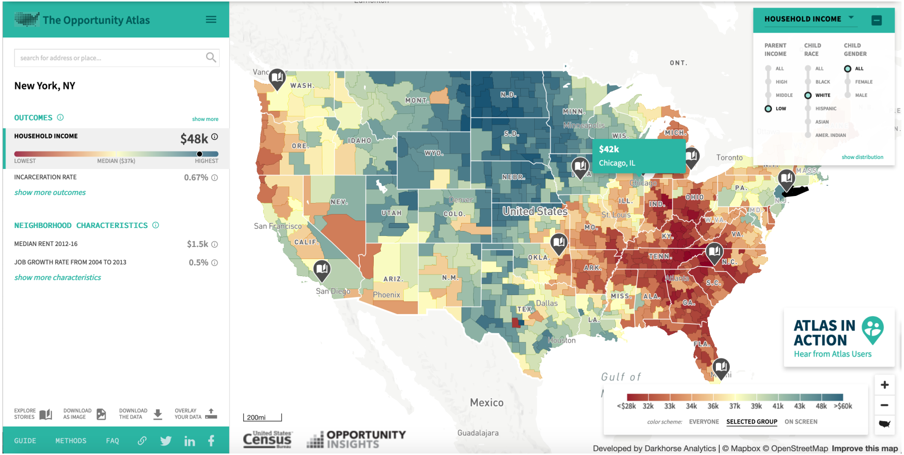
Figure: Response Rates CBSAs Correlations



Discriminatory Behavior and Segregation

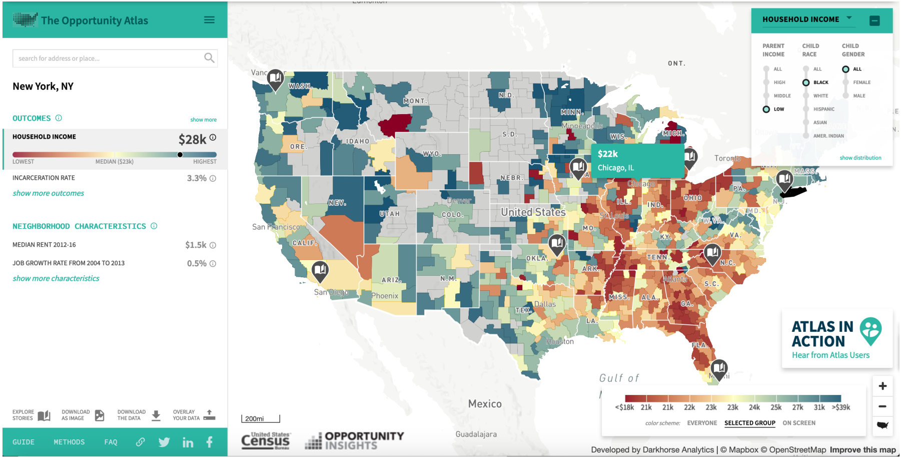


Discriminatory Behavior and the Income Mobility Gap



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

Discriminatory Behavior and the Income Mobility Gap



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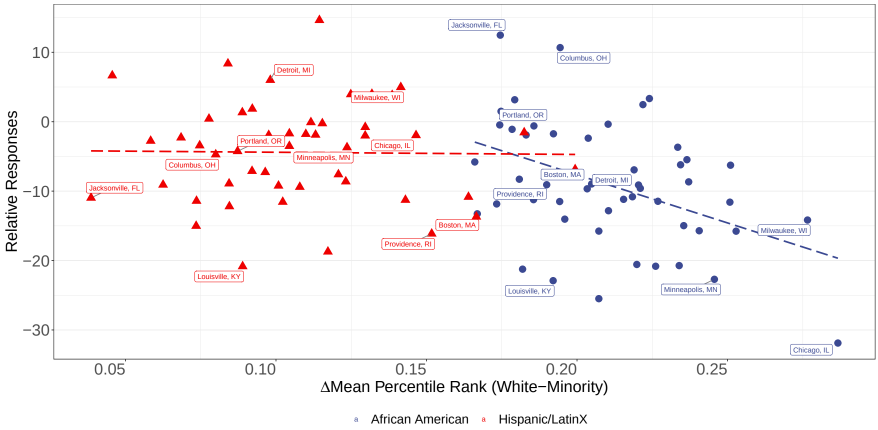


Discriminatory Behavior and Housing Outcomes

- 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, we leverage unique data on renters. Match 65% of our listings
  - InfoUSA's consumer database tracks 120 million households and 292 million individuals between 2006-2020, 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 a series of within-listing linear probability models

$$Same\ Race_{ij} = \beta_R Response_j + \alpha + \theta X_j + \delta_i + \epsilon_{ij} \tag{4}$$

  - $Same\ Race_{ij}$ (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.

Discriminatory Behavior and Housing Outcomes

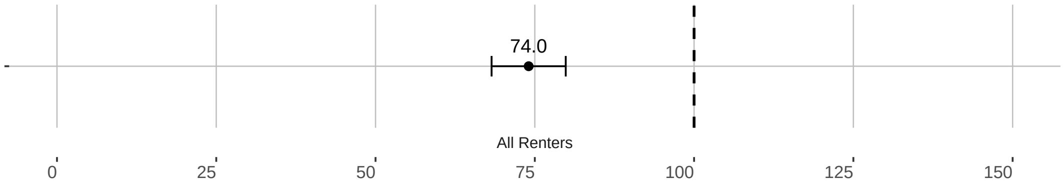
Tests of Differential Treatment and Housing Outcomes

- 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. 4 to compare these probabilities under the two experimental response conditions.

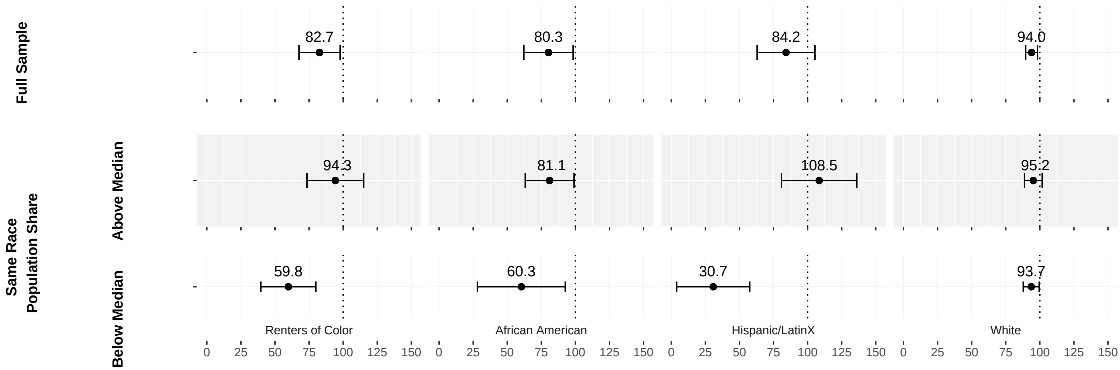
$$\frac{P(Same\,Race|Response=0)}{P(Same\,Race|Response=1)}=\frac{\alpha}{\beta_R+\alpha} \tag{5}$$

- 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



Discriminatory Behavior and Housing Outcomes



Conclusion I

- Housing discrimination can have a critical impact on residential location choices and access to opportunity.
- Our design provides a direct comparison of the magnitude of discriminatory behavior across the 50-city sample, allowing for a statistical ranking of the markets with the highest and lowest rates of discriminatory constraints.
- Our results indicate that households of color face higher constraints when searching for rental properties in most U.S. markets.
  - We find the strongest discriminatory constraints facing African Americans in Chicago, IL, Los Angeles, CA, and Louisville, KY.
  - We find the strongest constraints facing Hispanic/LatinX renters in Louisville, KY, Houston, TX, and Providence, RI.

Conclusion II

- We find a strong relationship
  - between neighborhood segregation and racial discrimination for African Americans in the rental market.
  - and the income mobility gap and discriminatory constraints facing African American renters.
- Researchers have been unclear about the power of the correspondence design to predict difference in actual housing outcomes.
- We provide the first test of the relationship between experimental evidence of disparate treatment and subsequent differences in renter outcomes, revealing that discriminatory constraints provide important information about market behavior.

Thanks!

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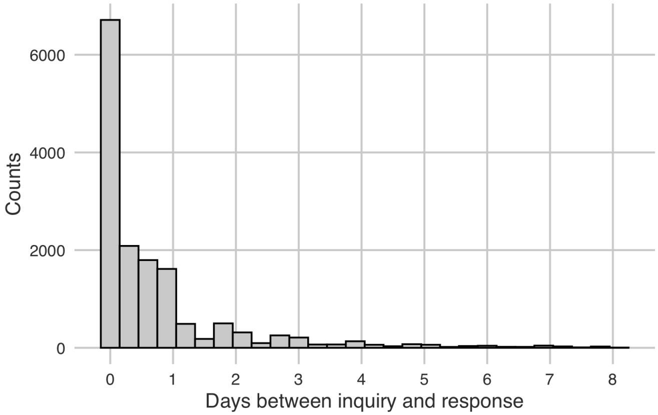
First Inquiry

	Dependent variable: *Response*	
	Full Sample	First Inquiry
	(1)	(2)
African American	-0.0561***	-0.0669***
	(0.0063)	(0.0133)
Hispanic/LatinX	-0.0277***	-0.0302**
	(0.0057)	(0.0133)
Mean Response (White)		
Gender	Yes	Yes
Education Level	Yes	Yes
Inquiry Order	Yes	
Observations	25428	8477

Notes: Table reports in column (1) coefficients from a within-property linear regression model including controls for gender, education and order the inquiry was sent. In column (2) from a linear model using only the sample of responses from the 1st inquiry made to a given listing. Standard errors clustered at the CBSA Downtown/Suburb level reported in parentheses.
* Significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Randomization



Randomization

	(1)	(2)	(3)	(4)	(5)
	Panel A: Inquiry Order				
	First	Second	Third		
African American	0.0101	-0.0073	-0.0028		
	(0.0093)	(0.0094)	(0.0094)		
Hispanic/LatinX	0.0074	0.0027	-0.0100		
	(0.0094)	(0.0094)	(0.0093)		
	Panel B: Evidence of Differential Choices by Weekday				
	Mon	Tue	Wed	Thurs	Fri
African American	-0.0011	-0.0015	-0.0013	0.0021	-0.0011
	(0.0058)	(0.0052)	(0.0063)	(0.0053)	(0.0062)
Hispanic/LatinX	0.0000	0.0017	0.0002	-0.0004	0.0012
	(0.0056)	(0.0055)	(0.0063)	(0.0053)	(0.0055)
	Panel C: Gender and Mother's Education Level				
	Gender		Mother's Education		
	Male	Female	Low	Medium	High
African American	-0.0006	0.0006	-0.0073	0.0024	0.0049
	(0.0080)	(0.0080)	(0.0075)	(0.0072)	(0.0070)
Hispanic/LatinX	-0.0027	0.0027	-0.0050	0.0016	0.0035
	(0.0076)	(0.0076)	(0.0072)	(0.0071)	(0.0079)
Mean Response (White)	0.60	0.60	0.60	0.60	0.60
Observations	25,428	25,428	25,428	25,428	25,428

Last Names

Panel B. Last Names Frequency of Occurrence in 2010 Census (%)				
Race	Last Name	African American	Hispanic/LatinX	White
African American	Harris	42.4	2.3	51.4
African American	Jackson	53.0	2.5	39.9
African American	James	38.9	3.1	51.6
African American	Williams	47.7	2.5	45.8
African American	Thomas	38.8	2.5	52.6
African American	Robinson	44.9	2.6	48.7
Hispanic/LatinX	Lopez	0.6	92.9	4.9
Hispanic/LatinX	Rodriguez	0.5	93.8	4.8
Hispanic/LatinX	Morales	0.6	93.2	4.6
Hispanic/LatinX	Sanchez	0.5	93.0	5.0
Hispanic/LatinX	Ramirez	0.3	94.5	3.9
Hispanic/LatinX	Torres	0.6	92.2	5.4
White	Murphy	11.5	2.3	83.1
White	Peterson	10.1	2.4	84.4
White	Cox	12.1	2.3	82.6
White	Myers	10.5	2.1	84.5
White	Wood	5.6	2.4	88.7
White	Miller	10.8	2.2	84.1

George Floyd and Covid

	Dependent variable: Response					
	Full Sample	Drop Month After G. Floyd Homicide	Lockdowns Before	Lockdowns After	*p-value* diff. (1)-(2)	*p-value* diff. (3)-(4)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Relative Responses						
African American × Midwest	-0.1231***	-0.1225***	-0.1168***	-0.1257***	0.946	0.970
	(0.0251)	(0.0288)	(0.0325)	(0.0334)		
African American × Northeast	-0.1215***	-0.1329***	-0.1362***	-0.1138***	0.294	0.176
	(0.0176)	(0.0196)	(0.0326)	(0.0151)		
African American × South	-0.0755***	-0.0808***	-0.1021***	-0.0599**	0.291	0.165
	(0.0159)	(0.0168)	(0.0261)	(0.0233)		
African American × West	-0.0788***	-0.0825***	-0.0724***	-0.0814***	0.104	0.948
	(0.0212)	(0.0205)	(0.0279)	(0.0260)		
Hispanic/LatinX × Midwest	-0.0359*	-0.0363*	-0.0607***	-0.0237	0.897	0.263
	(0.0207)	(0.0198)	(0.0217)	(0.0293)		
Hispanic/LatinX × Northeast	-0.0813***	-0.0895***	-0.1074***	-0.0686**	0.849	0.125
	(0.0278)	(0.0306)	(0.0345)	(0.0312)		
Hispanic/LatinX × South	-0.0516***	-0.0483***	-0.0701***	-0.0406*	0.397	0.279
	(0.0153)	(0.0156)	(0.0239)	(0.0213)		
Hispanic/LatinX × West	-0.0260*	-0.0116	0.0302	-0.0510**	0.016	0.033
	(0.0157)	(0.0179)	(0.0278)	(0.0201)		

Downtown and Suburbs

	Dependent variable: *Response*
	(1)
African American	-0.0545***
	(0.0091)
African American Suburb	-0.0033
	(0.0125)
Hispanic/LatinX	-0.0231***
	(0.0074)
Hispanic/LatinX Suburb	-0.0093
	(0.0114)
Mean Response (White) Downtown	0.62
Mean Response (White) Suburb	0.58
Gender	Yes
Education Level	Yes
Inquiry Order	Yes
Address FE	Yes
Observations	25,428

Gender

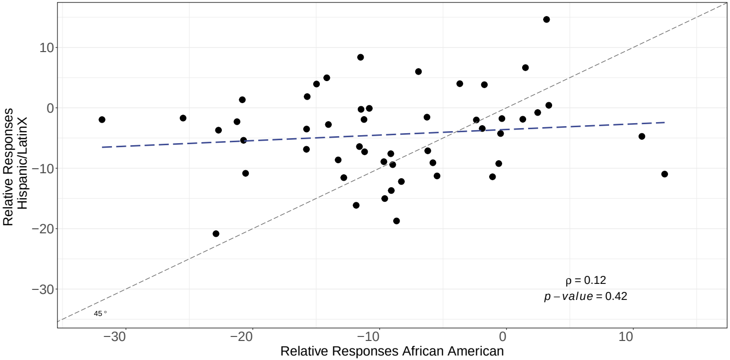
Table: Response Rates by Gender

	Dependent variable: Response	
	(1)	(2)
Panel A: Relative Responses		
Minority × Female	-0.0433***	
	(0.0080)	
Minority × Male	-0.0978***	
	(0.0115)	
African American × Female		-0.0394***
		(0.0102)
African American × Male		-0.1511***
		(0.0185)
Hispanic/LatinX × Female		-0.0473***
		(0.0112)
Hispanic/LatinX × Male		-0.0442***
		(0.0136)
Mean Response (White) Female	0.63	0.63
Mean Response (White) Male	0.58	0.58
Education Level	Yes	Yes
Inquiry Order	Yes	Yes
Address	Yes	Yes
Observations	25,428	25,428

Match Rate InfoUSA

Race	Freq.	Percent
Af. American	665	12.24
Hispanic/LatinX	605	11.14
Other	317	5.83
White	3,846	70.79
Total	5,433	100

Match Rate InfoUSA



Housing Discrimination and the Toxics Exposure Gap in the United States: Evidence from the Rental Market

Christensen, Sarmiento-Barbieri, Timmins

RESTAT 2020

Discrimination and Toxics

Christensen, Sarmiento-Barbieri, Timmins (2020) *RESTAT 2020*

- Growing Evidence of Long-Run Damages from Pollution Exposures
  1. Pre-natal and post-natal pollution exposures have long-run effects on health and development (Almond and Currie, 2011, Isen et al., 2017, Currie, 2009, Almond et al., 2017)
  2. Effects of TRI chemical toxics important effects on gestation and birth-weight (Currie et al., 2015, Currie and Schmieder, 2009)
  3. Differences in pre-natal and early life exposures may contribute to persistent inequality (Currie, 2011)
- Does housing discrimination impose constraints that induce a race gap in exposure to chemical toxics?

Discrimination and Toxics: Experimental Design

Sample of Markets

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

Discrimination and Toxics: Experimental Design

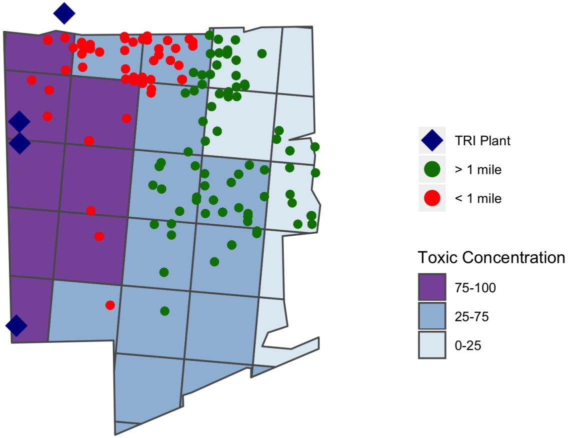
Zip Codes With TRI Toxic Plants within one mile

Discrimination and Toxics: Experimental Design

Sample of Markets

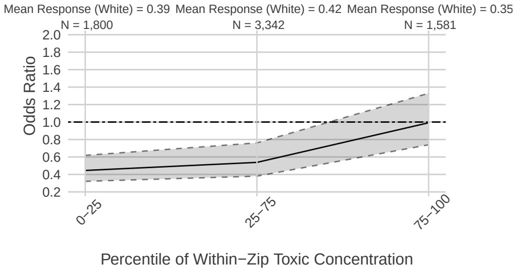
1. Markets: Zip codes with a high-emitting TRI plant within 1 mile of a residential neighborhood
   - High-emitting $\rightarrow$ above 80*th* percentile of airborne emissions
   - More than 150 active listings
2. Sample full set of advertised rental listings available on major online housing platform
   - Balanced sample of listings near and far TRI plants ($\approx$ 30%)
3. Use RSEI (Risk-Screening Environmental Indicators) within zip toxic concentrations from EPA
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

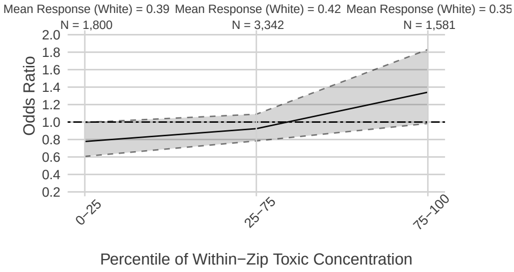


Discrimination and Toxics: Results

Figure: Odds Ratio by Within-ZIP Toxic Concentration



(a) African American



(b) Hispanic/LatinX

Discrimination and Toxics: Estimation

Based on the 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:

$$
\begin{aligned}
u_{i1}^* &= \sum_k (\psi_k + \beta_{k1} Minority_1) Z_{i \in k} + \theta X_1 + \delta_i + \epsilon_{i1} \\
u_{i2}^* &= \sum_k (\psi_k + \beta_{k2} Minority_2) Z_{i \in k} + \theta X_2 + \delta_i + \epsilon_{i2} \\
u_{i3}^* &= \sum_k (\psi_k + \beta_{k3} Minority_3) Z_{i \in k} + \theta X_3 + \delta_i + \epsilon_{i3}
\end{aligned}
\tag{6}
$$

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

Discrimination and Toxics: Estimation

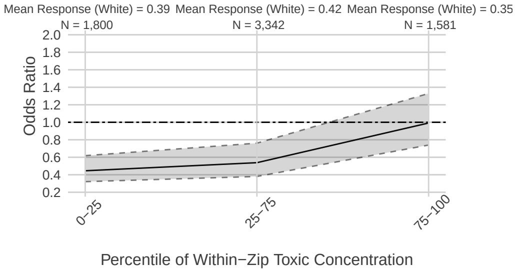
Therefore:

$$P(y_{ij} = 1 | X, Z, \delta) = F(\sum_k (\psi_k + \beta_{kj} Minority_j) Z_{i \in k} + \theta X_j + \delta_i) \tag{7}$$

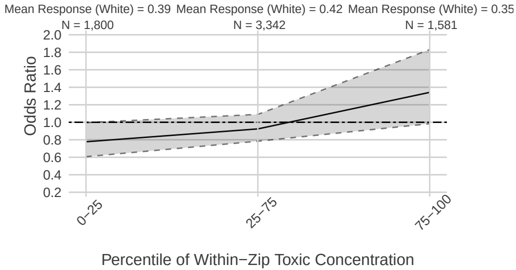
- F is the logistic cumulative distribution function.
- $Minority_j$ is an indicator that takes the value one if the race group associated with the identity is either African American or Hispanic/LatinX; and is zero if it is the White identity.
- X_j is a vector of renter-specific control variables: 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

Figure: Odds Ratio by Within-ZIP Toxic Concentration



(a) African American

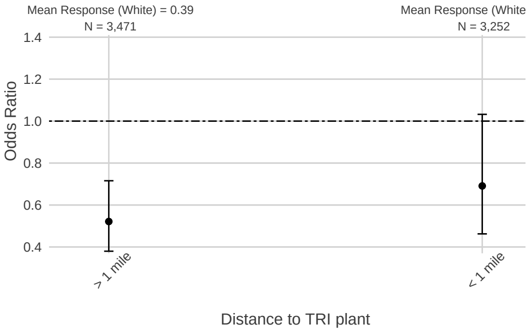


(b) Hispanic/LatinX

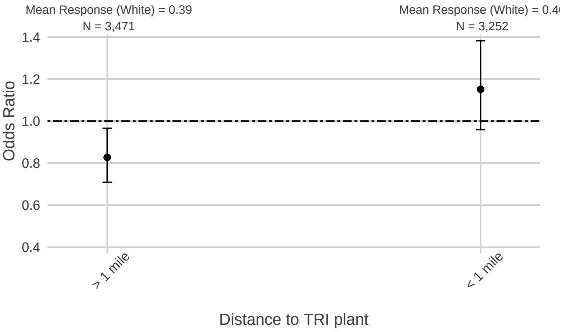
Results: Discrimination by Distance to Emissions Source

Figure: Odds Ratio by Proximity to Closest TRI Plant

Panel B: African American vs Hispanic/LatinX



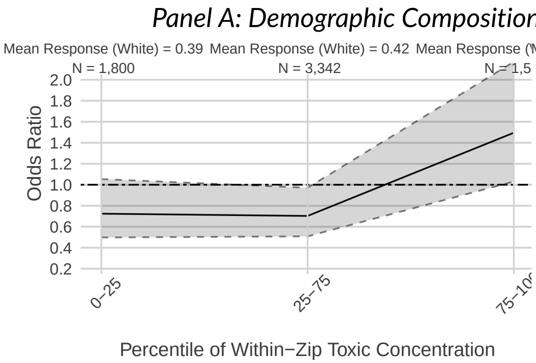
(a) African American



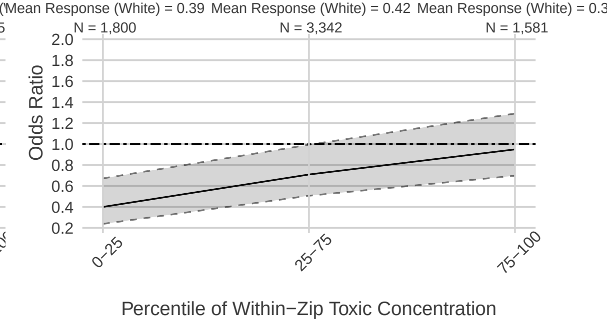
(b) Hispanic/LatinX

Heterogeneity in Discriminatory Constraints

Figure: Odds Ratio by Within-ZIP Toxic Concentration



(A.1) Above Median Minority Share

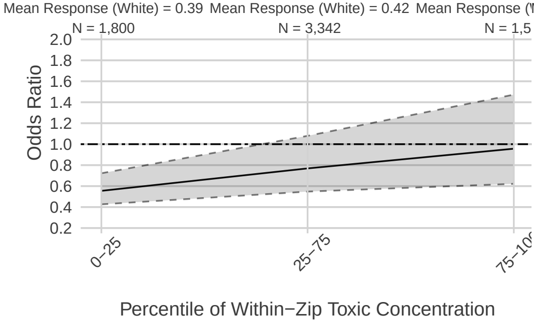


(A.2) Below Median Minority Share

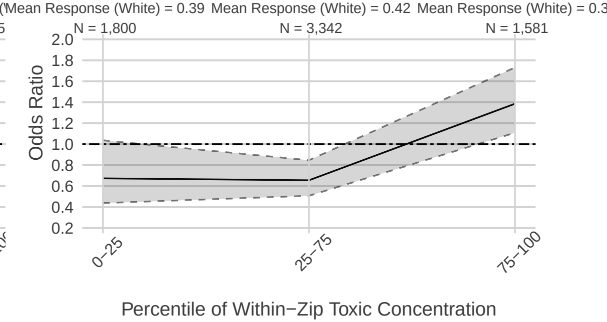
Heterogeneity in Discriminatory Constraints

Figure: Odds Ratio by Within-ZIP Toxic Concentration

Panel B: Above vs Below Median Rent



(B.1) Above Median Rent

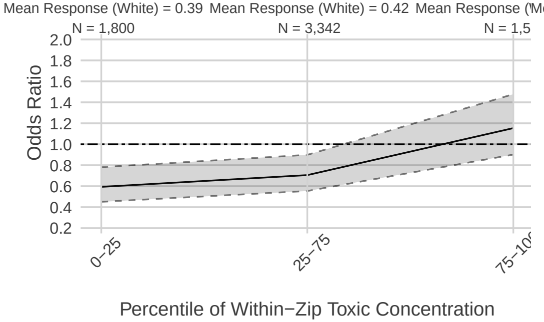


(B.2) Below Median Rent

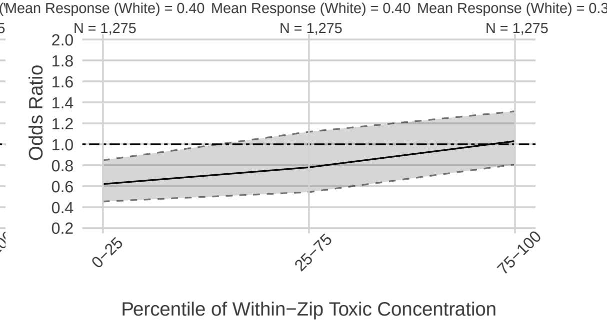
Heterogeneity in Discriminatory Constraints

Figure: Odds Ratio by Within-ZIP Toxic Concentration

Panel C: Full vs Matched Sample



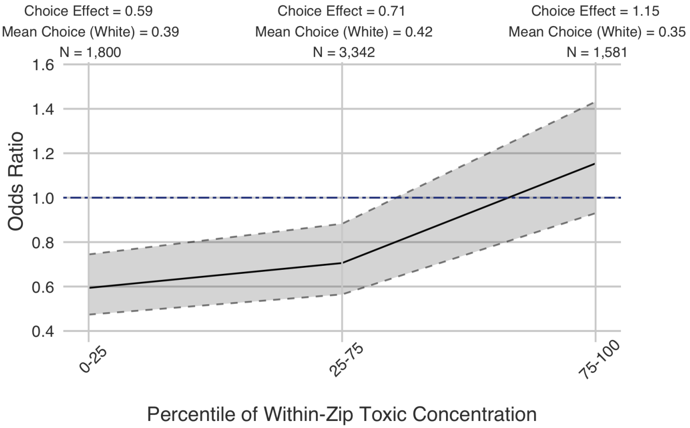
(C.1) Full Sample



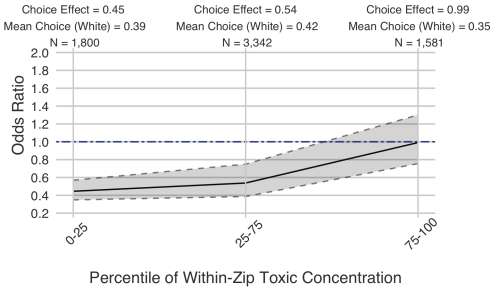
(C.2) Matched Sample

Choice Rates by Within-Zip Toxic Concentration: Minority

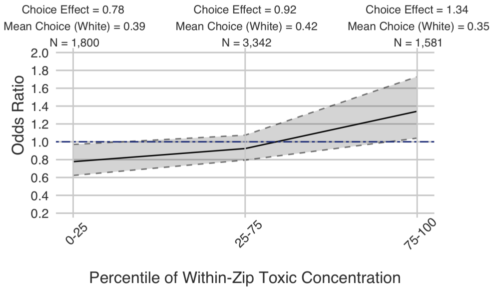
Figure: Choice Rates by Within-Zip Toxic Concentration



Choice Rates by Within-Zip Toxic Concentration: African American vs Hispanic/LatinX

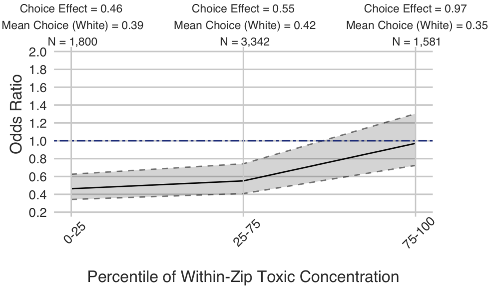


(a) African American

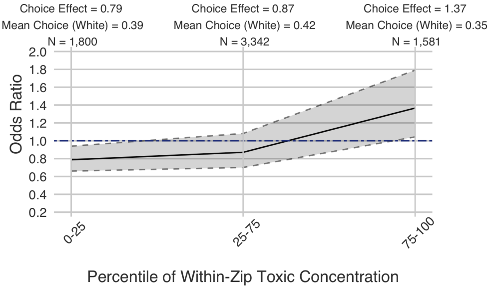


(b) Hispanic/LatinX

Heterogeneity in Discriminatory Constraints: Male vs Female



(a) Male

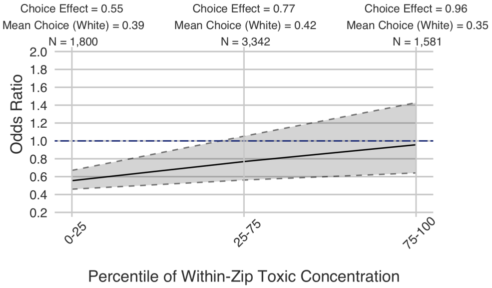


(b) Female

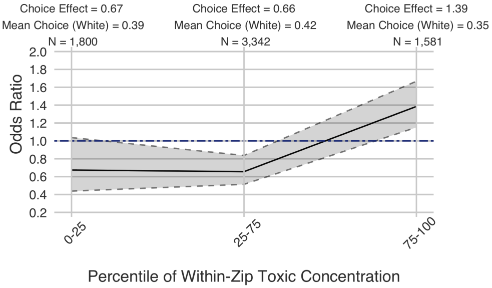
Heterogeneity within Zip Code Neighborhood Characteristics

- When we apply for rental we also observe property characteristics and neighborhood characteristics
- Within zip codes properties in the high concentration zones are
  - Rental prices are $278/month lower
  - Lower shares of Hispanic and white residents, but higher shares of African American residents.
  - Fewer grocery stores, and higher poverty rates
  - 10% less likely to be a single-family residence and more likely to be an apartment in a multi-family building

Heterogeneity in Discriminatory Constraints: Above vs Below Median Rent

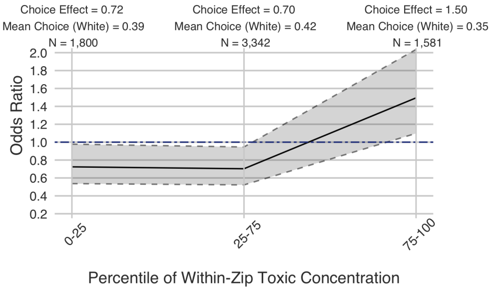


(a) Above Median Rent

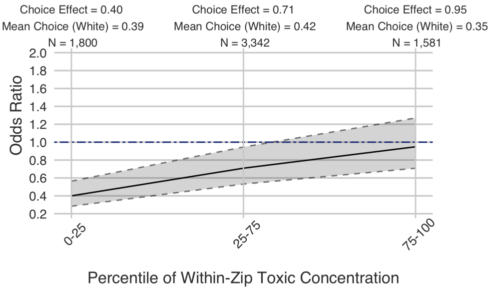


(b) Below Median Rent

Heterogeneity in Discriminatory Constraints: Above vs Below Minority Shares

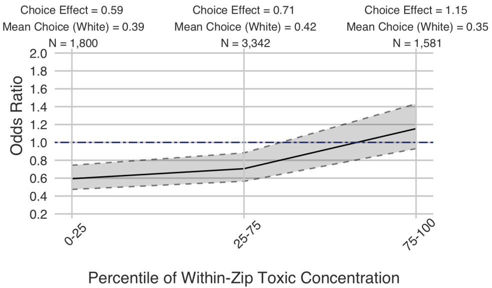


(a) Above Median Minority Share

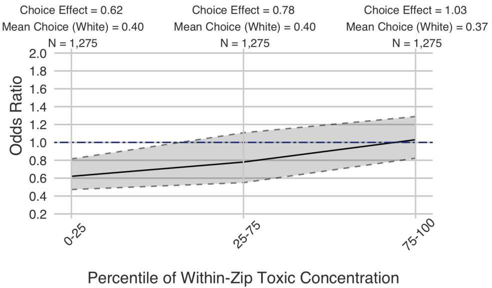


(b) Below Median Minority Share

Heterogeneity in Discriminatory Constraints: Full vs Matched Sample



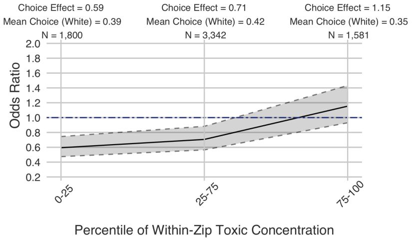
(a) Full Sample



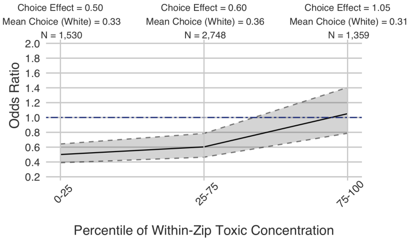
(b) Matched Sample

We match on housing and neighborhood characteristics. Housing characteristics include: rental price, bedrooms, bathrooms, square footage, and building type. Neighborhood characteristics include: crime, nearby grocery stores, demographic composition of census block group (share White, Black, Hispanic), poverty rate, unemployment rate, and share college educated.

Heterogeneity in Discriminatory Constraints: Full Sample vs Human-Generated Responses



(a) Full Sample

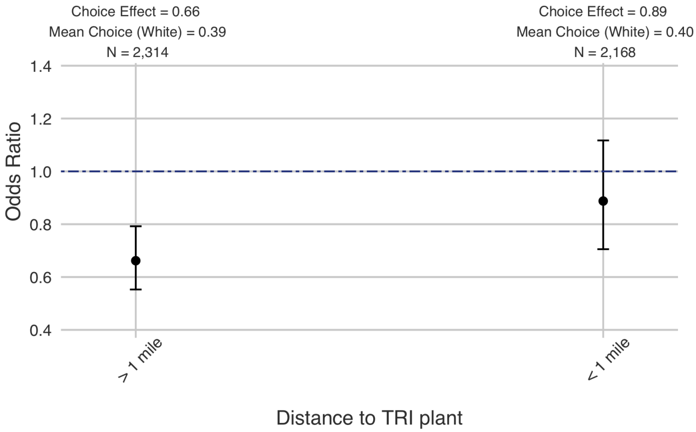


(b) Human-Generated Responses

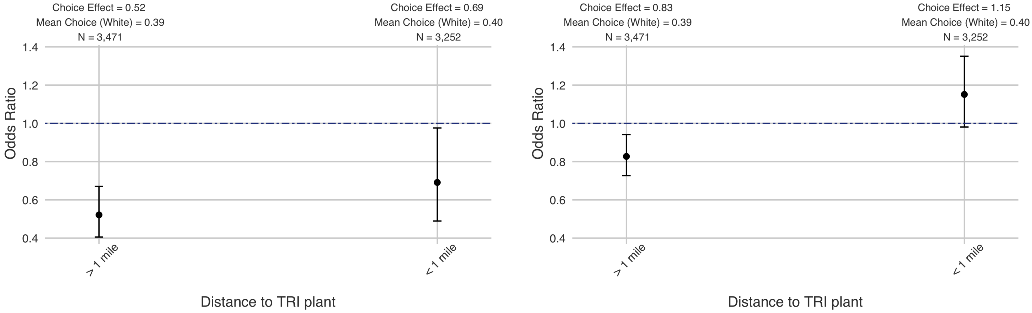
Choice Rates by Proximity to Closest TRI Plant

- Currie and Schmieder (2009) and Currie et al (2015) provides direct evidence that in utero exposures resulting from residential location choices surrounding TRI facilities have important effects on gestation and birth-weight
- Within 1 mile exposures are found to result in a 3-5% increase in the probability of low birth-weight
- Black et al (2007) estimate that 1% decrease in birth-weight decreases expected earnings by about 0.13%

Choice Rates by Proximity to Closest TRI Plant



Choice Rates by Proximity to Closest TRI Plant: African American vs Hispanic/LatinX



(a) African American (b) Hispanic/LatinX

Heterogeneity in Discriminatory Constraints: Zip Codes with Toxic Concentration and Distance Congruence