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

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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

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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 suggests that differences in residential location choices in US housing markets result in a persistent racial gap in exposure to chemical toxics and related health outcomes. However, 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. Researchers have hypothesized that housing discrimination may be an important factor in explaining the exposure gap in the United States and there is evidence that real estate agents are more likely to show properties at closer proximity to Superfund sites and toxic releases to minority homebuyers (Christensen and Timmins, 2018, Crowder and Downey, 2010). However, no prior study has provided an empirical test in the online rental housing market, where renters interact directly with property managers. Discriminatory behavior in the online rental market could eliminate access to certain properties entirely. 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 differences in housing/neighborhood preferences that also affect residential sorting behavior (Depro et al., 2015, Banzhaf and Walsh, 2013). The 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 rental markets with major pollution sources.[1] 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 share of African American renters living in high-exposure locations is 92% higher than the share living in low-exposure locations. Among Hispanic/LatinX renters, the share living in high-exposure locations is 90% higher. By contrast, the share of White renters living in high-exposure locations is just 32% higher than

[1]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.

the White share living in low-exposure locations. 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 odds of a response to an inquiry made by a minority renter by 41% in low-exposure locations – minority names receive only 59% as many responses as White names in these zones. However, 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 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, responding to recent calls for increased focus on the adverse impacts of discriminatory constraints (Bertrand and Duflo, 2017, Guryan and Charles, 2013). New work by Kline and Walters (2020) 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). Our findings demonstrate 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. Heterogeneous responses are potentially consistent with multiple models of discriminatory behavior, including racial animus originally proposed by Becker (1957), statistical discrimination as in Arrow (1972), or more recent attention-based mechanisms advanced by Bartoš et al. (2016).

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 examines 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.[2] 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 the compilation of the relevant listings in a given market, a name is randomly drawn and assigned from each of three racial groups.

Two recent experiments study the racial perceptions of names used in correspondence research by quantifying the congruence between the occurrence of distinctly African American, Hispanic/LatinX, and White names and the rate of identification (cognitive association with each group) among survey respondents in the United States (Gaddis, 2017a,b).[3] Using the results from Gaddis (2017a,b), we constructed 18 pairs of first and last names that have the highest probability of identification as belonging to each race group.

The resulting set of fictitious renter identities consists of 6 distinct first-last name pairs for each of the three groups. 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 stratify the sample of first names using statistical distribution of maternal educational attainment (low, medium, and high) and gender (male and female) reported in Gaddis (2017a,b). The resulting name groups consists of three male and three female names, one drawn from each of three levels of maternal educational

[2]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.

[3]See Appendix Section A1.1 for detail on name selection and the identification rates for each of the names in this study.

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. Names are drawn randomly from the full set of six for each race group. 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 within-property *relative response rates.* We use the term 'relative response rates' interchangeably with 'odds ratios' in this paper, since an odds ratio measures the within-property difference in the odds of a response to a minority identity relative to a White identity (the comparison group) for a given listing.

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]

Recent work has highlighted the importance of wind direction on pollution exposure

[4]Balance tests are reported in Table A4.

[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 A5 for the distribution of inquiry response time in the sample.

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

and health outcomes (Deryugina et al., 2019). We use RSEI as our preferred measure on concentrations as it accounts for differential releases, meteorological conditions such as wind speed and direction, decay rates, and other key characteristics of emissions that can affect exposures (EPA, 2018).[7] While potentially more informative than distance-based measures of toxics exposures, data on TRI releases are subject to potential reporting bias – firms may under-report their emissions if they perceive a relatively low risk of legal penalties for failure to comply with EPCRA reporting protocols.[8] We provide results using both the RSEI and distance-based measures. An empirical comparison of the two measures (Figure A4) shows that properties fall in the highest quartile of RSEI tend to be within 1 mile of a facility. Estimates of discriminatory constraints are also consistent, although those using the distance-based measure are somewhat less precise.

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.

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 much higher for African Americans and Hispanix/LatinX residents than for the population of White renters. Whereas the share of African American and Hispanic/LatinX

[7]The EPA's Risk-Screening Environmental Indicators (RSEI) model uses three primary data sets: Chemical toxicity data, TRI release and transfer quantities, and the location of facilities. RSEI uses the American Meteorological Society/EPA Regulatory Model (AERMOD). The model incorporates information about facilities (location, stack height, etc.), meteorology (wind, wind direction, and ambient temperature), and chemical specific decay rates to calculate toxic concentrations in a given grid.

[8]From the EPA's TRI website: "EPA investigates cases of EPCRA non-compliance and may issue civil penalties, including monetary fines, and may also require correction of the violation. EPCRA Section 313 compliance resources include inspectors and attorneys in each of EPA's 10 regional offices and at EPA headquarters" (EPA, 2020).

renters living in high-exposure locations are both more than 90% higher than their shares in low-exposure locations, the share of White renters living in high-exposure locations is just 32% higher than its share at low-exposure locations. (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

As described in the previous section, each rental apartment receives an inquiry from each of the racial groups in three separate days. For example, on day one, the manager of the unit could receive an inquiry from the White identity, then from an African American identity on day two, and from a Hispanic/LatinX identity on day three. Based on this design, we observe a sequence of binomial decisions, where the landlord-listing i decides whether to respond ($y_{ij} = 1,\ j = 1, 2, 3$) or not if her underlying utility is positive[9]:

$$\begin{aligned} u^*_{i1} &= \sum_k (\psi_k + \beta_{k1} Minority_1) Z_{i \in k} + \theta X_1 + \delta_i + \epsilon_{i1} \\ u^*_{i2} &= \sum_k (\psi_k + \beta_{k2} Minority_2) Z_{i \in k} + \theta X_2 + \delta_i + \epsilon_{i2} \\ u^*_{i3} &= \sum_k (\psi_k + \beta_{k3} Minority_3) Z_{i \in k} + \theta X_3 + \delta_i + \epsilon_{i3} \end{aligned} \tag{1}$$

where u^*_{ij} is the utility of the landlord i from inquiry j and ϵ_{ij} follows a logistic distribution.[10] Therefore:

[9] See Appendix A1.3 for more details.

[10] We assume that ϵ_{ij} are independent across j but may be correlated across ZIP codes (following our sampling design) (Abadie et al., 2017). For this reason, we report cluster standard errors at the ZIP code level. This assumption does not affect the interpretation of our results. Clustering at the listing j results in highly similar, but less conservative, estimates. See Appendix A1.3 for more details.

$$P(y_{ij} = 1|X, Z, \delta) = F(\sum_k (\psi_k + \beta_{kj} Minority_j) Z_{i\in k} + \theta X_j + \delta_i) \quad (2)$$

F is the logistic cumulative distribution function. $Minority_j$ is an indicator that takes the value one if the race group associated with the identity is either African American or Hispanic/LatinX; and is zero if it is the White identity. X_j is a vector of renter-specific control variables: gender, education level and the order in which the inquiry was sent. Assuming that names are drawn randomly and balanced across gender, education level, and inquiry order, estimates of β_{kj} should be robust to the inclusion/omission of X_j. In the Appendix, we show that point estimates are not sensitive to the inclusion of controls, though precision increases slightly.[11] δ_i is a landlord-property specific fixed effect. $Z_{i\in k}$ are indicators denoting the bin (k) of within-ZIP code percentile of pollution exposure of the listing.[12]

The primary set of tests defines pollution exposures using ambient concentrations from the RSEI model and concentrations are divided into 3 bins: $k = 0 - 25\%, 25 - 75\%, 75 - 100\%$.[13] A second set of tests defines exposures according to distance from active TRI facilities ($k =< 1$ mile, > 1 mile), which have been shown to directly affect the health

[11]See Table A5 for balance tests and Table A6 for robustness to the inclusion/omission of X_j.

[12]Our data set also includes information on characteristics of the block group the listing is in, e.g., rent, square footage, number of bedrooms, block-group racial composition. See Table A5 for a complete list of listing-specific attributes. We use these attributes for constructing matched samples shown in Figure 5, panel C.

[13]Table A2 shows average toxic concentrations by bin and within-ZIP code differences. On average, toxic concentrations for properties in the highest quartile are 2,786 points higher than those in the lowest quartile. The table also includes the complete set of characteristics for properties and the average share of listings in each bin in the sample and test of differences by bins of toxic concentration.

outcomes of the in utero population.[14] The likelihood can be written as:

$$\Pi_{i=1}^{N} P(y_{i1}|m, z, x, \delta) \times P(y_{i2}|m, z, x, \delta) \times P(y_{i3}|m, z, x, \delta) \quad (3)$$

where y_{ij} are independent conditional on m, z, x and δ. We impose the restriction: $\beta_{kj} = \beta_k$ $\forall j$.[15] In order to control for unobserved landlord-property heterogeneity (δ_i) and avoid the incidental parameter problem, we estimate (3) using Chamberlain's (1980) conditional logit function.[16]

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 the odds of a response that yields a choice are 41% lower for inquiries from 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.

[14]RSEI concentrations are strongly but not perfectly correlated with ambient concentrations studied in the tests reported in Figure 3. Figure A4 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.

[15]Table A7 shows estimations for separate logits

[16]See A1.3 for more details

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 $p < .01$. These results imply that minority renters receive 1 response per 3.8 inquires in low-exposure zones, compared to 2.5 for White renters. In high-exposure zones, they receive a response with 2.6 inquiries (2.8 for White renters). Taken together, these findings imply that minority households face ex-ante constraints that reduce their access to housing choices in low-exposure locations relative to high-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 $p < .01$. These results imply that at low-exposure locations, African Americans can expect to receive one response per 4.6 inquires. Hispanic/LatinX renters can expect one response per 3.1 inquiries. White renters can expect one response per 2.5 inquiries. In high-exposure locations, African Americans also face similar search costs (one response per 2.8 inquiries vs one response per 2.8 inquiries for White renters).[17] Taken together, these findings illustrate that African Americans face lower returns to their search efforts at all locations and also bear a higher incremental cost of search in low-exposure neighborhoods. African American renters in our sample must send 1.8 more inquires to secure an expected re-

[17]See Appendix Section A2 for a discussion of this transformation and all calculations.

sponse for properties located in low-exposure locations relative to what they can expect in high-exposure locations.[18]

Panel C provides evidence of stronger discriminatory constraints facing male minority identities, especially among properties in 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.[19] We find 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.[20]

[18]We thank an anonymous referee for pointing out this novel interpretation of results from correspondence studies.

[19]We refer interested readers to Tables A12, and A11

[20]Results provided in Table A8.

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 birth weight 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 locations 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% relative 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 indicate 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.[21] 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 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, rela-

[21] Table A2 shows descriptive statistics of the complete set of characteristics for properties in the sample and tests of differences by bins of toxic concentration.

tive 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.

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.[22] 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

[22]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.

test, reducing the sample size to 1,275. Relative 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, discriminatory behavior reduces the odds of response to minority renters with racially perceptible names by 41% in low-exposure locations. Among African American renters, discriminatory behavior reduces the odds 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. This result implies that benefits from the enforcement fair housing policy may be larger than previously thought, since they reduce the cost of avoiding harmful exposures for African American and Hispanic/LatinX households. This is important given that the investigation and enforcement of fair housing policy can involve non-negligible costs and that funding for these programs has been reduced over the past decade.[23] The results also raise a question about the distribution of benefits from toxic abatement programs, which will disproportionately benefit white residents if minority households are systematically excluded from low exposure neighborhoods.

While the finding that discriminatory constraints are disproportionately stronger in low-exposure zones is consistent across groups, our results indicate that discriminatory constraints facing African American renters (especially men) impose higher opportunity costs in all locations. Our tests reveal evidence of higher response rates for Hispanic/LatinX renters in high-exposure zones, indicating that discriminatory behavior results in greater access to housing than to White renters in those zones. We find a parallel result for the full sample of minority identities in neighborhoods with high minority shares or below-median rents. These results are consistent with statistical discrimination, since property managers in these locations may view Hispanic/LatinX renters as most likely to sign a lease or maximize returns from a response. They could also be driven by racial animus if property

[23]Enforcement of anti-discrimination policy is primarily managed by local agencies and funded by grants from the Fair Housing Initiatives Program (FHIP). Federal appropriations to the FHIP grew from \$24.0 Million in 2000 to \$42.1 Million in 2010, but fell to \$39.6 Million in 2018.

managers who favor these groups of renters disproportionately operate in high-exposure locations.

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 searches 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 suggests that reducing illegal discriminatory behavior could be important for reducing the racial gap in pollution exposures in the US.

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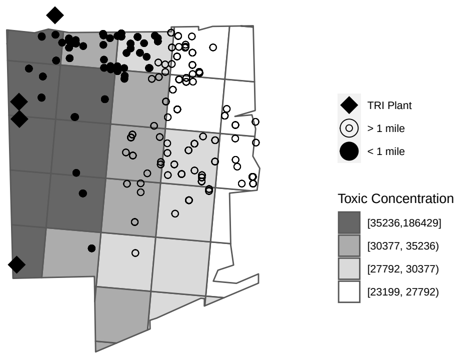
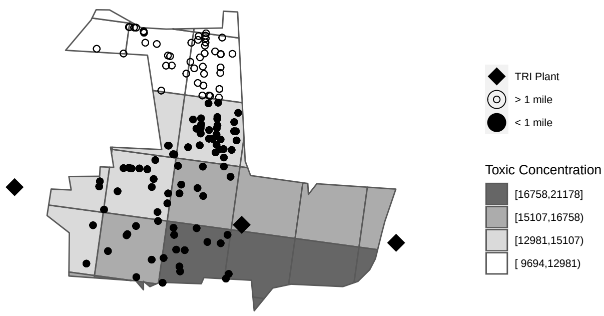
Tables and Figures

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



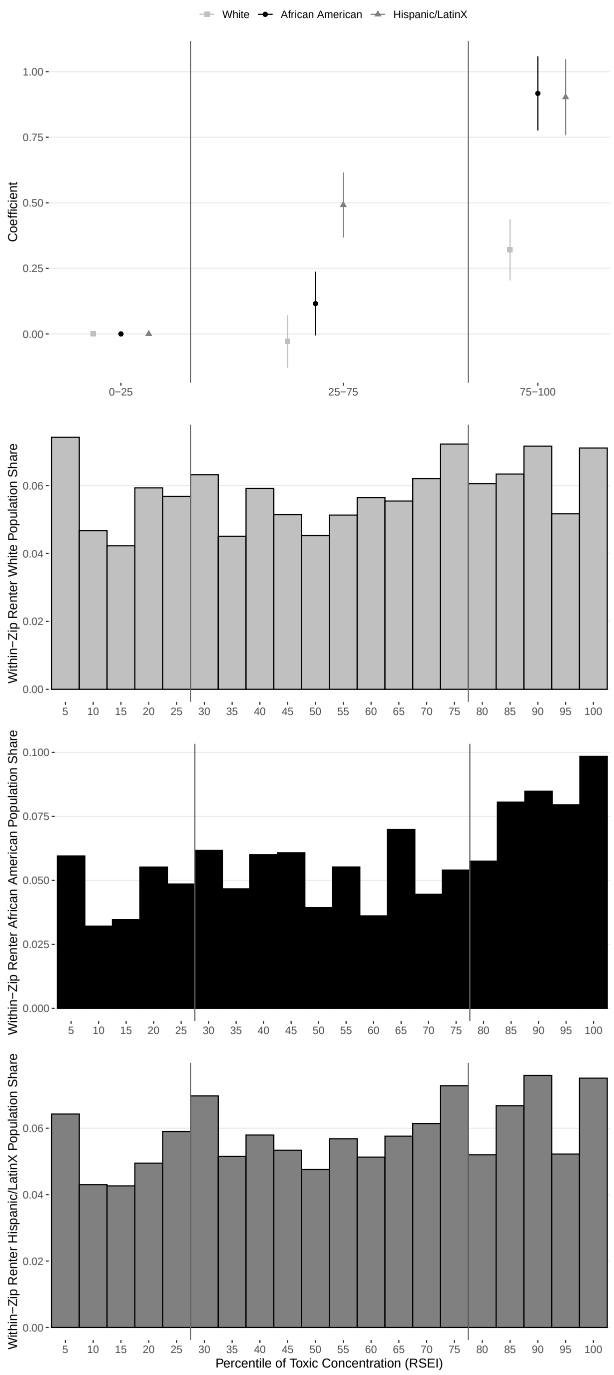
Sample ZIP A



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. Rhomboids denote the location of TRI facilities. Circular and cross markers illustrate property listings where the experiment was conducted, with circular markers illustrating the sample of listings within one mile of a toxic plant and cross markers denoting listings outside 1 mile. Refer to Figure A3 for full set of maps of ZIP codes in the experimental sample.

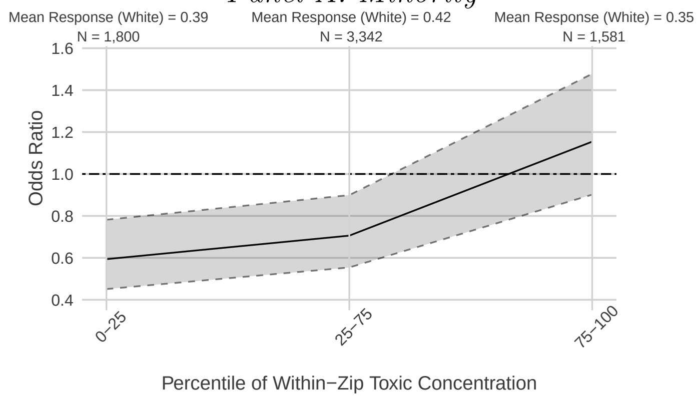
Figure 2. Observed Exposure Gap and Renter Population Distribution



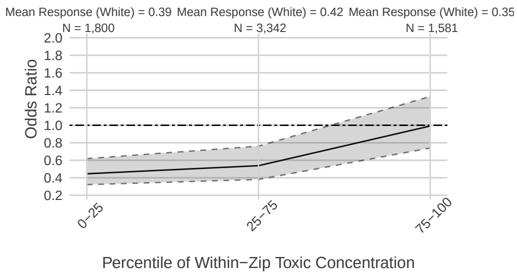
Note: Top panel plots differences in renter population shares in the highest quartile and interquartile range of toxic concentration exposures relative to lowest quartile (omitted category) for each racial group. Points represent coefficients with lines show 90% CI from the following regression: $y_{ij} = \beta_0 + \beta_{25-75} RSEI_{25-75} + \beta_{75-100} RSEI_{75-100} + \alpha_j + \epsilon_{ij}$, 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. 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. Odds Ratio by Within-ZIP Toxic Concentration

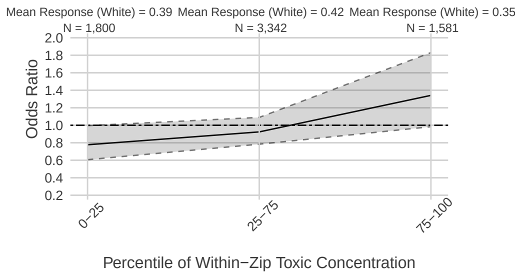
Panel A: Minority



Panel B: African American vs Hispanic/LatinX

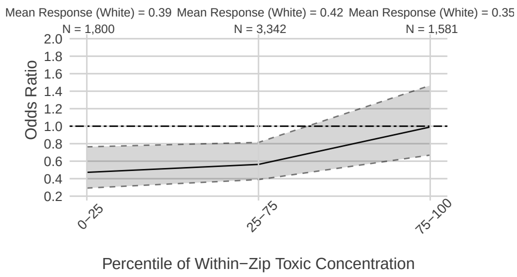


(a) African American

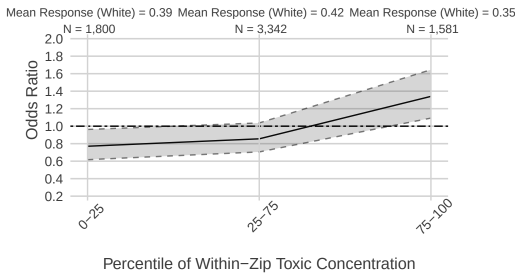


(b) Hispanic/LatinX

Panel C: Male vs Female



(c) Male

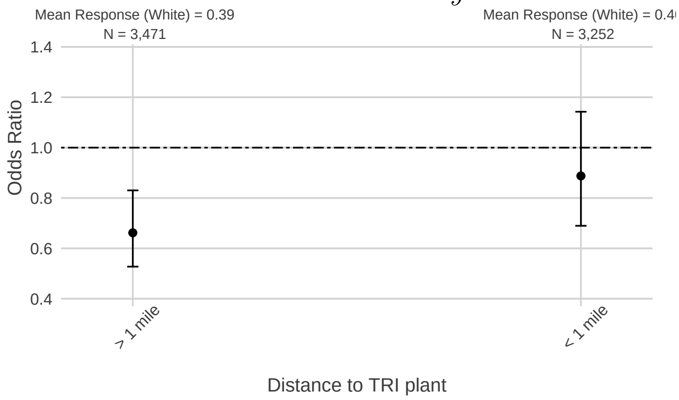


(d) Female

Note: Figure plots odds ratios relative to the White identity. Odds ratios 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 A6 and A12 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. Odds Ratio by Proximity to Closest TRI Plant

Panel A: Minority



Panel B: African American vs Hispanic/LatinX

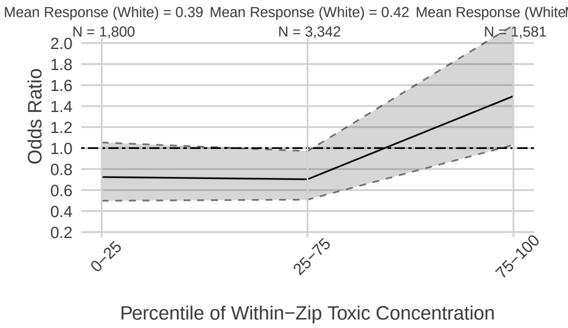
(a) African American

(b) Hispanic/LatinX

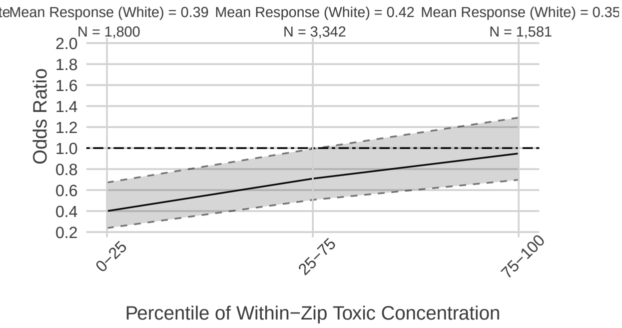
Note: Figure plots odds ratios relative to the White identity. Odds ratios are estimated using a within-property conditional logit assuming a random utility model described in Eq. (1). Standard errors are clustered at the ZIP code level using a score wild bootstrap proposed by Kline and Santos (2012) to account for the small number of clusters. 90% confidence intervals are plotted in grey. Refer to Table A6 and A12 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. Odds Ratio by Within-ZIP Toxic Concentration

Panel A: Demographic Composition, Above vs Below Minority Shares

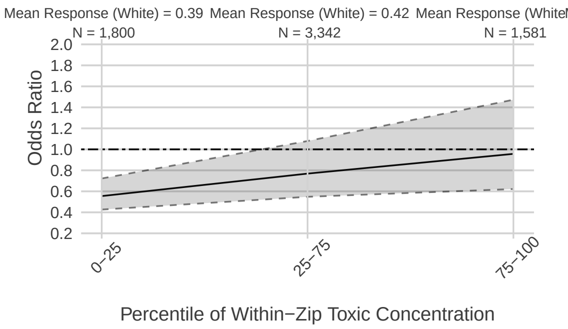


(A.1) Above Median Minority Share

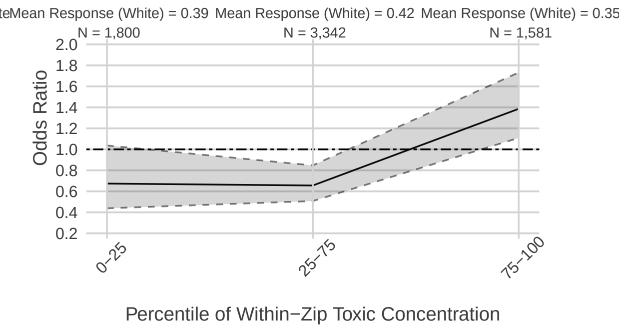


(A.2) Below Median Minority Share

Panel B: Above vs Below Median Rent

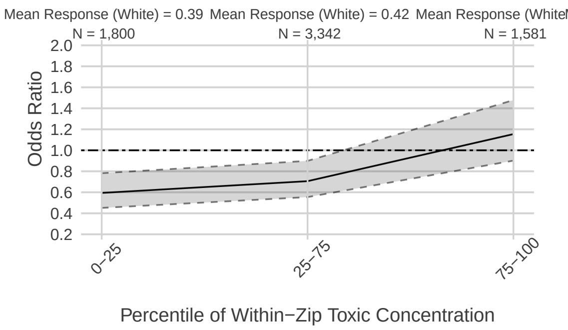


(B.1) Above Median Rent

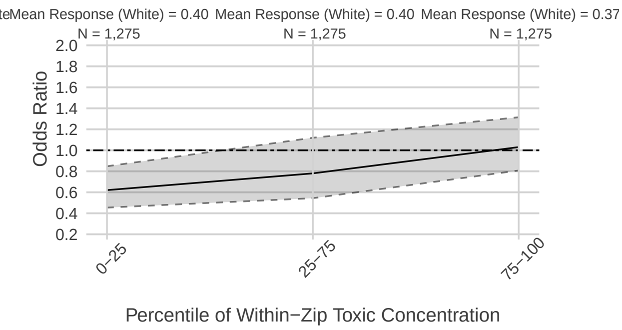


(B.2) Below Median Rent

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 ratios 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).