Housing Discrimination and Pollution Exposures in the United States

Peter Christensen, Ignacio Sarmiento-Barbieri and Christopher Timmins*

April 9, 2020

Abstract

Local pollution exposures disproportionately impact minority households, but the root causes remain unclear. This study conducts a correspondence experiment on a major online housing platform to test whether housing discrimination constrains minority access to housing options in markets with significant sources of airborne chemical toxics. We find that renters with African American or Hispanic/LatinX names are 41% less likely than renters with White names to receive responses for properties in low-exposure locations. We find no evidence of discriminatory constraints in high-exposure locations, indicating that discrimination increases relative access to housing choices at elevated exposure risk.

Key words: Housing Discrimination, Correspondence Experiment, Air Toxics
JEL Classification: Q51, Q53, R310

*Christensen: Department of Agricultural and Consumer Economics, University of Illinois, 431 Mumford Hall, 1301 W. Gregory Urbana Illinois 61801 (email: pchrist@illinois.edu); Sarmiento-Barbieri: Department of Economics, University of Illinois, 216 David Kinley Hall, 1407 W. Gregory, Urbana, IL 61801 (email: srmntbr2@illinois.edu); Timmins: 209 Social Sciences Building, P.O. Box 90097, Durham, North Carolina 27708 (email: christopher.timmins@duke.edu). We thank David Albouy, Spencer Banzhaf, Pat Bayer, Johnathan Colmer, Rebecca Diamond, Nick Kuminoff, Juan Carlos Serrato, Daniel Sullivan, Reed Walker, Randy Walsh, and seminar participants at NBER Energy and Environmental Economics, The Workshop on Environmental Economics and Data Science, Triangle Resources and Environmental Economics (TREE) Seminar, UC Berkeley, UC Santa Cruz, UC San Diego, UC Santa Barbara Occasional Workshop in Environmental Economics, UNLV, University of Miami, University of Virginia, and Wharton School for excellent comments. We thank Davis Berlind, Christopher Kim, Daniel Rychel, Tom Phillips and student assistants in the University of Illinois Big Data and Environmental Economics and Policy (BDEEP) Group and the Duke Environmental Justice Lab for research assistance. We acknowledge generous support from the Russell Sage Foundation, National Science Foundation, and the National Center for Supercomputing Applications. The experiment was registered on the AEA RCT Registry as trial 3366 (Christensen et al., 2018) and the human subjects protocol for this research design was approved by the University of Illinois Institutional Review Board (IRB #18381) on 12/07/2017. All data and code will be available prior to publication using DOI 10.5281/zenodo.3492234. All errors are our own.

1 Introduction

Over the past three decades, a range of studies have demonstrated that minority households in the United States are disproportionately exposed to harmful pollutants (Rosofsky et al., 2018, Clark et al., 2017, Ard, 2015, Shapiro, 2005, Ash and Fetter, 2004). This 'race gap' in pollution exposures is found both in cross-sectional data and also in neighborhood demographic changes following shifts in pollution concentrations (Mohai and Saha, 2015, Cushing et al., 2015, Mohai et al., 2009). Other work has revealed relationships between pollution exposures and persistent inequity in lifetime cancer risk (Collins et al., 2015, Morello-Frosch and Jesdale, 2006, Morello-Frosch et al., 2001) and chronic respiratory conditions such as asthma (Alexander and Currie, 2017, Currie, 2009). Studies of long-run impacts on in utero populations demonstrate that emissions exposures from nearby toxic plants or traffic congestion in close proximity to a home residence have critical effects on infant health and birth-weight (Currie et al., 2015, Currie and Walker, 2011, Currie and Schmieder, 2009, Currie and Neidell, 2005). This body of research elevates concern that differential location choices in US housing markets result in a persistent racial gap in exposure to chemical toxics and related health outcomes.

While evidence of an exposure gap is clear, it has been challenging to identify root causes. A key question involves whether housing market discrimination actively constrains choices available to minority households in low-exposure neighborhoods. For over two decades, researchers have hypothesized that housing discrimination may be an important factor in explaining the exposure gap in the United States (Crowder and Downey, 2010, Logan and Alba, 1993). However, no prior study has provided an empirical test in the rental housing market.[1] This is challenging in observational data, as it requires disentangling discriminatory constraints from disparities in income (Banzhaf et al., 2019, Aliprantis et al., 2019, Logan, 2011), differences in information about exposure risk (Hausman and Stolper, 2019, Currie, 2011) and housing/neighborhood preferences that also affect residential sorting behavior (Depro et al., 2015, Banzhaf and Walsh, 2013). The

[1]Using data from a HUD paired actor study, Christensen and Timmins (2018) provide evidence that real estate agents steer minority homebuyers into properties at closer proximity to Superfund sites and TRI facilities.

discrimination mechanism differs fundamentally from the other factors in that it involves illegal behavior that imposes ex-ante constraints on the choices of minority renters, potentially distorting sorting behavior even when households are perfectly informed about the risk of exposures. Examining the effect of housing discrimination on ex-ante choice constraints is important for analyzing the race-gap in pollution exposures and for studying the channels through which housing discrimination may create barriers to human capital accumulation that contribute to racial inequality in the United States (Akbar et al., 2019, Graham, 2018, Chetty et al., 2018, Christensen and Timmins, 2018).

This paper uses a correspondence study conducted on a major online rental housing search platform to provide the first experimental evidence on the effect of discriminatory constraints on access to housing choices in markets with major pollution sources.[2] We define a representative sample of local rental housing markets using the set of US ZIP codes that contain major sources of toxic emissions (using the Toxic Release Inventory). In this sample of markets, the shares of African American and Hispanic/LatinX renters living in high versus low-exposure locations are more than 50% higher than the White renter population. We then use the within-property randomization to test whether discrimination constrains the housing choices available to minority households at high-exposure locations relative to comparable listings at low-exposure locations that are available at the same time within the same market. We find that discriminatory behavior reduces the likelihood of response to minority renters with racially perceptible names by 41% in low-exposure locations, though we find no evidence of discriminatory constraints operating in the high-exposure zones of the same markets. Our tests reveal that constraints in low-exposure neighborhoods are considerably stronger for African American renters, especially for African American men.

We then examine how the discrimination-exposure relationship varies by neighborhood racial composition, rental price, and among properties that are matched using the housing/neighborhood characteristics that are visible to prospective renters on the search

[2]While online housing markets do not reflect all options available in the markets that we study, online housing platforms have increasingly become the locus of housing search and constitute an important channel for discriminatory behavior Apartments.com (2015).The referenced survey reports that 72% of housing searches were initiated on online platforms in 2015.

platform. We find that the relationship holds across neighborhoods with high/low shares of minority households, across segments of the rental price distribution, and within sets of highly comparable properties. By constraining the housing choices of minority renters in low-exposure neighborhoods, discriminatory constraints in markets with major toxic facilities result in a ceteris paribus welfare effect for minority households that value clean air. Among renters that are informed about pollution exposures and are willing to pay to avoid them during a search, these constraints will increase the cost of that avoidance behavior. Among minority renters who may not be informed or who may not structure their search to specifically avoid high-exposure neighborhoods, discriminatory constraints reduce the probability of sorting into low-exposure locations relative to high-exposure locations, thereby contributing to the race gap in exposures and related health outcomes.

Beyond the exposure gap, this paper contributes to a growing literature that uses correspondence and other experimental methods to study discriminatory behavior in labor and housing markets (Bertrand and Duflo, 2017). While recent literature has mainly focused on detecting discrimination or examining the mechanisms that underlie discriminatory behavior, the current study responds to recent calls for increased focus on the adverse impacts of discriminatory constraints (Kline and Walters, 2019, Guryan and Charles, 2013). New work by Kline and Walters (2019) illustrates the importance of heterogeneity in discriminatory behavior in the labor market. In the housing market, relatively little is known about the characteristics of neighborhoods where minority households face systematically stronger constraints (Phillips, 2017, Ewens et al., 2014, Hanson and Hawley, 2011). This study demonstrates that estimates of average effects can mask heterogeneity along dimensions that drive search and sorting processes and are therefore important for determining the adverse impacts of discriminatory behavior.

This paper proceeds as follows. The following section provides background on the experimental design and sample. Section 3 discusses results on the discrimination-exposure relationship by toxic concentration and by distance to TRI facility. Section 4 discusses heterogeneity in the discrimination-exposure relationship by price and housing/neighborhood characteristics. Section 5 concludes.

2 Study Area and Correspondence Design

We define a sampling frame that includes all ZIP codes surrounding major point sources of airborne chemical toxics, which are defined using facilities reporting emissions through the EPA's Toxic Release Inventory (TRI). This design yields a sample that is representative of localized housing markets that are characterized by substantial within-market variation in pollution exposures. Panel A of Figure 1 maps the set of US ZIP codes that contain a nearby high emitting facility.[3] The final study area uses a sample of 2,918 listings from 19 ZIP codes drawn at random from the set of high emissions markets.

Within each of the ZIP codes that we sample, we compile the full set of property listings on the day of data collection to simulate the choices available in a search. The sampling design ensures that estimates reflect differences across the full set of housing options advertised to prospective renters at the time of an experimental trial, simulating the set of options available to a prospective renter that is searching on the platform at that time. Immediately following compilation of the relevant listings in a given market, a name is randomly drawn and assigned from each of three racial groups.

Using prior literature on racialized perceptions in US populations, we select 18 first-last name pairs that are shown to have a high probability of cognitive association with each of 3 racial categories – African American, Hispanic/LatinX, White (Gaddis, 2017a,b). A question that has emerged in prior correspondence studies using racialized names is the possibility that any given name may signal race as well as other unobserved characteristics such as income (Guryan and Charles, 2013, Fryer Jr and Levitt, 2004). To test this empirically, we construct groups with each consisting of 3 male and 3 female names and stratify the sample of first names using statistical distribution of mother's educational attainment (low, medium, and high) from hospital birth records. The first name labels for this study are constructed using recent experimental work that tested the racialized perceptions of first and last names for African American, Hispanic/LatinX, and White social groups (Gaddis, 2017a,b). Last name labels were also taken from this work and

[3] A nearby facility is defined as a facility within one mile of the ZIP code boundary. High emitting facilities are defined as those with annual emissions ('stack and fugitive air releases') that fall above the 80th percentile of annual emissions.

tested for any geographic variability using related research (Crabtree and Chykina, 2018). Each of the resulting name groups consists of three male and three female names, one drawn from each of three levels of maternal educational attainment (high/medium/low).

Each rental apartment receives a sequence of three separate inquiries directly through the online platform in the course of an experimental trial. The sequence of inquiries from the different race groups is randomly assigned. Inquiries for the same listing are never sent from the same identity or from two different identities on the same day.[4] Responses to inquiries are coded using two criteria that determine whether or not a housing choice is made available: (1) a response is received within 7 days of the associated inquiry and (2) the response indicates that the property is available for rent.[5] Discriminatory constraints are expressed in terms of *relative response rates*, which measure within-property differences in access to a given listing relative to an inquiry sent from a White name (the comparison group). We use the terms relative response rates, response rates, and likelihood of response interchangeably to refer to this measure throughout the paper.

Within each ZIP code, the concentration of airborne toxics is measured using the level of ambient concentrations in 810 square meter grid cells in the US Environmental Protection Agency's Risk-Screening Environmental Indicators (RSEI) Model. We use the RSEI measure of toxic concentration to define the level of exposure at each of the properties in the sample of available listings – the terms concentration and exposure are used interchangeably to refer to the RSEI measure at residential locations. Panel B of Figure 1 maps the locations of emissions sources, RSEI concentrations, and the approximate locations of properties using 2 of the ZIP codes in the sample.[6]

Figure 2 provides a descriptive analysis of the race gap in exposures in the sample using data on the renter populations data from the 2016 American Community Survey (ACS). The top panel summarizes the within-ZIP share of renters living in the highest quartile (and interquartile range) of exposures, relative to the lowest quartile. Dotted

[4]Balance tests are reported in Table A3.

[5]52% of responses are received within the first 8 hours of an inquiry, 74% are received within 24 hours and 98% are received within 5 days. The 7-day cutoff is used to restrict responses that may be received weeks or months after an inquiry and are not counted as choices in the study. We refer interested readers to Figure A6 for the distribution of inquiry response time in the sample.

[6]Maps of all ZIP codes provided in Figure A3.

lines illustrate the differences for the African American and Hispanic/LatinX groups relative to White renters. The bottom panel plots the fraction of the population shares for each group living in each quantile of the RSEI distribution for each ZIP code. Two facts emerge from the ACS data: (1) the relative shares of minority households living in the highest quartile of exposures is 60% higher for African Americans and 58% higher for Hispanix/LatinX residents than for the population of White renters and (2) households in all race groups sort across the full support of the exposure distribution in their ZIP code.

3 Housing Discrimination and Toxics Exposures

We estimate relative response rates using a within-property conditional logit estimator that measures the likelihood of access to listing j for a minority identity i (treatment), relative to an inquiry made to the same listing (j) from a White identity (comparison):

$$P(response_{ij}) = \sum_{\substack{Race \in \{Af.\,Am.,\\ LatinX\}}} \sum_{j} (\beta_{j,race} 1[i \in b_j] \times Race) + \theta X_i + \alpha_j + \epsilon_{ij} \tag{1}$$

where b denotes a bin of within-ZIP toxic concentration. *Race* indicates the race group associated with the identity from which an inquiry is sent. X_i is a vector of individual control variables: gender, education level and the order in which the inquiry was sent. Point estimates are not sensitive to the inclusion of controls though precision increases slightly.[7] α_j is a listing fixed effect.

The primary set of tests defines exposures using ambient concentrations from the RSEI model and concentrations are divided into 3 bins: 0-25%, 25-75%, 75-100%. A second set of tests defines exposures according to distance from active TRI facilities, which have been shown to directly affect the health outcomes of the in utero population.[8]

[7] See Table A5 for comparison across specifications.

[8] RSEI concentrations are strongly but not perfectly correlated with ambient concentrations studied in the tests reported in Figure 3. Figure A5 plots the distribution of properties in each RSEI percentile by distance to TRI plants for the full sample. Figure A3 maps the relationship for each individual ZIP code.

Discrimination by RSEI Concentration

Figure 3 plots estimates of within-property response rates at different levels of pollution exposure, where exposures are defined using the RSEI measure of toxic concentrations, with properties divided into the lowest quartile, the interquartile range, and in the highest quartile of ambient emissions concentrations within a ZIP code. The plots measure differential constraints within the full set of properties simultaneously listed for rent in markets containing a major emissions source. Panel A plots estimates of discriminatory constraints facing minority identities as a whole. We estimate a 59% relative response rate to inquiries for properties located in the lowest quartile of the within-ZIP toxics concentration, indicating that inquiries from minority identities are 41% less likely to yield choices for minority renters at low levels of exposure. The strength of choice constraints declines as toxic exposure increases within a ZIP code. The relative response rate is 71% in the interquartile range of exposures. Among properties located in the *highest* quartile of toxics exposures, we find no statistical difference in the rate of response to minority identities. The difference between relative response rates in the lowest quartile and in the highest quartile is statistically significant at $p < .01$. Taken together, these findings imply that minority households face ex-ante constraints that increase access to housing choices in high-exposure locations relative to low-exposure locations.

Panel B plots estimates independently for African American and Hispanic/LatinX identities. While both groups face discriminatory constraints at low-exposure locations, the relative response rates are substantially lower for African American identities (45%) than for Hispanic/LatinX identities (78%). Discriminatory constraints are smaller for both groups in the interquartile range of exposure risk. At the highest levels of exposure risk within a ZIP code, response rates to African American identities are equivalent to the White names. At high-exposure locations, Hispanic/LatinX identities are 34% *more likely* than a White identity to receive a response. The difference between relative response rates in the lowest quartile and in the highest quartile is statistically significant at $p < .01$.

Panel C provides evidence of stronger discriminatory constraints facing male minority identities, especially among properties at low-exposure locations. We estimate relative response rates of 46% for minority male identities versus 79% among minority female identities. We conduct additional tests to further decompose and explore these effects.[9] We find that the strongest discriminatory constraints in inquiries sent from African American male identities, where relative response rates are 28% in low-exposure locations. We test for heterogeneity by income within race using first names associated with high/medium/low levels of maternal educational attainment. These tests provide suggestive evidence of somewhat stronger constraints facing minorities with names that signal a low SES background, though we do not detect statistical differences in the strength of constraints facing low/medium/high minority identities in low-exposure zones. When facing discriminatory constraints, renters may also make multiple inquiries about a property to increase the likelihood of gaining access. We simulate this process by running two rounds using the same names. All tests indicate a *stronger* discriminatory response in follow-up inquiries. Whereas response rates for first inquiries are 58% from minority identities, 41% from African American identities, and 86% from Hispanic/LatinX identities, response rates to second inquiries are 38% from minority, 51% from Hispanic, and 27% from African American identities.[10]

Discrimination by Distance to Emissions Source

Prior work provides direct evidence that in utero exposures resulting from residential location choices surrounding TRI facilities have important effects on gestation and birthweight and that ambient pollution decays rapidly as a function of distance to the nearest plant, such that damages are concentrated within 1 mile (Currie et al., 2015, Currie and Schmieder, 2009).

Figure 4 reports evidence on discriminatory constraints using distance to the nearest TRI facility. The results mirror the findings on concentrations. We find no statistical difference in relative response rates among properties located within the 1 mile radius, indicating that minority renters do not face discriminatory barriers to access at loca-

[9] We refer interested readers to Tables A9, and A10

[10] Results provided in Table A7.

tions that are linked to a 3-5% increase in the probability of low birth-weight (Currie et al., 2015). Among properties located beyond 1 mile from a TRI facility, we find a 66% response rate to inquiries made from minority identities. The tests again reveal substantially stronger constraints facing African American identities (52%) when compared to Hispanic/LatinX identities (83%). In high-exposure zones, we detect no evidence of statistical differences facing African American identities and a 15% *higher* relative response rates for inquiries made from Hispanic/LatinX identities. These estimates provide evidence that discriminatory constraints reduce housing choices at safe distances from TRI facilities and, through that mechanism, may contribute to adverse gestational outcomes in minority households. The difference between relative response rates near vs. far from facilities are statistically significant for all minorities at p¡.1 and for Hispanic/LatinX identities at p¡.01. The difference is not significant for African American identities.

4 Heterogeneity in Discriminatory Constraints

Given the within-property randomization, the estimates in the prior section provide evidence on the discrimination-exposure relationship among all available properties in our sample of markets and indicates that discriminatory constraints limit the access of minority renters to housing in low-exposure zones. In this section, we dig deeper into this relationship by examining how it varies with other housing and neighborhood attributes. Not surprisingly, properties in low/high-exposure locations vary along several dimensions. The average price of a rental property in the highest quartile of within-ZIP toxics exposure is $278 lower than those in the lowest quartile. high-exposure properties are more likely to be apartments in multi-family buildings and located in census block groups with higher shares of African American households, lower shares of Hispanic/White households, higher poverty rates, and higher rates of college educated households.[11] Results reported in Figure 5 examine heterogeneity in discriminatory constraints by: A) neighborhood racial composition, (B) rental price, and (C) the full set of matched housing and

[11]See Table A2 for descriptive statistics of complete set of characteristics for properties in the sample and tests of differences by quartile of concentration.

neighborhood characteristics available on the rental search platform.

Prior work demonstrates that discriminatory constraints tend to be stronger in neighborhoods with a higher share of non-minority (White) households (Hanson and Hawley, 2011, Ewens et al., 2014, Christensen and Timmins, 2018). This is illustrated in Panel A, which plots relative response rates for listings in census block groups with shares of minority households that fall above or below the median share in a ZIP code. The strongest constraints facing minorities are observed in low-exposure zones with low shares of minority households. Relative response rates in the lowest quartile of concentrations are 40% in census block groups with below-median minority shares and 72% among census block groups with above-median minority shares. In the interquartile range of exposures, relative response rates are 71% among census block groups with below-median minority shares and 70% among census block groups with above-median minority shares. In the upper quartile of exposures, relative response rates are 150% among census block groups with above-median minority shares and 95% (not statistically significant) among census block groups with below-median minority shares. The difference between relative response rates in the lowest quartile and in the highest quartile in both of these samples is statistically significant at p¡.05.

Plots in Panel B examine discriminatory constraints among listings that fall above or below the median rental price within a ZIP code. These results indicate that minority identities face the strongest constraints when requesting properties listed at high prices in low-exposure zones. Minority response rates are 55% for high priced properties in low-exposure locations in the sample. Relative response rates are highest among low priced properties in high-exposure zones. In both quantiles of the price distribution, constraints are stronger in low-exposure than in high-exposure locations. Differences between relative response rates in the lowest quartile and in the highest quartile are significant at p¡.01 in the low-rent sample and at p¡.01 in the high-rent sample. In an alternate test, we restrict the sample to listings that fall within 25% of the median rent in each ZIP code and find consistent results.[12]

[12]We refer interested readers to Figure A8, which provides tests using a restricted sample of listings that fall within 25% of the median rent in each ZIP code.

Estimates in Panel C compare response rates among properties that are matched on price as well as housing/neighborhood characteristics that are visible to renters on the search platform.[13] These tests examine relative response rates among comparable properties that are simultaneously listed for rent and therefore reflect exact differences in comparable choices available to prospective renters in these markets at the time of the experiment. Response rates at each level of toxics exposure (quartile) are estimated relative to the most comparable properties at the other levels. 966 unmatched properties are dropped from this test, reducing the sample size to 1,275. Response rates in the matched test (62%) are highly similar to those in the full sample test (59%) in the lowest quartile of exposures, indicating that the relationship between choice constraints and toxic concentrations is present when accounting for differences in other housing and neighborhood characteristics. Estimates of response rates for the interquartile range of concentrations are less precise, likely resulting from the sampling restriction. Differences at the highest level of concentrations are somewhat smaller than, though not statistically different from, the full sample test. The difference between relative response rates in the lowest quartile and in the highest quartile of the matched sample are significant at p¡.01.

5 Conclusion

For over two decades, researchers have advanced a *racial discrimination hypothesis* to explain the factors underlying the disparity in exposures to chemical toxics and other harmful pollutants in the United States. However, no prior study has provided an empirical test. This paper presents experimental evidence that racial discrimination constrains the housing choices of minority households with respect to major polluting facilities in the United States. We find that Hispanic/LatinX and African American renters face strong discriminatory constraints when searching for housing that would limit their exposure to emissions from major sources of chemical toxics in the US.

When initiating a search in a market containing a major pollution source, discrimi-

[13]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.

natory behavior reduces the likelihood of response to minority renters with racially perceptible names by 41% in low-exposure locations. Among African American renters, discriminatory behavior reduces the likelihood of response by 55% and by 72% for African American men. We find no evidence of discriminatory constraints operating in the high-exposure zones of the same markets. The pattern holds in tests between properties that are matched on comparable characteristics, in different segments of the rental price distribution, and in neighborhoods with different shares of minority households. By reducing the set of choices available in less polluted neighborhoods relative to more polluted ones, choice constraints resulting from discriminatory behavior increase the cost of averting prolonged exposures to chemical toxics and directly affect the welfare of households that value clean air.

We emphasize the need for further study of the effects of discriminatory constraints on the location choices of minority households and highlight four limitations of the correspondence design to be addressed in future research. First, the present experimental results are limited to listings that appear on a single rental housing platform. There is evidence that digital platforms are used to initiate the majority of rental housing search processes in the US, but the study does not account for sub-markets that are advertised separately. Second, our estimates reflect the signal produced by a sample of names that is designed to elicit racialized perceptions and allows for analysis of heterogeneity in the effects by gender and maternal educational attainment. It is not representative of the total population of renters in the United States. Third, correspondence research designs do not capture discrimination in subsequent interactions that could further affect the probability of a viable lease.

Finally, the effects of constraints found in this study ultimately depend upon the extent to which they bind on the decisions of minority households. While correspondence designs provide important information on ex-ante constraints, they do not alone provide information on the market outcomes of individuals that face discrimination. In ongoing research, we further examine interactions between discriminatory constraints and incomes, neighborhood preferences, and additional factors that also contribute to differential sorting behavior (Christensen and Timmins, 2020). In some settings, renters may not search in neighborhoods where discriminatory constraints bind or may invest in additional search to avoid adverse outcomes such as local pollution exposures. Data on renter population distributions from the ACS provides evidence that minority households sort across the full support of the distribution of pollution exposures in our study area and tend to sort into neighborhoods with elevated exposures. This indicates that while some minority households may structure their search or invest in additional search to avoid high-exposure locations, others do not. These findings suggest that discriminatory behavior increases the cost of avoiding harmful exposures and suggest that reducing illegal discriminatory behavior could be important for reducing the racial gap in pollution exposures in the US.

References

Akbar, P. A., Li, S., Shertzer, A., and Walsh, R. P. (2019). Racial segregation in housing markets and the erosion of black wealth. National Bureau of Economic Research.

Alexander, D. and Currie, J. (2017). Is it Who You Are or Where You Live? Residential Segregation and Racial Gaps in Childhood Asthma. *Journal of Health Economics*, 55:186–200.

Aliprantis, D., Carroll, D., Young, E., et al. (2019). What explains neighborhood sorting by income and race? *FRB of Cleveland WP 18-08R*.

Apartments.com (2015). Online Search Behavior and Trends of Apartment Renters: A Joint Study by Apartments.com and Google. *https://bit.ly/32eSzKc*.

Ard, K. (2015). Trends in Exposure to Industrial Air Toxins for Different Racial and Socioeconomic Groups: A Spatial and Temporal Examination of Environmental Inequality in the US from 1995 to 2004. *Social Science Research*, 53:375–390.

Ash, M. and Fetter, T. R. (2004). Who Lives on the Wrong Side of the Environmental Tracks? Evidence from the EPA's Risk-Screening Environmental Indicators Model. *Social Science Quarterly*, 85(2):441–462.

Banzhaf, H. S. and Walsh, R. P. (2013). Segregation and tiebout sorting: The link between place-based investments and neighborhood tipping. *Journal of Urban Economics*, 74:83–98.

Banzhaf, S., Ma, L., and Timmins, C. (2019). Environmental Justice: The Economics of Race, Place, and Pollution. *Journal of Economic Perspectives*, 33(1):185–208.

Bertrand, M. and Duflo, E. (2017). Field Experiments on Discrimination. In *Handbook of Economic Field Experiments*, volume 1, pages 309–393. Elsevier.

Cameron, A. C. and Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. *Journal of human resources*, 50(2):317–372.

Chetty, R., Hendren, N., Jones, M. R., and Porter, S. R. (2018). Race and Economic Opportunity in the United States: An Intergenerational Perspective. National Bureau of Economic Research, Working Paper No. w24441.

Christensen, P., Sarmiento-Barbieri, I., and Timmins, C. (2018). The Impact of Housing Discrimination on the Pollution Exposure Gap in the United States. *AEA RCT Registry*.

Christensen, P. and Timmins, C. (2018). Sorting or Steering: Experimental Evidence on the Economic Effects of Housing Discrimination. *NBER Working Paper No. w24826*.

Christensen, P. and Timmins, C. (2020). Does Racial Bias Distort Neighborhood Choice? the Impacts of Discrimination on Renter Welfare and Revealed Preference in the Housing Market. Working Paper.

Clark, L. P., Millet, D. B., and Marshall, J. D. (2017). Changes in transportation-related air pollution exposures by race-ethnicity and socioeconomic status: outdoor nitrogen dioxide in the united states in 2000 and 2010. *Environmental Health Perspectives*, 125(9).

Collins, T. W., Grineski, S. E., and Chakraborty, J. (2015). Household-level disparities in cancer risks from vehicular air pollution in miami. *Environmental Research Letters*, 10(9):095008.

Crabtree, C. and Chykina, V. (2018). Last name selection in audit studies. *Sociological Science*, 5:21–28.

Crowder, K. and Downey, L. (2010). Interneighborhood migration, race, and environmental hazards: Modeling microlevel processes of environmental inequality. *American Journal of Sociology*, 115(4):1110–1149.

Currie, J. (2009). Healthy, wealthy, and wise: Socioeconomic status, poor health in childhood, and human capital development. *Journal of Economic Literature*, 47(1):87–122.

Currie, J. (2011). Inequality at Birth: Some causes and consequences. *American Economic Review*, 101(3):1–22.

Currie, J., Davis, L., Greenstone, M., and Walker, R. (2015). Environmental Health Risks and Housing Values: Evidence from 1,600 Toxic Plant Openings and Closings. *American Economic Review*, 105(2):678–709.

Currie, J. and Neidell, M. (2005). Air Pollution and Infant Health: What can we learn from California's recent experience? *The Quarterly Journal of Economics*, 120(3):1003–1030.

Currie, J. and Schmieder, J. F. (2009). Fetal Exposures to Toxic Releases and Infant Health. *American Economic Review*, 99(2):177–83.

Currie, J. and Walker, R. (2011). Traffic Congestion and Infant Health: Evidence from E-ZPass. *American Economic Journal: Applied Economics*, 3(1):65–90.

Cushing, L., Morello-Frosch, R., Wander, M., and Pastor, M. (2015). The haves, the have-nots, and the health of everyone: The Relationship Between Social Inequality and Environmental Quality. *Annual Review of Public Health*, 36:193–209.

Depro, B., Timmins, C., and O'Neil, M. (2015). White Flight and Coming to the Nuisance: Can Residential Mobility Explain Environmental Injustice? *Journal of the Association of Environmental and resource Economists*, 2(3):439–468.

Ewens, M., Tomlin, B., and Wang, L. C. (2014). Statistical Discrimination or Prejudice? A Large Sample Field Experiment. *Review of Economics and Statistics*, 96(1):119–134.

Fryer Jr, R. G. and Levitt, S. D. (2004). The Causes and Consequences of Distinctively Black Names. *The Quarterly Journal of Economics*, 119(3):767–805.

Gaddis, S. M. (2017a). How Black are Lakisha and Jamal? Racial perceptions from names used in correspondence audit studies. *Sociological Science*, 4:469–489.

Gaddis, S. M. (2017b). Racial/Ethnic Perceptions from Hispanic Names: Selecting Names to Test for Discrimination. *Socius*, 3:1–11.

Graham, B. S. (2018). Identifying and Estimating Neighborhood Effects. *Journal of Economic Literature*, 56(2):450–500.

Guryan, J. and Charles, K. K. (2013). Taste-Based or Statistical Discrimination: The Economics of Discrimination Returns to Its Roots. *The Economic Journal*, 123(572).

Hanson, A. and Hawley, Z. (2011). Do Landlords Discriminate in the Rental Housing Market? Evidence from an Internet Field Experiment in US Cities. *Journal of Urban Economics*, 70(2-3):99–114.

Hausman, C. and Stolper, S. (2019). Information and inequity: An Application to Environmental Quality. Working Paper.

Kline, P. and Santos, A. (2012). A score based approach to wild bootstrap inference. *Journal of Econometric Methods*, 1(1):23–41.

Kline, P. and Walters, C. (2019). Audits as evidence: Experiments, ensembles, and enforcement. Working Paper.

Logan, J. R. (2011). Separate and Unequal: The Neighborhood Gap for Blacks, Hispanics and Asians in Metropolitan America. *Project US2010 Report*, pages 1–22.

Logan, J. R. and Alba, R. D. (1993). Locational Returns to Human Capital: Minority Access to Suburban Community Resources. *Demography*, 30(2):243–268.

Mohai, P., 660-1809, ., and Roberts, J. T. (2009). Environmental Justice. *Annual Review of Environment and Resources*, 34:405–430.

Mohai, P. and Saha, R. (2015). Which came first, people or pollution? assessing the disparate siting and post-siting demographic change hypotheses of environmental injustice. *Environmental Research Letters*, 10(11):115008.

Morello-Frosch, R. and Jesdale, B. M. (2006). Separate and unequal: residential segregation and estimated cancer risks associated with ambient air toxics in us metropolitan areas. *Environmental health perspectives*, 114(3):386.

Morello-Frosch, R., Pastor, M., and Sadd, J. (2001). Environmental justice and southern california's "riskscape" the distribution of air toxics exposures and health risks among diverse communities. *Urban Affairs Review*, 36(4):551–578.

Phillips, D. C. (2016). Do Comparisons of Fictional Applicants Measure Discrimination When Search Externalities are Present? Evidence from existing experiments. *The Economic Journal.*

Phillips, D. C. (2017). Landlords Avoid Tenants who Pay with Vouchers. *Economics Letters*, 151:48–52.

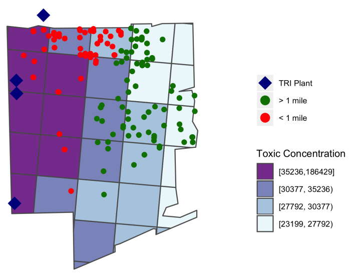
Rosofsky, A., Levy, J. I., Zanobetti, A., Janulewicz, P., and Fabian, M. P. (2018). Temporal trends in air pollution exposure inequality in massachusetts. *Environmental Research*, 161:76–86.

Shapiro, M. D. (2005). Equity and Information: Information Regulation, Environmental Justice, and Risks from Toxic Chemicals. *Journal of Policy Analysis and Management: The Journal of the Association for Public Policy Analysis and Management*, 24(2):373–398.

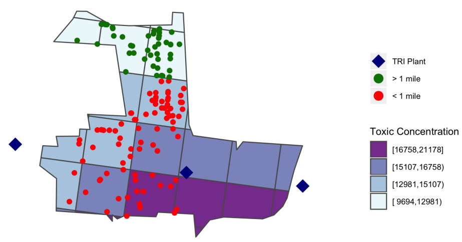
Tables and Figures

Figure 1. ZIP Codes Within One Mile of a TRI Facility and Two Sample ZIP Code Maps

ZIP Codes Within One Mile of a TRI Facility



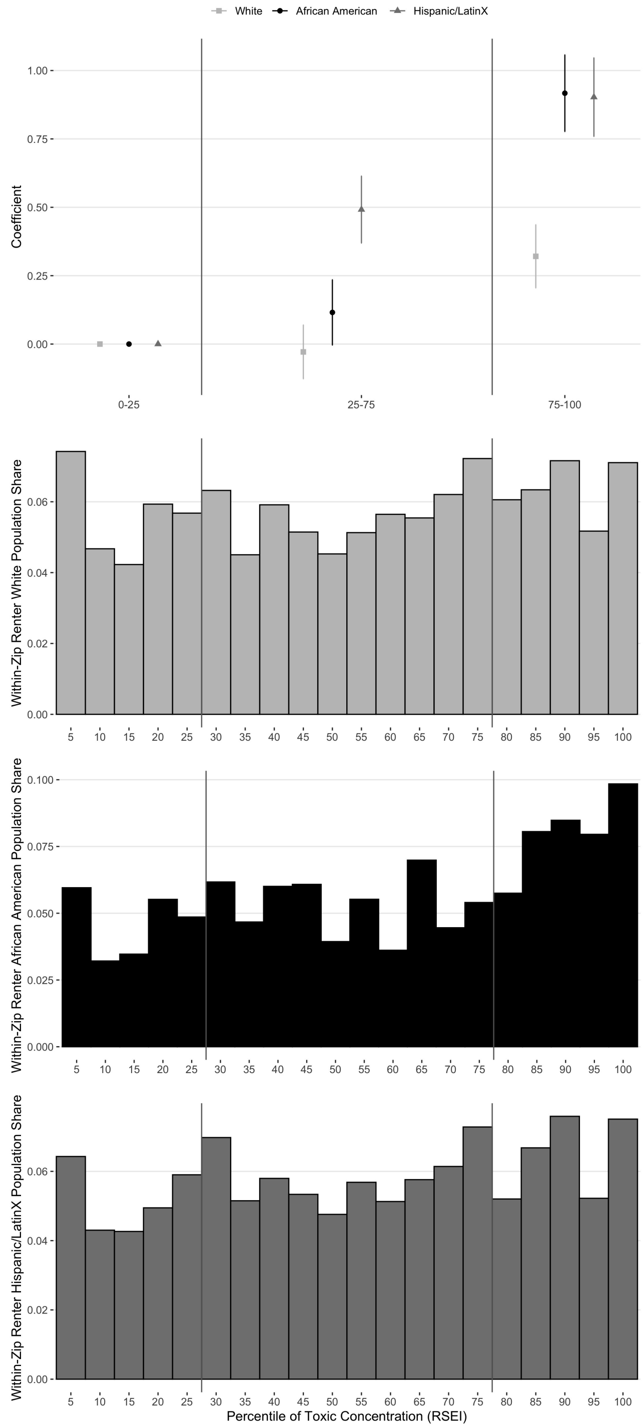
Sample ZIP A



Sample ZIP B

Note: Figure maps the 111 ZIP codes that are above the 80th percentile of TRI stack air releases, which are listed by name in Table A1. The lower panel maps two sample ZIP codes that are included in the experimental sample. Grid cells are shaded according to quartiles of RSEI toxic concentration. The blue rhomboids denote the location of TRI facilities. Circular markers illustrate property listings where the experiment was conducted, with red markers illustrating the sample of listings within one mile of a toxic plant and green markers denoting listings outside 1 mile. Refer to Figure A3 for full set of maps of ZIP codes in the experimental sample.

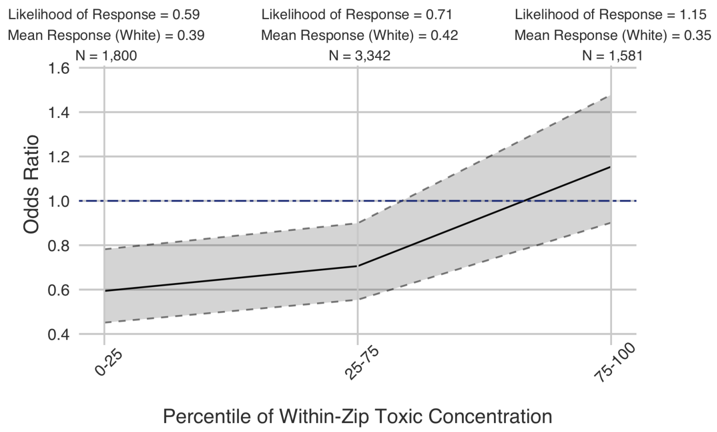
Figure 2. Observed Exposure Gap and Renter Population Distribution



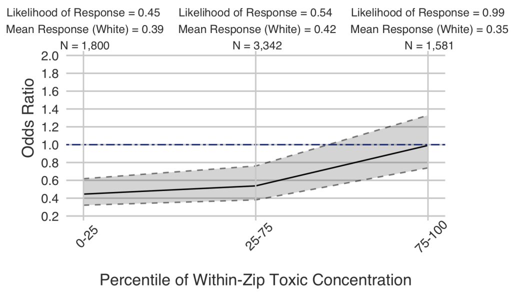
Note: Top panel plots differences in renter population shares in the highest quartile and interquartile range of toxic concentration exposures relative to lowest quartile (omitted category) for each racial group. Points represent coefficients with lines show 90% CI from the following regression: $y_{ij} = \beta_0 + \beta_{25-75} RSEI_{25-75} + \beta_{75-100} RSEI_{75-100} + \alpha_j + \epsilon_{ij}$, where y_{ij} is the inverse hyperbolic sine of renter population in block i from ZIP j. $RSEI_{25-75}$ is an indicator that takes the value one if the block is in the interquartile range and $RSEI_{75-100}$ if in the highest quartile of exposures. α_j is a ZIP code specific fixed effect. Vertical dotted and dashed lines illustrate the size of the exposure gap in terms of differences in renter shares living at high versus low-exposures for each renter group minority group. Histograms in the bottom 3 panels illustrates raw renter population shares by within-ZIP toxic concentration exposure percentile. Vertical lines delineate bin definitions used in both panels. Data for renters in block group comes from the 2016 ACS.

Figure 3. Relative Response Rates by Within-ZIP Toxic Concentration

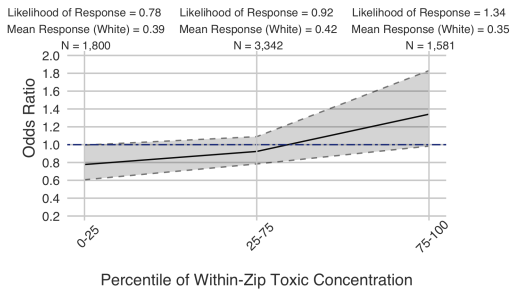
Panel A: Minority



Panel B: African American vs Hispanic/LatinX

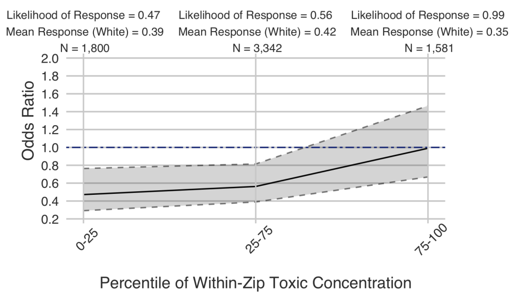


(a) African American

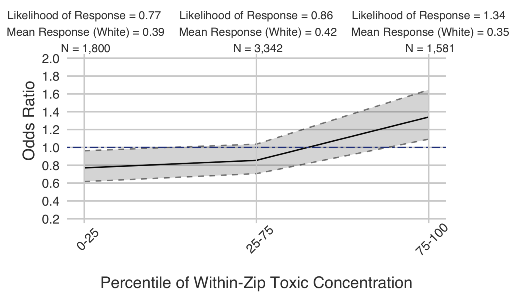


(b) Hispanic/LatinX

Panel C: Male vs Female



(c) Male

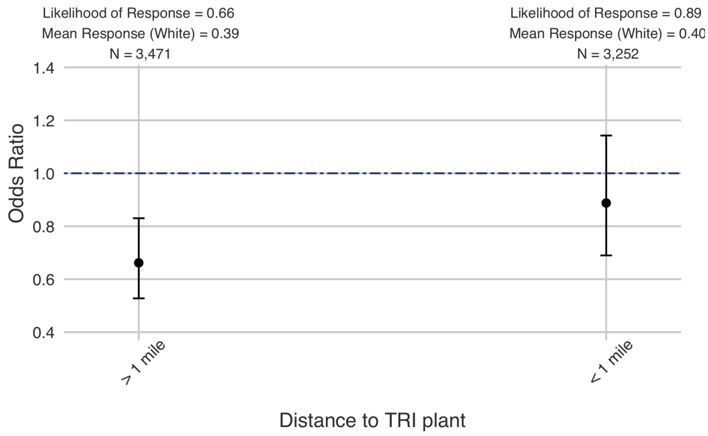


(d) Female

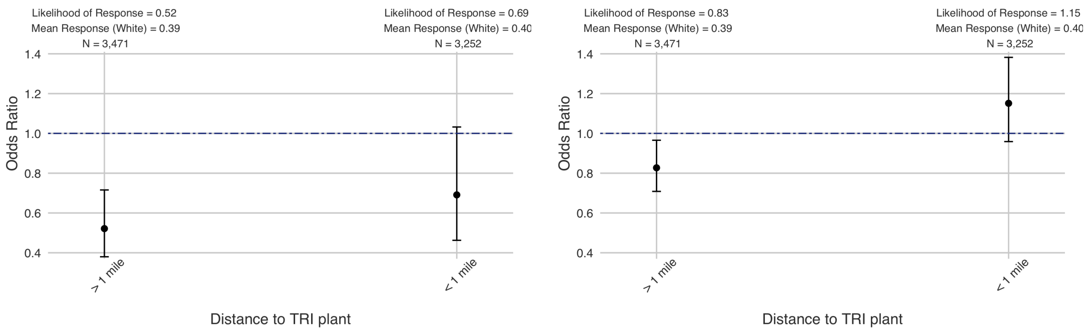
Note: Figure plots odds ratios relative to the White identity. Odds ratio are estimated using a within-property conditional logit assuming a random utility model described in Eq. (1). Standard errors are clustered at the ZIP code level using a score wild bootstrap proposed by Kline and Santos (2012) to account for the small number of clusters. 90% confidence intervals are plotted in grey. Refer to Table A5 and A10 for full set of point estimates and significance tests at 10%, 5% and 1% levels. All estimates are robust to inclusion/omission of controls. Rao score tests reject the equality of coefficients between the lowest and highest quartiles in Panels A, B, and C. Panel A: ($pval = 0.0002$); Panel B: ($pval = 0.0001$ and $pval = 0.0015$); Panel C: ($pval = 0.0017$ and $pval = 0.0075$). Rao score tests were performed using the Stata `boottest` command to correct for the small number of clusters (Cameron and Miller, 2015).

Figure 4. Relative Response Rates by Proximity to Closest TRI Plant

Panel A: Minority



Panel B: African American vs Hispanic/LatinX



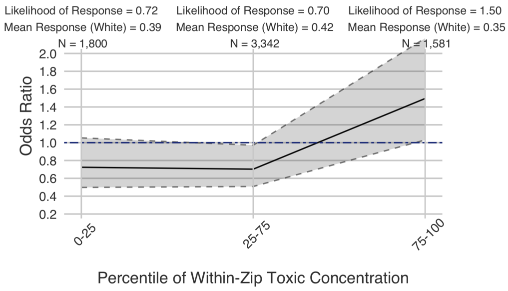
(a) African American

(b) Hispanic/LatinX

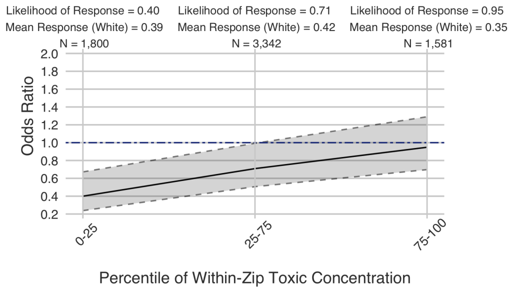
Note: Figure plots odds ratios relative to the White identity. Odds ratio are estimated using a within-property conditional logit assuming a random utility model described in Eq. (1). Standard errors are clustered at the ZIP code level using a score wild bootstrap proposed by Kline and Santos (2012) to account for the small number of clusters. 90% confidence intervals are plotted in grey. Refer to Table A5 and A10 for full set of point estimates and significance tests at 10%, 5% and 1% levels. All estimates are robust to inclusion/omission of controls. Panel A shows odd ratio for minorities relative to whites at different proximity bins from TRI plant: within one mile and more than a mile. A Rao score test of equality between odds ratio rejects the null at the 10% level ($pval = 0.0731$). Panel B separates between African American and Hispanic/LatinX, the Rao score test does not reject the equality of coefficients between proximity bins for African Americans ($pval = 0.2156$), but does reject it for Hispanic/LatinX ($pval = 0.0047$). Rao score tests were performed using the Stata `boottest` command to correct for the small number of clusters (Cameron and Miller, 2015).

Figure 5. Relative Response Rates by Within-ZIP Toxic Concentration

Panel A: Demographic Composition, Above vs Below Minority Shares

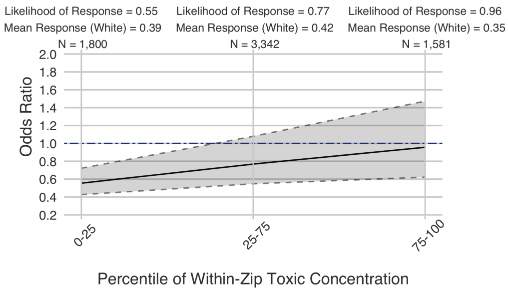


(A.1) Above Median Minority Share

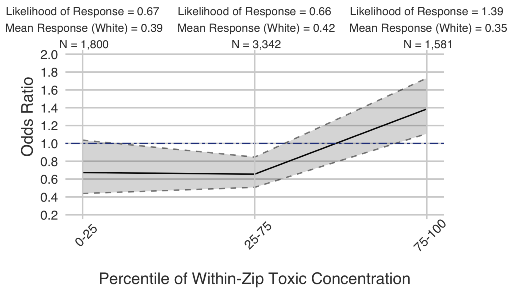


(A.2) Below Median Minority Share

Panel B: Above vs Below Median Rent

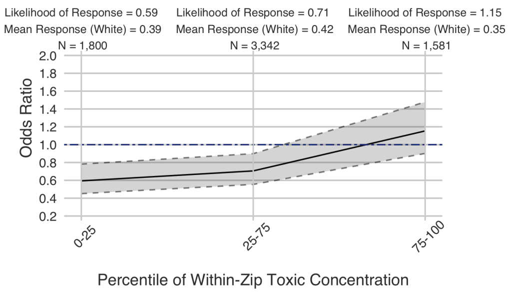


(B.1) Above Median Rent

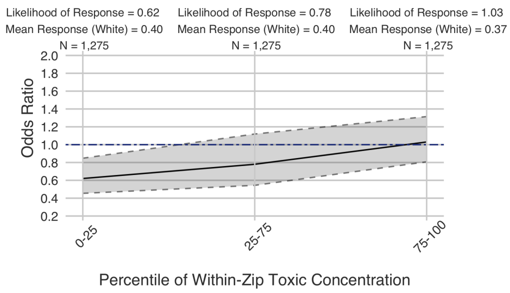


(B.2) Below Median Rent

Panel C: Full vs Matched Sample



(C.1) Full Sample



(C.2) Matched Sample

Note: Figure plots odds ratios relative to the White identity. Odds ratio are estimated using a within-property conditional logit assuming a random utility model described in Eq. (1). Standard errors are clustered at the ZIP code level using a score wild bootstrap proposed Kline and Santos (2012) to account for the small number of clusters 90% confidence intervals are plotted in grey. All estimates are robust to inclusion/omission of controls. Panel A reports odd ratios for minorities relative to whites at different levels of within ZIP RSEI measure of toxic concentrations and by neighborhood racial composition. A Rao score test of equality of coefficients in the lowest and highest quartile of toxic concentration rejects the null for listings in above median minority share neighborhoods ($pval = 0.04$) and below median minority share neighborhoods ($pval = 0.0001$). Panel B divides listings that fall above or below the median rental price within a ZIP code. The Rao score test rejects the equality of coefficients between the lowest and highest quartiles of exposure in both groups ($pval = 0.008$ and $pval = 0.08$). Panel C compares results between our full set shown in Figure 3 panel A and with properties that are matched on price as well as housing/neighborhood characteristics that are visible to renters on the search platform. The Rao score test rejects the equality between the odds of the lowest quartile and highest quartile in the matched sample ($pval = 0.0019$). Rao score tests were performed using the Stata `boottest` command to correct for the small number of clusters (Cameron and Miller, 2015).

Appendix

Experimental Design: Sample of Housing Markets and Rental Properties

The study focuses on exposures to toxic emissions reported in the Toxic Release Inventory (TRI), which identifies the exact location of major point sources in housing markets throughout the United States. Based on prior research reported in Currie et al. (2015), we define a potential study area that consists of all ZIP codes that contain at least one high-emitting TRI facility, defined using stack air emissions above the 80th percentile, located within one mile of a residential neighborhood. Table A1 lists the 111 ZIP codes that contain a high-emitting facility and at least 150 rental housing listings at the time of sample construction in September 2018.

Table A1. Zip Codes within One Mile of a Toxic Plant

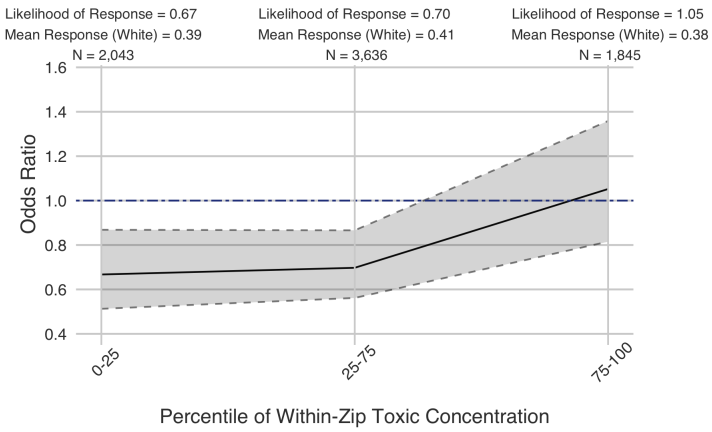
Zip code	City, State	Zip code	City, State	Zip code	City, State
35215	Birmingham, AL	60641	Chicago, IL	12866	Saratoga Springs, NY
85281	Tempe, AZ	60617	Chicago, IL	10012	New York, NY
85705	Tucson, AZ	60657	Chicago, IL	10009	New York, NY
92118	Coronado, CA	60617	Chicago, IL	10028	New York, NY
92672	San Clemente, CA	60616	Chicago, IL	10010	New York, NY
92101	San Diego, CA	60623	Chicago, IL	10016	New York, NY
92037	La Jolla, CA	61820	Champaign, IL	11206	Brooklyn, NY
90802	Long Beach, CA	60618	Chicago, IL	10021	New York, NY
80210	Denver, CO	60615	Chicago, IL	11238	Brooklyn, NY
80211	Denver, CO	60613	Chicago, IL	43201	Columbus, OH
20002	Washington, DC	60624	Chicago, IL	44107	Lakewood, OH
20001	Washington, DC	60647	Chicago, IL	73505	Lawton, OK
20009	Washington, DC	60651	Chicago, IL	19146	Philadelphia, PA
33021	Hollywood, FL	60619	Chicago, IL	19147	Philadelphia, PA
33025	Hollywood, FL	47906	West Lafayette, IN	19128	Philadelphia, PA
33312	Fort Lauderdale, FL	70118	New Orleans, LA	19148	Philadelphia, PA
33404	West Palm Beach, FL	70115	New Orleans, LA	19145	Philadelphia, PA
33410	West Palm Beach, FL	21224	Baltimore, MD	29403	Charleston, SC
32169	New Smyrna Beach, FL	21201	Baltimore, MD	37040	Clarksville, TN
33418	West Palm Beach, FL	21230	Baltimore, MD	37042	Clarksville, TN
33602	Tampa, FL	21229	Baltimore, MD	37042	Clarksville, TN
33178	Miami, FL	49503	Grand Rapids, MI	76549	Killeen, TX
33179	Miami, FL	63118	Saint Louis, MO	78666	San Marcos, TX
34243	Sarasota, FL	63118	Saint Louis, MO	79938	El Paso, TX
33019	Hollywood, FL	58103	Fargo, ND	79936	El Paso, TX
33018	Hialeah, FL	88101	Clovis, NM	77007	Houston, TX
33301	Fort Lauderdale, FL	10002	New York, NY	76543	Killeen, TX
33480	Palm Beach, FL	11211	Brooklyn, NY	78130	New Braunfels, TX
33033	Homestead, FL	11101	Long Island City, NY	77479	Sugar Land, TX
33407	West Palm Beach, FL	11217	Brooklyn, NY	77450	Katy , TX
33316	Fort Lauderdale, FL	11222	Brooklyn, NY	77054	Houston, TX
33020	Hollywood, FL	10022	New York, NY	77479	Sugar Land, TX
30906	Augusta, GA	11201	Brooklyn, NY	54751	Menomonie, WI
30309	Atlanta, GA	11205	Brooklyn, NY	54901	Oshkosh, WI
52240	Iowa City, IA	10065	New York, NY	53202	Milwaukee, WI
60614	Chicago, IL	10003	New York, NY	53212	Milwaukee, WI
60608	Chicago, IL	10314	Staten Island, NY	26505	Morgantown, WV

Note: Sample of zip codes with reported emissions that fall above the 80th percentile of the TRI, which constitute potential zip codes in the study.

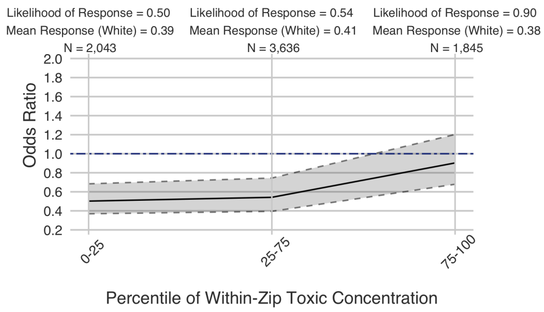
Figure 1 maps the ZIP codes with high emitting facilities. We select a random sample of ZIP codes from this set and compile the full set of property listings in each ZIP. We exclude ZIP codes that do not have at least 30% of listings within and at least 30% of listings beyond 1 mile of a facility, which is necessary to ensure the statistical power of tests for discriminatory response by exposure zone/level. ZIP codes were sampled at random until the total sample of listings matched the number that was suggested by ex-ante power calculations (2400-2700 listings). The full experimental sample includes 2,918 listings distributed across 19 ZIP codes. Of the total sample, 3 ZIP code trials were dropped as a result of small samples of listings when the trial was run (less than 30 listings) and 2 were dropped as a result of concern about rate limiting practices on the online platform during the associated trials. Rate limiting can affect experimental results by reducing the likelihood that property managers receive an inquiry and artificially lowering average response rates. We report estimates from the full sample of listings in Figures A1 and A2. Point estimates are consistent with the primary results, although the estimates are somewhat less precise. After removing the rate-limited trials from the dataset, the resulting sample includes 2,241 listings distributed across 14 ZIP codes.

Figure A1. Relative Response Rates by Within-ZIP Toxic Concentration
Full Set of Experimental ZIP Codes

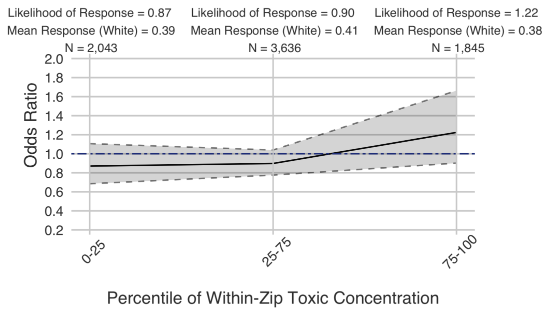
Panel A: Minority



Panel B: African American vs Hispanic/LatinX



(a) African American

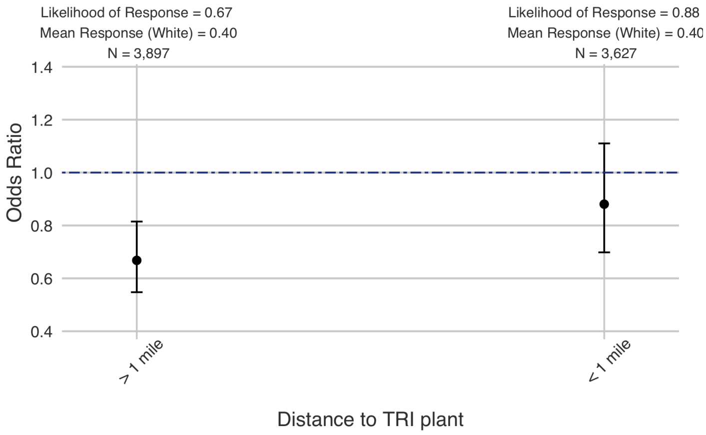


(b) Hispanic/LatinX

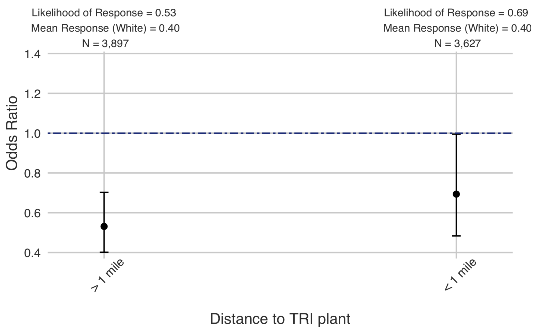
Note: The sample adds 3 ZIP code trials that where dropped as a result of small samples of listings when the trial was run (less than 30 listings) and 2 were dropped as a result of concern about rate limiting practices. The figure plots odds ratios relative to the White identity. Odds ratio are estimated using a within-property conditional logit assuming a random utility model described in Eq. (1). Standard errors are clustered at the ZIP code level using a score wild bootstrap proposed Kline and Santos (2012) to account for the small number of clusters. 90% confidence intervals are plotted in grey. All estimates are robust to inclusion/omission of controls.

Figure A2. Relative Response Rates by Proximity to Closest TRI Plant
Full Set of Experimental ZIP Codes

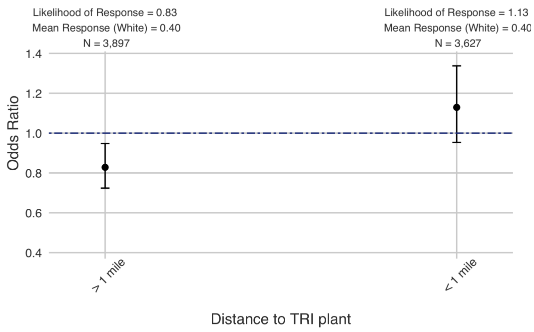
Panel A: Minority



Panel B: African American vs Hispanic/LatinX



(a) African American

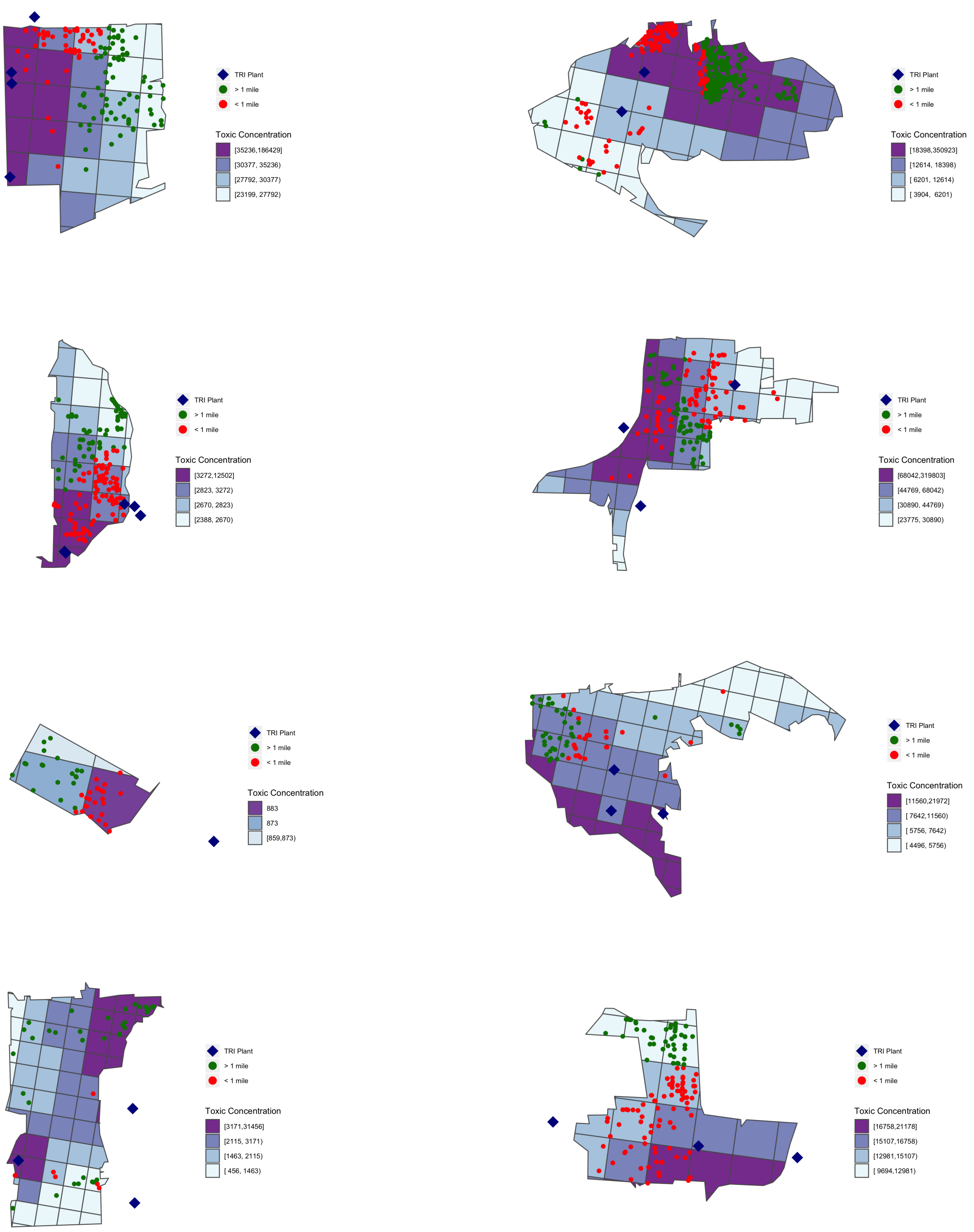


(b) Hispanic/LatinX

Note: The sample adds 3 ZIP code trials that where dropped as a result of small samples of listings when the trial was run (less than 30 listings) and 2 were dropped as a result of concern about rate limiting practices. The figure plots odds ratios relative to the White identity. Odds ratio are estimated using a within-property conditional logit assuming a random utility model described in Eq. (1). Standard errors are clustered at the ZIP code level using a score wild bootstrap proposed Kline and Santos (2012) to account for the small number of clusters. All estimates are robust to inclusion/omission of controls.

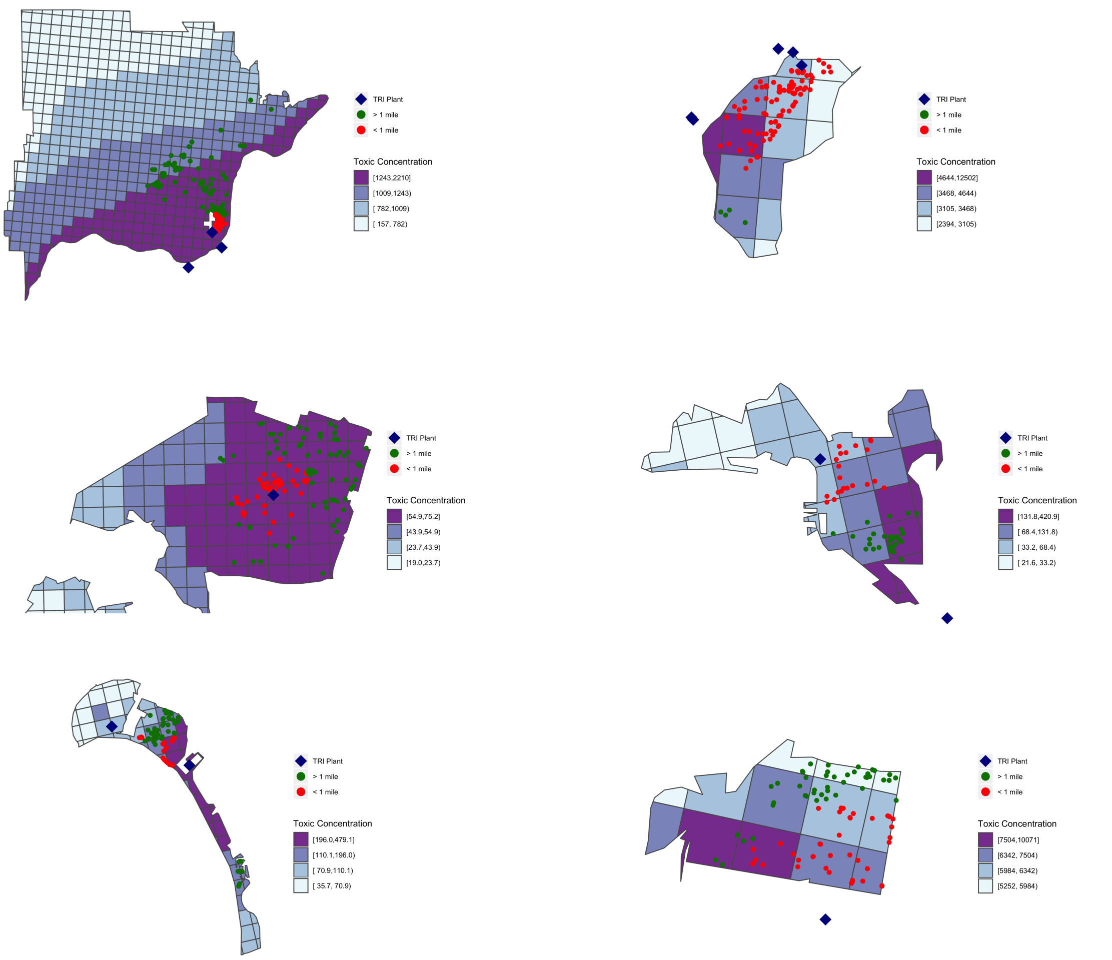
We define the level of exposure for each of the properties within the resulting sample based on their ambient concentrations of toxic pollutants using the Risk Screening Environmental Indicators (RSEI) measure developed by the US Environmental Protection Agency. Facilities report stack and fugitive air releases, direct water releases, and transfers to publicly-owned treatment works to the TRI in pounds per year. Aggregate concentrations in the RSEI model include the fate and transport of all chemical releases in the TRI and apply an inhalation toxicity weight. Direct water releases and transfers to publicly-owned treatment works (POTWs) use the higher of the oral slope factor toxicity weight or the reference dose toxicity weight for the chemical. Air releases and off-site transfers to incineration use the higher of the inhalation unit risk toxicity weight or the reference concentration toxicity weight. Figure A3 maps the locations of properties with respect to high-emitting facilities and gridded measures of concentrations from the RSEI model.

Figure A3. ZIP Codes in Experiment



Note: Figure shows ZIP codes where the experiment was conducted. Shades of purple denote the quartiles of RSEI toxic concentration. The blue rhomboids denote the location of TRI plants. Circular markers illustrate property listings where the experiment was conducted, with red markers illustrating the sample of listings within one mile of a toxic plant and green markers denoting listings outside 1 mile.

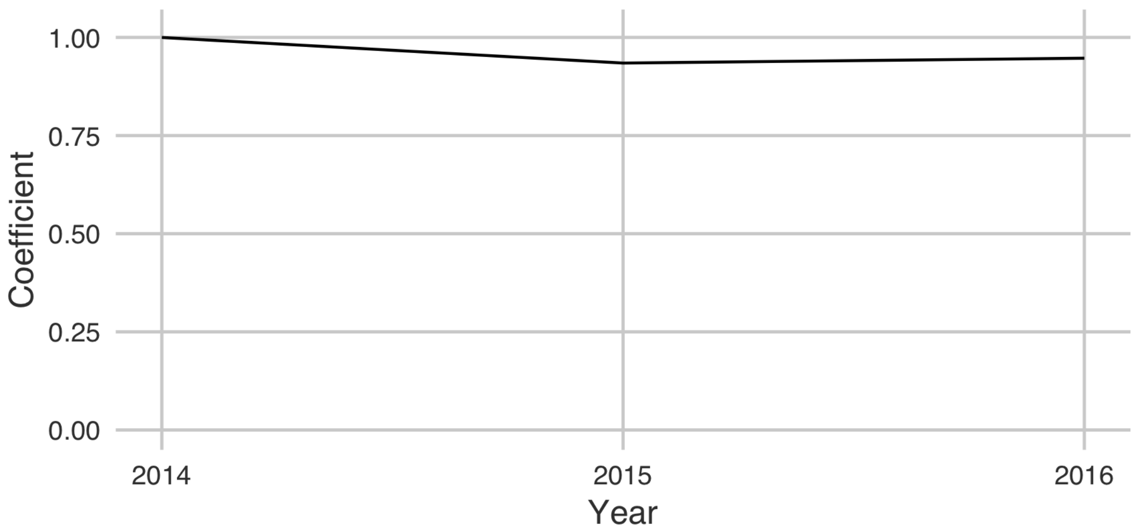
Figure A3.(cont.) ZIP Codes in Experiment



Note: Figure shows ZIP codes where the experiment was conducted. Shades of purple denote the quartiles of RSEI toxic concentration. The blue rhomboids denote the location of TRI plants. Circular markers illustrate property listings where the experiment was conducted, with red markers illustrating the sample of listings within one mile of a toxic plant and green markers denoting listings outside 1 mile.

We use a measure of concentrations from the RSEI model that correspond to TRI emissions in 2016, which is the most recent available data. The experimental was conducted during 2018-2019. In order to evaluate the time-consistency of RSEI estimates, Figure A4 plots the correlation between observations in the percentile of exposure in our study area using the RSEI measure of concentrations during the 3-year period from 2014 to 2016. The figure indicates a correlation of over 90% across the 3-year period.

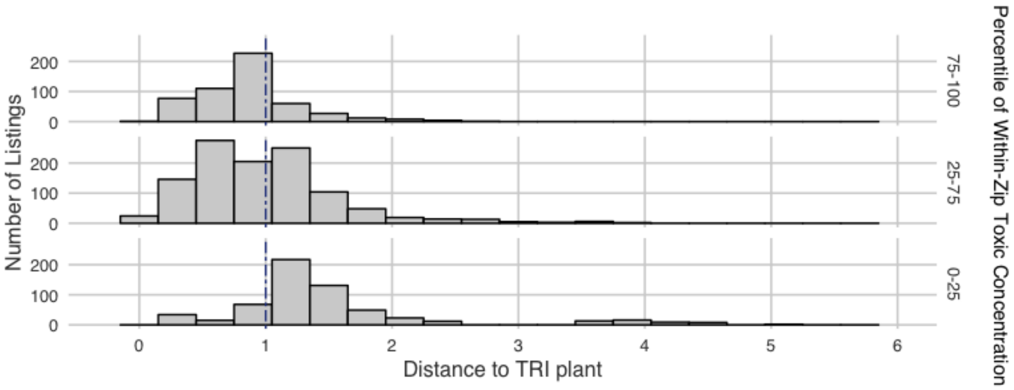
Figure A4. Persistence in Percentiles of Within-ZIP Toxic Concentration



Note: Figure shows correlation of percentiles of RSEI measure of toxic concentration during the 3-year period (2014-2016).

We study the relationship between housing discrimination in high/low-exposure zones using the definition of a high-exposure area (within a mile of the toxic plant) that is consistent with prior evidence of gestational and birth-weight effects resulting from in utero exposures (Currie et al., 2015). Figure A5 plots the distribution of properties that are located within vs. outside 1 mile of a TRI facility for each quantile of within-ZIP toxics concentrations (RSEI). It is clear that the majority of properties in the upper quartile of concentrations are located within 1 mile of a facility and the majority of properties in the lowest quartile are located beyond 1 mile. The distribution of properties in the interquartile range of RSEI concentrations are relatively evenly located within/beyond 1 mile. The figure also illustrates that proximity is not a perfect measure of exposure in the sample, as there are some properties located within 1 mile that have low levels of exposure and vice versa.

Figure A5. Listings Within-ZIP RSEI Toxic Concentration and Proximity to closest TRI



Note: Figure plots the number of listings by distance to TRI plant and percentiles of within-ZIP toxic concentrations in the sample. Dotted vertical line denotes the one mile threshold used to estimate differences.

Table A2 details the characteristics of properties at different levels of concentrations as well as reporting tests for within-ZIP differences in property/neighborhood characteristics. On average, toxic concentrations for properties in the highest quartile are 2,786 points higher than those in the lowest quartile. The RSEI cancer scores for these properties are 2.7 points higher and the non-cancer scores are 4.2 points higher. We also find significant differences in the rental prices and housing/neighborhood characteristics of properties in the different quartiles. Properties in the highest quartile are 10% less likely to be a single-family residence and more likely to be an apartment in a multi-family building. The rental prices of properties at higher concentrations are $278/month lower than properties at lower exposures. On average, they tend to have 0.13 fewer bedrooms. They also tend to be located in neighborhoods with fewer grocery stores, lower shares of Hispanic and White residents, but higher shares of African American residents. On average, they have higher poverty rates and higher shares of college educated residents.

Table A2. Property and Neighborhood Descriptive Statistics

	Percentiles of Within-Zip Toxic Concentration				
	0th-25th	25th-75th	75th-100th	Within-Zip Differences	
	(1)	(2)	(3)	(2)-(1)	(3)-(1)
Toxic Concentration (1000)	11.903	19.730	30.604	0.495***	0.569***
	(11.987)	(23.091)	(46.262)	(0.495)	(0.569)
Cancer Score	5.759	7.871	10.361	0.227***	0.260***
	(9.591)	(11.310)	(15.157)	(0.227)	(0.260)
Non Cancer Score	3.231	5.791	6.273	0.263***	0.303***
	(10.368)	(13.041)	(12.170)	(0.263)	(0.303)
Rent (1000)	2.235	1.703	1.840	0.038***	0.044***
	(2.436)	(1.335)	(1.549)	(0.038)	(0.044)
Single Family Home	0.213	0.171	0.114	0.011***	0.012***
	(0.410)	(0.376)	(0.318)	(0.011)	(0.012)
Apartment	0.128	0.131	0.152	0.010	0.011**
	(0.335)	(0.338)	(0.359)	(0.010)	(0.011)
Multi Family	0.490	0.523	0.577	0.013*	0.015***
	(0.500)	(0.500)	(0.494)	(0.013)	(0.015)
Other Bldg. Type	0.168	0.175	0.157	0.009***	0.010
	(0.374)	(0.380)	(0.364)	(0.009)	(0.010)
Bedrooms	2.435	2.267	2.331	0.029***	0.033***
	(1.129)	(0.981)	(0.934)	(0.029)	(0.033)
Bathrooms	1.540	1.425	1.485	0.018***	0.021
	(0.764)	(0.630)	(0.640)	(0.018)	(0.021)
Sqft.	716.327	749.188	694.330	21.817	25.083
	(730.209)	(759.089)	(756.266)	(21.817)	(25.083)
Assault	220.546	183.757	253.292	4.140***	4.756
	(319.979)	(272.190)	(387.808)	(4.140)	(4.756)
Groceries	31.926	25.144	28.438	0.366**	0.420***
	(44.011)	(22.791)	(35.535)	(0.366)	(0.420)
Share of Hispanics	0.101	0.131	0.089	0.005***	0.005***
	(0.163)	(0.208)	(0.130)	(0.005)	(0.005)
Share of African American	0.208	0.233	0.299	0.007***	0.008***
	(0.271)	(0.286)	(0.337)	(0.007)	(0.008)
Share of Whites	0.687	0.643	0.612	0.006***	0.007***
	(0.274)	(0.270)	(0.316)	(0.006)	(0.007)
Poverty Rate	0.238	0.291	0.274	0.005***	0.005***
	(0.206)	(0.219)	(0.228)	(0.005)	(0.005)
Unemployment Rate	0.084	0.087	0.093	0.002	0.002
	(0.079)	(0.083)	(0.099)	(0.002)	(0.002)
Share of College Educated	0.286	0.264	0.281	0.004***	0.004***
	(0.155)	(0.149)	(0.182)	(0.004)	(0.004)
Observations	1,800	3,342	1,581		
Listings	600	1,114	527		

Notes: Table shows mean and standard deviation (in parentheses) of property and neighborhood characteristics for the experimental data for listings by percentile of within-zip toxic concentration. Share of Hispanic, African American, White, poverty rate, unemployment rate, and share of college educated are measured at the block group level and come from the ACS 2015.

Correspondence Research Design

In a correspondence experiment, a researcher elicits racialized perceptions in a trial by constructing fictitious identities and experimentally varying a single trait (Bertrand and Duflo, 2017). The majority of correspondence research has focused on the use of racially distinct names as the trait used to elicit discriminatory behavior. While there are limitations associated with the use of any one particular trait, the consistent use of this design has enabled researchers to learn about racial perceptions of names across studies as well as in the general population. Correspondence studies select names that are likely to elicit behavior, such that the resulting actions can be clearly attributed to racialized perceptions. These names that are not necessarily representative of names in the population at large. Multiple randomized experiments have focused exclusively on the alignment between perceived associations with an ethnic/racial group and self-identified racial identity (Crabtree and Chykina, 2018, Gaddis, 2017a,b). Recent advances in this literature yield three important insights: (1) racialized perceptions of first names in the general population are, on average, 73-75% congruent with the observed racial/ethnic identity of names drawn from samples of birth record data when mothers from a given racial/ethnic group constitute the majority (ex. names for which more than 50% of children are born to Black/White/Hispanic mothers), (2) congruence between perceived and observed race/ethnicity increases (to 82% for African American and 92% White) with the addition of a last name that is consistent with the racial/ethnic population in birth records (congruence falls sharply when the last name is selected from a different group), (3) congruence is somewhat higher for White names drawn from mothers with high educational attainment and higher for black names when associated with a mother with low educational attainment (Gaddis, 2017a,b).[14]

Consistent with prior correspondence research, we assign a racial/ethnic identity using a set of 18 names that are shown to have a high probability of association with each of 3 racial categories throughout the United States: African American, Hispanic/LatinX, White. A question that has emerged in prior correspondence studies using racialized names is the possibility that any given name may signal race as well as other unobserved characteristics such as income (Guryan and Charles, 2013, Fryer Jr and Levitt, 2004). To test this empirically, we construct groups with each consisting of 3 male and 3 female names and stratify the sample of first names using statistical distribution of mother's educational attainment (low, medium, and high) from hospital birth records. The first name labels for this study are constructed using recent experimental work that tested the racialized perceptions of first and last names for African American, Hispanic/LatinX, and White social groups (Gaddis, 2017a,b). Last name labels were also taken from this work and tested for any geographic variability using related research (Crabtree and Chykina, 2018).

Randomization Protocol and Response Coding

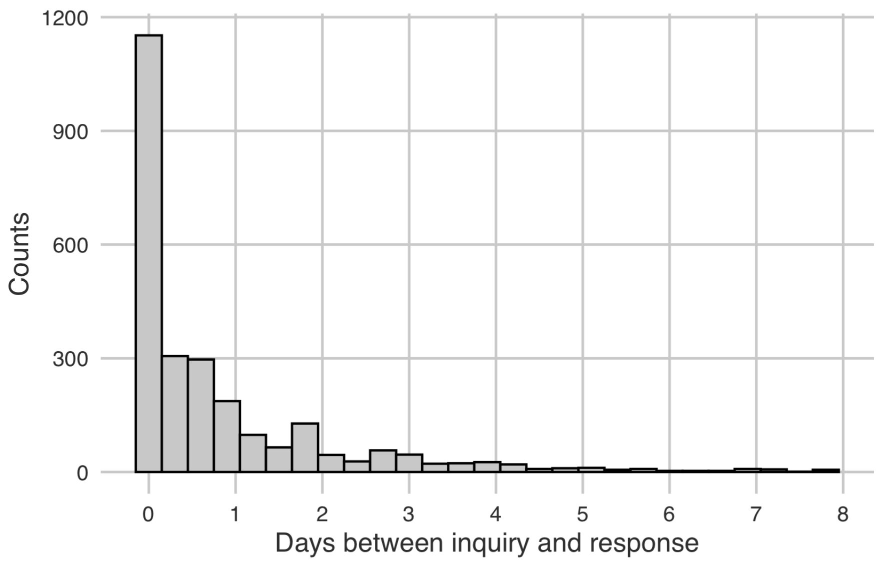
The research design simulates a housing search using all available listings in a ZIP code at a given time and is therefore reflective of the true set of options available in the given online market. By generating within-property estimates of response for each racial group,

[14]These studies use name distributions from New York state birth record data for all births from 1994 to 2012 obtained from the New York State Department of Health. Congruence experiments are implemented on Amazon Mechanical Turk and reflect the perceptions of users on that platform across the United States.

we can more directly examine the effect of discriminatory constraints on each choice set in the sample.

Immediately following the compilation of the relevant listings in a given market, a name is randomly drawn and assigned from each of three racial groups. Each rental apartment therefore receives a sequence of three separate inquiries in the course of an experimental trial (one from each group). The sequence of inquiries from the different race groups is randomized and inquiries for the same listing are never sent from two race groups on the same day. Responses from property managers are transmitted via email (gmail address associated with each name), phone messages (individual phone numbers associated with each name), and text messages. The content of phone, text, and email responses from property managers are recorded by a team of human coders to ensure the quality of the data. They are coded using two criteria that determine whether or not a response indicates that a housing choice is made available to a prospective renter: (1) a response is received within 7 days of the associated inquiry and (2) the response indicates that the property is available for rent.[15] Figure A6 plots the distribution of inquiry response time in the sample: 52% of responses are received within the first 8 hours of an inquiry, 74% are received within 24 hours and 98% are received within 5 days. The 7-day cutoff is used to restrict responses that may be received weeks or months after an inquiry and are not counted as choices in the study. Discriminatory constraints are expressed in terms of relative response rates, which measure the within-property difference in access to a housing choice. Relative response rates are estimated relative to an inquiry made to the same property from a White identity.

Figure A6. Days between Inquiry and Response



Note: Figure plots times elapsed between inquiries and responses in the sample using the timestamp given at the moment that an inquiry is sent and the timestamp given on the phone, email, or text response.

[15]Further details on inquiry response time are provided in Figure A6. 52% of responses are received within the first 8 hours of an inquiry, 74% are received within 24 hours and 98% are received within 5 days.

Table A3 reports the average response rate for inquiries made from a Hispanic or African American identity. Column 1 reports a relative response rate of 77% for the full set of minority identities in the sample, indicating that an inquiry made for the average listed property is 23% less likely to yield a housing choice when sent from a minority identity. The estimates in column 2 show that discriminatory constraints for the average home vary substantially between African American and Hispanic/LatinX renter identities. While inquiries made from African American identities are 60% less likely to yield a choice, there is no statistical difference in response to Hispanic/LatinX identities on average.

Table A3. Overall Discrimination Rates

	Dependent variable: *Response*	
	(1)	(2)
Minority	0.7673**	
	(0.6387,0.9217)	
African American		0.6016***
		(0.4607,0.7855)
Hispanic		0.9748
		(0.8423,1.1282)
Mean Response (White)	0.39	0.39
Gender	Yes	Yes
Education Level	Yes	Yes
Inquiry Order	Yes	Yes
Observations	6,723	6,723
Listings	2,241	2,241
% w. diff. response	0.41	0.41

Notes: Table reports odds ratios from a within-property conditional logit. Standard errors are clustered at the ZIP code level using a score wild bootstrap proposed Kline and Santos (2012) to account for the small number of clusters. 90% confidence intervals reported in parentheses.*$P < 10\%$ level, **$P < 5\%$ level, ***$P < 1\%$ level.

Table A4 reports balance statistics for our experimental dataset. We note that some differences in name pairs or timing can occur if a listing is taken offline during a trial. We do not find any evidence of differences in the sequence of inquiries or the day of week, or the frequency of names associated with a given race-gender pair. We detect a small difference in the frequency of inquiries associated with different levels of maternal education – African American names associated with higher maternal education are slightly more common in our trials and Hispanic/LatinX names with high levels of maternal education are slightly less common in our trials. These variables are used as controls in our tests. Columns 1-4 of Table A5 report results with successive sets of controls, which indicate that there is no difference in estimates that include or omit the maternal education or other controls.

Table A4. Balance Statistics

	Dependent variable: Response				
	(1)	(2)	(3)	(4)	(5)
Panel A: Inquiry Order					
	First	Second	Third		
African American	-0.0683	0.0343	0.0340		
	(0.0307)	(0.0248)	(0.0293)		
Hispanic/LatinX	-0.0316	-0.0313	0.0630		
	(0.0161)	(0.0311)	(0.0292)		
Panel B: Evidence of Differential Choices by Weekday					
	Mon	Tue	Wed	Thurs	Fri
African American	-0.0583	0.0222	0.0316	-0.0801	0.0561
	(0.0527)	(0.0651)	(0.0381)	(0.0554)	(0.0671)
Hispanic/LatinX	-0.0550	0.0149	-0.0071	-0.0677	0.0734
	(0.0439)	(0.0614)	(0.0585)	(0.0764)	(0.0523)
Panel C: Gender and Mother's Education Level					
	Gender		Mother's Education		
	Male	Female	Low	Medium	High
African American	-0.0448	0.0448	-0.0753	-0.0973	0.1529**
	(0.0599)	(0.0599)	(0.0477)	(0.0640)	(0.0616)
Hispanic/LatinX	-0.0896	0.0896	0.0518	0.0605	-0.1046
	(0.0603)	(0.0603)	(0.0716)	(0.0515)	(0.1034)
Observations	6,723	6,723	6,723	6,723	6,723
Listings	2,241	2,241	2,241	2,241	2,241

Notes: Table reports balance statistics for the experimental data set. It shows the coefficients of logistic regression on different outcomes. In Panel A, the dependent variable takes 1 or 0 depending the order in which the inquiry was sent out, i.e. in Column (1) takes 1 if the inquiry was sent first and 0 otherwise. In Panel B, takes 1 or 0 depending the weekday the inquiry was sent. Panel C, does the same for male and females, and levels of maternal education. Standard errors are clustered at the ZIP code level using a score wild bootstrap proposed Kline and Santos (2012) to account for the small number of clusters. *$P < 10\%$ level, **$P < 5\%$ level, ***$P < 1\%$ level.

Table A5. Estimates of Discriminatory Constraint on Housing Choice: Varying Controls

	Dependent variable: Response			
	(1)	(2)	(3)	(4)
Panel A: Quartiles of RSEI Toxic Concentration				
Panel A.1.: Minority				
Minority 0-25th perc. Toxic Concentration	0.5830***	0.5860***	0.5804***	0.5939***
	(0.4597,0.7395)	(0.4607,0.7454)	(0.4516,0.7458)	(0.4510,0.7820)
Minority 25-75th perc. Toxic Concentration	0.7033**	0.7124**	0.7114**	0.7059**
	(0.5464,0.9052)	(0.5601,0.9061)	(0.5617,0.9010)	(0.5541,0.8994)
Minority 75-100th perc. Toxic Concentration	1.1857	1.1850	1.1872	1.1542
	(0.9182,1.5310)	(0.9323,1.5063)	(0.9398,1.4997)	(0.9014,1.4781)
Panel A.2.: By Race				
Af. American 0-25th perc. Toxic Concentration	0.4560***	0.4519***	0.4419***	0.4456***
	(0.3378,0.6154)	(0.3345,0.6106)	(0.3248,0.6012)	(0.3209,0.6187)
Af. American 25-75th perc. Toxic Concentration	0.5299**	0.5411**	0.5386***	0.5380***
	(0.3628,0.7739)	(0.3758,0.7792)	(0.3782,0.7670)	(0.3802,0.7614)
Af. American 75-100th perc. Toxic Concentration	1.0265	1.0273	1.0230	0.9912
	(0.7436,1.4172)	(0.7545,1.3987)	(0.7584,1.3799)	(0.7392,1.3292)
Hispanic/LatinX 0-25th perc. Toxic Concentration	0.7399**	0.7515**	0.7487**	0.7771*
	(0.5946,0.9206)	(0.6029,0.9368)	(0.5909,0.9487)	(0.6066,0.9957)
Hispanic/LatinX 25-75th perc. Toxic Concentration	0.9228	0.9252	0.9251	0.9240
	(0.7971,1.0683)	(0.8036,1.0652)	(0.7994,1.0705)	(0.7833,1.0901)
Hispanic/LatinX 75-100th perc. Toxic Concentration	1.3728*	1.3694*	1.3792*	1.3416
	(1.0224,1.8432)	(1.0323,1.8166)	(1.0411,1.8270)	(0.9831,1.8309)
Panel B: Proximity to TRI Plant				
Panel B.1.: Minority				
TRI plant less than 1 mile × Minority	0.8940	0.9056	0.9053	0.8877
	(0.6981,1.1449)	(0.7153,1.1465)	(0.7149,1.1464)	(0.6897,1.1426)
TRI plant more than 1 mile × Minority	0.6576***	0.6581***	0.6554***	0.6618***
	(0.5235,0.8260)	(0.5293,0.8181)	(0.5245,0.8189)	(0.5275,0.8302)
Panel B.2.: By Race				
TRI plant less than 1 mile × African American	0.6999	0.7140	0.7099	0.6910
	(0.4727,1.0362)	(0.4851,1.0508)	(0.4821,1.0453)	(0.4626,1.0322)
TRI plant more than 1 mile × African American	0.5236***	0.5213***	0.5159***	0.5215***
	(0.3770,0.7273)	(0.3785,0.7180)	(0.3755,0.7089)	(0.3800,0.7157)
TRI plant less than 1 mile × Hispanic/LatinX	1.1435	1.1477	1.1515	1.1512
	(0.9641,1.3564)	(0.9749,1.3511)	(0.9724,1.3637)	(0.9589,1.3821)
TRI plant more than 1 mile × Hispanic/LatinX	0.8184**	0.8214**	0.8208**	0.8271**
	(0.7050,0.9501)	(0.7171,0.9409)	(0.7079,0.9517)	(0.7085,0.9655)
Mean Response (White)	0.39	0.39	0.39	0.39
Gender		Yes	Yes	Yes
Education Level			Yes	Yes
Inquiry Order				Yes
Observations	6,723	6,723	6,723	6,723
Listings	2,241	2,241	2,241	2,241
% w. diff. response	0.41	0.41	0.41	0.41

Notes: Table reports odd ratios relative to the White identity. Odds ratio are estimated using from a within-property conditional logit model with successive inclusion of controls. Panel A reports results based on the percentile of within-zip toxic concentration. Panel A.1. shows odd ratio of minority names relative to white names. Panel A.2. separates minority names into African American and Hispanic/LatinX names. Panel B report results based on distance to closest TRI plant. Panel B.1 reports odd ratio of minority names relative to White. Panel B.2. separates minority into African American and Hispanic/LatinX names. Standard errors are clustered at the ZIP code level using a score wild bootstrap proposed Kline and Santos (2012) to account for the small number of clusters. 90% confidence Intervals reported in parentheses.*$P < 10\%$ level, **$P < 5\%$ level, ***$P < 1\%$ level.

Prior correspondence studies have found evidence of a within-trial impact when multiple inquiries are sent in matched correspondence designs in competitive labor markets (Phillips, 2016). Table A6 compares results using data from 1st inquiries, 2nd inquiries, or 3rd inquiries, rather than matched inquiries. While the power of these tests is limited, these estimates indicate that the average within-trial effect may be smaller on minority renters that make first inquiries.

Table A6. Estimates of Discriminatory Constraint on Housing Choice: Inquiry Order

	Dependent variable: Response		
	(1)	(2)	(3)
	1st Inquiry	2nd Inquiry	3rd Inquiry
Panel A: Quartiles of RSEI Toxic Concentration			
Panel A.1.: Minority			
Minority 0-25th perc. Toxic Concentration	0.7431**	0.7212***	0.7849*
	(0.6026,0.9163)	(0.6011,0.8654)	(0.6297,0.9783)
Minority 25-75th perc. Toxic Concentration	0.8877	0.9238	0.8666
	(0.7495,1.0515)	(0.7903,1.0798)	(0.7322,1.0258)
Minority 75-100th perc. Toxic Concentration	1.1433	0.8300	0.8475
	(0.9002,1.4521)	(0.6831,1.0083)	(0.6594,1.0893)
Panel A.2.: By Race			
Af. American 0-25th perc. Toxic Concentration	0.5926***	0.6870***	0.6696**
	(0.4446,0.7899)	(0.5624,0.8392)	(0.5025,0.8923)
Af. American 25-75th perc. Toxic Concentration	0.7707	0.7811**	0.7406**
	(0.5765,1.0304)	(0.6579,0.9273)	(0.6001,0.9139)
Af. American 75-100th perc. Toxic Concentration	1.0022	0.7050**	0.8502
	(0.7643,1.3141)	(0.5483,0.9066)	(0.5909,1.2232)
Hispanic/LatinX 0-25th perc. Toxic Concentration	0.9366	0.7691*	0.8973
	(0.7339,1.1951)	(0.5963,0.9920)	(0.7158,1.1249)
Hispanic/LatinX 25-75th perc. Toxic Concentration	1.0086	1.1003	1.0150
	(0.8330,1.2213)	(0.8948,1.3530)	(0.8532,1.2075)
Hispanic/LatinX 75-100th perc. Toxic Concentration	1.3063	0.9690	0.8464
	(0.9468,1.8024)	(0.7371,1.2740)	(0.6120,1.1707)
Panel B: Proximity to TRI Plant			
Panel B.1.: Minority			
TRI plant less than 1 mile × Minority	1.0135	0.8883	0.9274
	(0.8447,1.2162)	(0.7723,1.0217)	(0.7926,1.0851)
TRI plant more than 1 mile × Minority	0.8069**	0.8001**	0.7603**
	(0.6965,0.9348)	(0.6818,0.9389)	(0.6330,0.9131)
Panel B.2.: By Race			
TRI plant less than 1 mile × African American	0.8784	0.7467**	0.8236
	(0.7171,1.0759)	(0.6181,0.9020)	(0.6582,1.0307)
TRI plant more than 1 mile × African American	0.6761***	0.7240**	0.6707***
	(0.5373,0.8509)	(0.5902,0.8882)	(0.5522,0.8146)
TRI plant less than 1 mile × Hispanic/LatinX	1.1586	1.0516	1.0501
	(0.8897,1.5087)	(0.8629,1.2816)	(0.8814,1.2510)
TRI plant more than 1 mile × Hispanic/LatinX	0.9587	0.8985	0.8552
	(0.8413,1.0926)	(0.7523,1.0731)	(0.6972,1.0491)
Gender	Yes	Yes	Yes
Education Level	Yes	Yes	Yes
Observations	2241	2241	2241

Notes: Table reports odd ratios relative to the White identity. Odds ratio are estimated using a logistic regressions with columns referring to the order in which inquiries were sent out. Panel A reports results based on the percentile of within-zip toxic concentration. Panel A.1. reports odd ratios of minority names relative to White names. Panel A.2. separates minority names into African American and Hispanic/LatinX names. Panel B reports results based on distance to closest TRI plant. Panel B.1 reports odd ratio of minority names relative to White, and Panel B.2. separates minority into African American and Hispanic/LatinX names. Standard errors are clustered at the ZIP code level using a score wild bootstrap proposed Kline and Santos (2012) to account for the small number of clusters. 90% confidence intervals reported in parentheses.*$P < 10\%$ level, **$P < 5\%$ level, ***$P < 1\%$ level.

When facing discriminatory constraints, renters may make multiple inquiries on a property to increase the likelihood of gaining access. It is not clear whether a renter who sends additional inquiries will face different constraints in subsequent rounds. We test this in a sub-sample of the markets in the study, where we simulate this process by running two rounds using the same names. Table A7 reports relative response rates from tests using the first and second round of inquiries on the same properties. All tests indicate a *stronger* discriminatory response in follow-up inquiries. Whereas relative response rates for first inquiries are 58% from minority identities, 41% from African American identities, and 86% from Hispanic/LatinX identities, relative response rates to second inquiries are 38% from minority, 51% from Hispanic, and 27% from African American identities.

Table A7. Overall Discrimination Rates
Properties with Two Inquiries

	Dependent variable: *Response* (1)	(2)
Minority First Inquiry	0.5805	
	(0.3047,1.1059)	
Minority Second Inquiry	0.3804***	
	(0.2955,0.4897)	
African American First Inquiry		0.4052*
		(0.2008,0.8175)
African American Second Inquiry		0.2723***
		(0.1784,0.4157)
Hispanic/LatinX First Inquiry		0.8587
		(0.3894,1.8936)
Hispanic/LatinX Second Inquiry		0.5129***
		(0.3991,0.6590)
Mean Response (White)	0.45	0.45
Gender	Yes	Yes
Education Level	Yes	Yes
Inquiry Order	Yes	Yes
Observations	1,572	1,572
Listings	524	524
% w. diff. response	0.38	0.38

Notes: Table reports odd ratios relative to the White identity. Odds ratio are estimated using from a within-property conditional logit model including controls for gender, education and order the inquiry was sent. Standard errors are clustered at the ZIP code level using a score wild bootstrap proposed Kline and Santos (2012) to account for the small number of clusters. 90% confidence intervals reported in parentheses.*$P < 10\%$ level, **$P < 5\%$ level, ***$P < 1\%$ level.

Table A8 plots relative response rates within the subset of listings after removing responses from computer-generated response systems (16% of the sample). Computer-generated responses are unlikely to exhibit discriminatory behavior in this market, though we note that later interactions with property managers for the same homes may present discriminatory constraints. Baseline estimates in the paper include both human- and computer-generated responses, which together characterize the level of discriminatory constraint facing prospective renters. The estimates in Table A8 estimates indicate that relative response rates from human-generated responses are somewhat lower than estimate from the full sample – 50% in the lowest quartile, 60% in the interquartile range, and not different from the response to White identities in the highest quartile of concentrations.

Table A8. Estimates of Discriminatory Constraint on Housing Choice
Heterogeneity by Response Origin: Human or Computer

	Dependent variable: Response	
	Full Sample	Human-Generated Responses
	(1)	(2)
Panel A.: Minority		
Minority 0-25th perc. Toxic Concentration	0.5939***	0.5005***
	(0.4510,0.7820)	(0.3652,0.6860)
Minority 25-75th perc. Toxic Concentration	0.7059**	0.6036***
	(0.5541,0.8994)	(0.4568,0.7975)
Minority 75-100th perc. Toxic Concentration	1.1542	1.0513
	(0.9014,1.4781)	(0.7643,1.4461)
Panel B: By Race		
Af. American 0-25th perc. Toxic Concentration	0.4456***	0.3898***
	(0.3209,0.6187)	(0.2587,0.5873)
Af. American 25-75th perc. Toxic Concentration	0.5380***	0.4804***
	(0.3802,0.7614)	(0.3201,0.7210)
Af. American 75-100th perc. Toxic Concentration	0.9912	0.8205
	(0.7392,1.3292)	(0.5641,1.1934)
Hispanic/LatinX 0-25th perc. Toxic Concentration	0.7771*	0.6274***
	(0.6066,0.9957)	(0.4905,0.8023)
Hispanic/LatinX 25-75th perc. Toxic Concentration	0.9240	0.7505**
	(0.7833,1.0901)	(0.6206,0.9077)
Hispanic/LatinX 75-100th perc. Toxic Concentration	1.3416	1.3388
	(0.9831,1.8309)	(0.9251,1.9374)
Mean Response (White)	0.39	0.34
Gender	Yes	Yes
Education Level	Yes	Yes
Inquiry Order	Yes	Yes
Observations	6,723	5,637
Listings	2,241	1,879
% w. diff. response	0.41	0.38

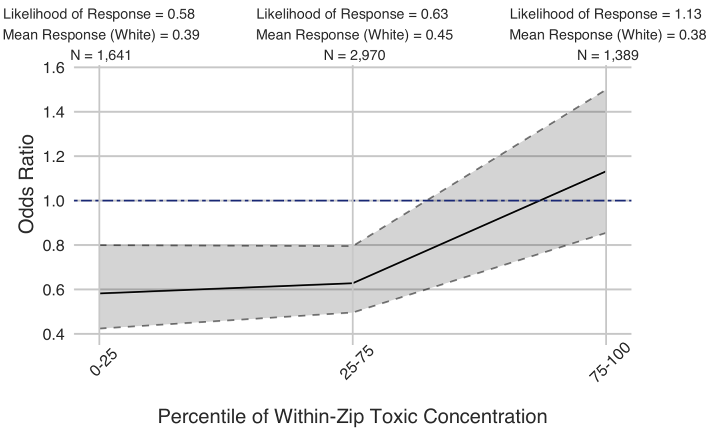
Notes: Notes: Table reports odd ratios relative to the White identity. Odds ratio are estimated using a within-property conditional logit regression for the full sample and excluding computer-generated responses. Column (1) reports results for the full sample. Column (2) excludes 362 listings that responded with computer-automated responses. Panel A shows odds ratio of minority names relative to White names. Panel B separates minority names into African American and Hispanic/LatinX names. Standard errors are clustered at the ZIP code level using a score wild bootstrap proposed Kline and Santos (2012) to account for the small number of clusters. 90% confidence intervals reported in parentheses.*$P < 10\%$ level, **$P < 5\%$ level, ***$P < 1\%$ level.

Robustness of Results to Sampling Restrictions

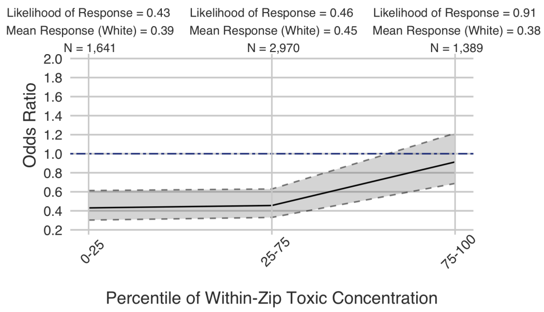
This section evaluates the robustness of main experimental estimates to various sample restrictions. We begin by testing the robustness of our results to potential issues with baseline toxicity levels. In a small number of ZIP codes, properties within 1 mile of a facility have a relatively low level of toxicity as measured by RSEI (below 1,000). Figure A7 tests the robustness of our main results to incongruence between distance-based measure and the RSEI-based measure of exposure. We exclude the ZIP codes that are located within 1 mile of a high-emitting TRI facility but where properties in the zip are located at concentrations measured below 1,000 by RSEI. The relative likelihood of response to a renter with a name associated with minority groups is 58% at locations in the lowest quartile of the within-ZIP concentration, which is very similar to the 59% response rate when using the full data. The response rate for African American identities in the restricted sample (43%) and for Hispanic/LatinX (78%) are very similar to the main experimental full-sample estimate, 45% and 78% respectively.

Figure A7. Relative Response Rates by Within-ZIP Toxic Concentration
RSEI Toxic Concentrations above 1,000

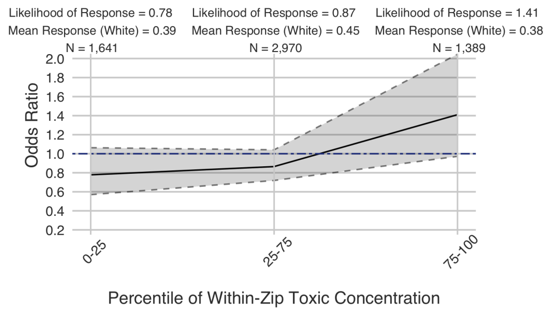
Panel A: Minority



Panel B: African American vs Hispanic/LatinX



(a) African American



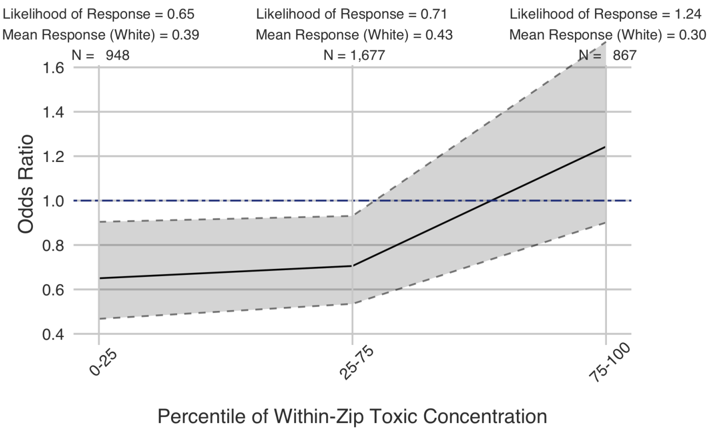
(b) Hispanic/LatinX

Note: Sample drops 3 ZIP codes with RSEI toxic concentrations below 1,000. Figure plots odds ratios relative to the White identity. Odds ratio are estimated using a within-property conditional logit assuming a random utility model described in Eq. (1). Standard errors are clustered at the ZIP code level using a score wild bootstrap proposed Kline and Santos (2012) to account for the small number of clusters. 90% confidence intervals are plotted in grey. All estimates are robust to inclusion/omission of controls.

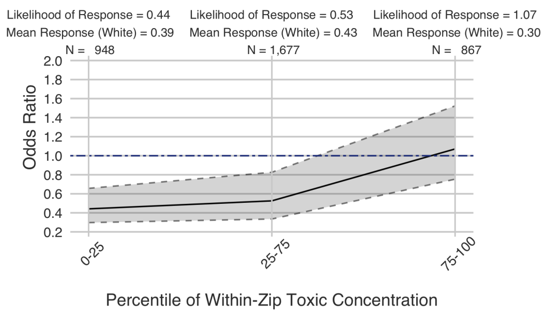
Figure A8 provides tests using a restricted sample of listings that fall within 25% of the median rent in each ZIP code. While the sample restriction reduces the precision of the estimates, the patterns in constraints are consistent with main results reported in the paper. The relative likelihood of response to a renter with a name associated with minority groups is 65% at locations in the lowest quartile of the within-ZIP concentration, which is very similar to the 59% response rate when using the full data. The response rate for African American identities in the restricted sample (44%) is very similar to the main experimental full-sample estimate (45%). The estimate for Hispanic/LatinX identities (90%) is somewhat higher than the full sample estimate (78%).

Figure A8. Relative Response Rates by Within-ZIP Toxic Concentration
Restricted Sample (within 25% of the ZIP-median rent)

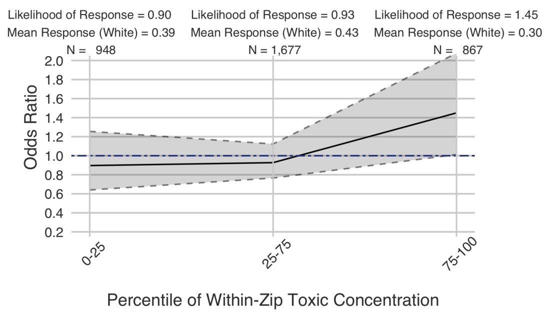
Panel A: Minority



Panel B: African American vs Hispanic/LatinX



(a) African American



(b) Hispanic/LatinX

Note: The sample is restricted to properties within 25% of the median rent, reducing it to 1,164 listings (3,492 observations). Figure plots odds ratios relative to the White identity. Odds ratio are estimated using a within-property conditional logit assuming a random utility model described in Eq. (1). Standard errors are clustered at the ZIP code level using a score wild bootstrap proposed Kline and Santos (2012) to account for the small number of clusters. 90% confidence intervals are plotted in grey. All estimates are robust to inclusion/omission of controls.

Heterogeneity by Maternal Education

Table A9 reports estimates by maternal education using information on first names from hospital birth records. Point estimates from these tests provide suggestive evidence of stronger discriminatory constraints facing minority renters with names that are associated with low maternal educational attainment. For listings in the lowest quartile of concentrations, relative response rates to inquiries from African American names are 28% when associated with low maternal educational attainment, 47% when associated with medium maternal educational attainment, and 60% when associated with high maternal educational attainment. We find similar patterns for Hispanic/LatinX identities, although we do not detect statistical differences in relative response rates between the groups.

Table A9. Estimates of Discriminatory Constraint on Housing Choice Heterogeneity by Maternal Education

	Dependent variable: Response	
	(1)	(2)
Minority 0-25th perc. Toxic Concentration × Low	0.5240**	
	(0.3275,0.8384)	
Minority 25-75th perc. Toxic Concentration × Low	0.6020**	
	(0.4257,0.8512)	
Minority 75-100th perc. Toxic Concentration × Low	1.3000	
	(0.9294,1.8183)	
Minority 0-25th perc. Toxic Concentration × Medium	0.5514**	
	(0.3732,0.8148)	
Minority 25-75th perc. Toxic Concentration × Medium	0.6227*	
	(0.4110,0.9436)	
Minority 75-100th perc. Toxic Concentration × Medium	0.9094	
	(0.5665,1.4599)	
Minority 0-25th perc. Toxic Concentration × High	0.7472	
	(0.5502,1.0147)	
Minority 25-75th perc. Toxic Concentration × High	0.9275	
	(0.7259,1.1851)	
Minority 75-100th perc. Toxic Concentration × High	1.3712	
	(0.9966,1.8865)	
Af. American 0-25th perc. Toxic Concentration × Low		0.3225**
		(0.1638,0.6348)
Af. American 25-75th perc. Toxic Concentration × Low		0.3931**
		(0.2152,0.7181)
Af. American 75-100th perc. Toxic Concentration × Low		1.3821
		(0.8368,2.2825)
Af. American 0-25th perc. Toxic Concentration × Medium		0.4414**
		(0.2609,0.7467)
Af. American 25-75th perc. Toxic Concentration × Medium		0.4672**
		(0.2572,0.8484)
Af. American 75-100th perc. Toxic Concentration × Medium		0.6321
		(0.3511,1.1378)
Af. American 0-25th perc. Toxic Concentration × High		0.6314*
		(0.4301,0.9269)
Af. American 25-75th perc. Toxic Concentration × High		0.8232
		(0.6135,1.1047)
Af. American 75-100th perc. Toxic Concentration × High		1.2721
		(0.7756,2.0864)
Hispanic/LatinX 0-25th perc. Toxic Concentration × Low		0.7981
		(0.4721,1.3492)
Hispanic/LatinX 25-75th perc. Toxic Concentration × Low		0.8324
		(0.6026,1.1499)
Hispanic/LatinX 75-100th perc. Toxic Concentration × Low		1.2223
		(0.8231,1.8151)
Hispanic/LatinX 0-25th perc. Toxic Concentration × Medium		0.6600**
		(0.4938,0.8821)
Hispanic/LatinX 25-75th perc. Toxic Concentration × Medium		0.8755
		(0.6536,1.1728)
Hispanic/LatinX 75-100th perc. Toxic Concentration × Medium		1.2661
		(0.7199,2.2267)
Hispanic/LatinX 0-25th perc. Toxic Concentration × High		0.9398
		(0.6470,1.3651)
Hispanic/LatinX 25-75th perc. Toxic Concentration × High		1.0789
		(0.7152,1.6275)
Hispanic/LatinX 75-100th perc. Toxic Concentration × High		1.5021*
		(1.0688,2.1111)
Mean Response (White)	0.39	0.39
Gender	Yes	Yes
Inquiry Order	Yes	Yes
Observations	6,723	6,723
Listings	2,241	2,241
% w. diff. response	0.41	0.41

Notes: Table reports odd ratios relative to the White identity. Odds ratio are estimated using a within-property conditional logit by percentile of within-zip toxic concentration and for different levels of maternal education. Column (1) reports the odd ratio for minority names relative to white names. Column (2) separates minority names into African American and Hispanic/LatinX names. Standard errors are clustered at the ZIP code level using a score wild bootstrap proposed Kline and Santos (2012) to account for the small number of clusters. 90% confidence intervals reported in parentheses.*$P < 10\%$ level, **$P < 5\%$ level, ***$P < 1\%$ level.

Table A10. Estimates of Discriminatory Constraint on Housing Choice
Heterogeneity by Gender

	Dependent variable: Response	
	(1)	(2)
Minority 0-25th perc. Toxic Concentration × Female	0.7873*	
	(0.6444,0.9619)	
Minority 25-75th perc. Toxic Concentration × Female	0.8707	
	(0.6906,1.0979)	
Minority 75-100th perc. Toxic Concentration × Female	1.3668	
	(0.9891,1.8887)	
Minority 0-25th perc. Toxic Concentration × Male	0.4628***	
	(0.3127,0.6848)	
Minority 25-75th perc. Toxic Concentration × Male	0.5508***	
	(0.3949,0.7683)	
Minority 75-100th perc. Toxic Concentration × Male	0.9711	
	(0.7091,1.3300)	
Af. American 0-25th perc. Toxic Concentration × Female		0.7005**
		(0.5642,0.8695)
Af. American 25-75th perc. Toxic Concentration × Female		0.8366
		(0.6096,1.1481)
Af. American 75-100th perc. Toxic Concentration × Female		1.3792
		(0.9134,2.0825)
Af. American 0-25th perc. Toxic Concentration × Male		0.2788***
		(0.1704,0.4563)
Af. American 25-75th perc. Toxic Concentration × Male		0.3448***
		(0.2251,0.5281)
Af. American 75-100th perc. Toxic Concentration × Male		0.7095
		(0.4926,1.0221)
Hispanic/LatinX 0-25th perc. Toxic Concentration × Female		0.9143
		(0.6961,1.2009)
Hispanic/LatinX 25-75th perc. Toxic Concentration × Female		0.9047
		(0.7175,1.1408)
Hispanic/LatinX 75-100th perc. Toxic Concentration × Female		1.3565
		(0.8890,2.0699)
Hispanic/LatinX 0-25th perc. Toxic Concentration × Male		0.6756*
		(0.4784,0.9541)
Hispanic/LatinX 25-75th perc. Toxic Concentration × Male		0.9525
		(0.6837,1.3270)
Hispanic/LatinX 75-100th perc. Toxic Concentration × Male		1.3581
		(0.8990,2.0517)
Mean Response (White)	0.39	0.39
Education Level	Yes	Yes
Inquiry Order	Yes	Yes
Observations	6,723	6,723
Listings	2,241	2,241
% w. diff. response	0.41	0.41

Notes: Table reports odd ratios relative to the White identity. Odds ratio are estimated using a within-property conditional logit by percentile of within-zip toxic concentration and applicant gender. Column (1) reports odds ratios for minority names relative to White names. Column (2) separates minority names into African American and Hispanic/LatinX names. Standard errors are clustered at the ZIP code level using a score wild bootstrap proposed Kline and Santos (2012) to account for the small number of clusters. 90% confidence intervals reported in parentheses.*$P < 10\%$ level, **$P < 5\%$ level, ***$P < 1\%$ level.