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
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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 that are properties 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, and discriminatory behavior 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 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 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

[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.

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,

[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.

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 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

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

[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.

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 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

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

[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, 2020a)

higher for African Americans and Hispanix/LatinX residents than for the population of White renters. Whereas the share of African American and Hispanic/LatinX 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 have 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 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. In our estimation we restrict

[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

[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.

[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.

$\beta_{kj} = \beta_k \; \forall j$.[15] In order to control for the 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. 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 increase their 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%)

[15]Table A7 shows estimations for separate logits

[16]See A1.3 for more details

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 Americans must send, on average, 1.8 more inquires to secure an expected response 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

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

[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

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]

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

[20]Results provided in Table A8.

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,

[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.

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.

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 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

[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.

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 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

[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.

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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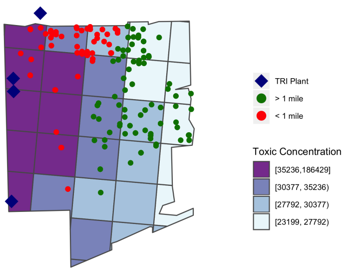
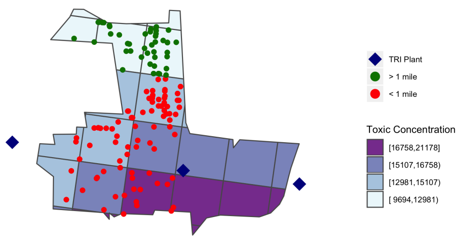
Tables and Figures

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



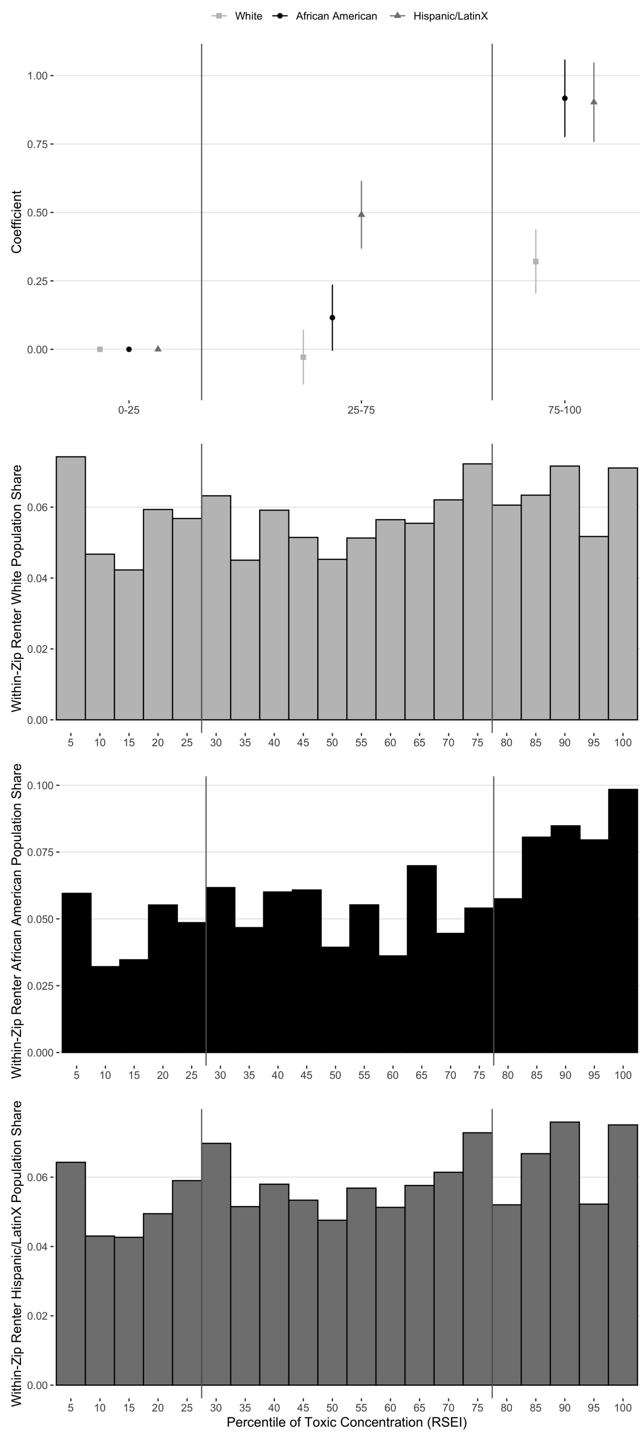
Sample ZIP A



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. 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.

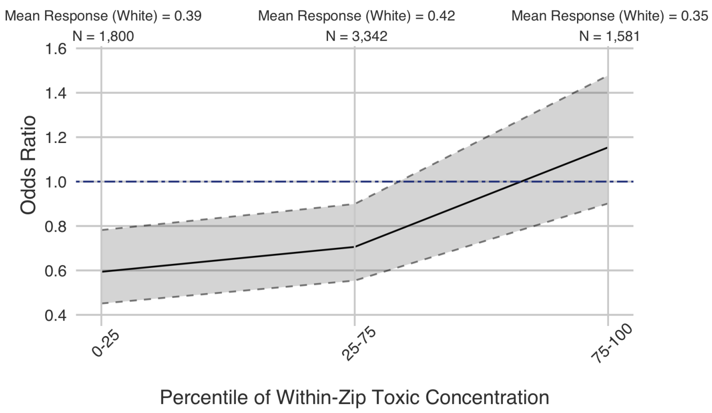
Figure 2. Observed Exposure Gap and Renter Population Distribution



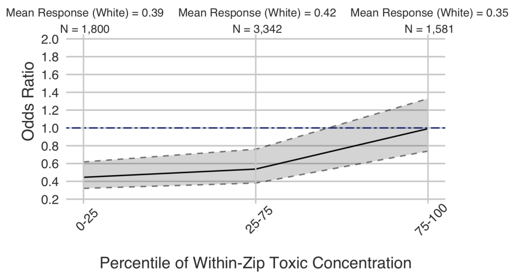
Note: Top panel plots differences in renter population shares in the highest quartile and interquartile range of toxic concentration exposures relative to lowest quartile (omitted category) for each racial group. Points represent coefficients with lines show 90% CI from the following regression: $y_{ij}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

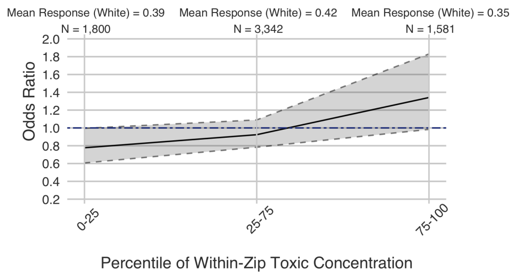
Panel A: Minority



Panel B: African American vs Hispanic/LatinX

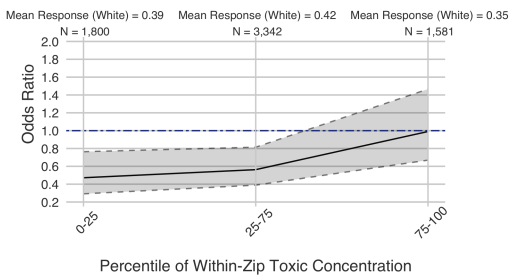


(a) African American

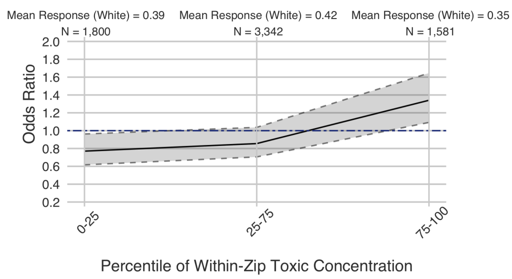


(b) Hispanic/LatinX

Panel C: Male vs Female



(c) Male

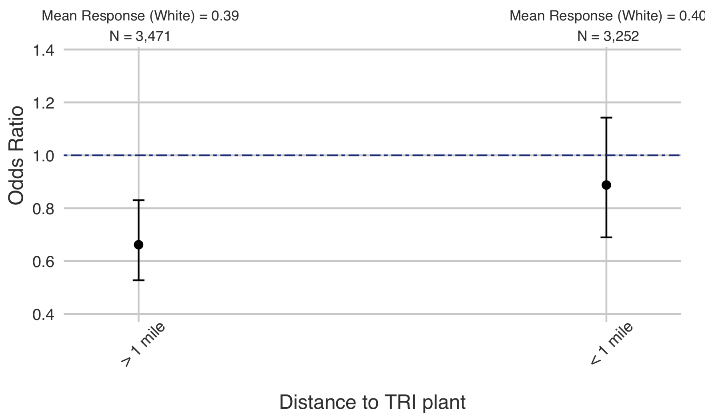


(d) Female

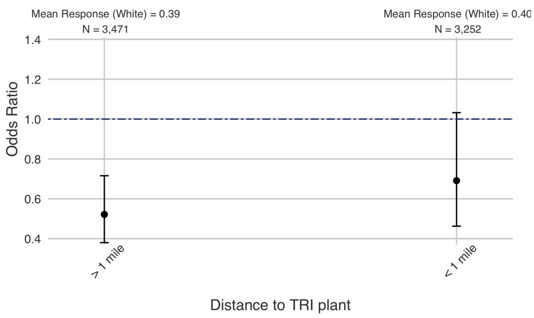
Note: Figure plots odds ratios relative to the White identity. Odds ratios are estimated using a within-property conditional logit assuming a random utility model described in Eq. (1). Standard errors are clustered at the ZIP code level using a score wild bootstrap proposed by Kline and Santos (2012) 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

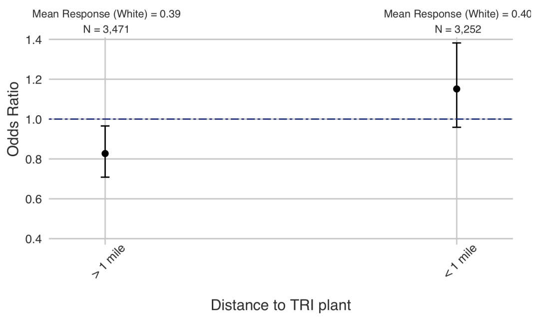
Panel A: Minority



Panel B: African American vs Hispanic/LatinX



(a) African American

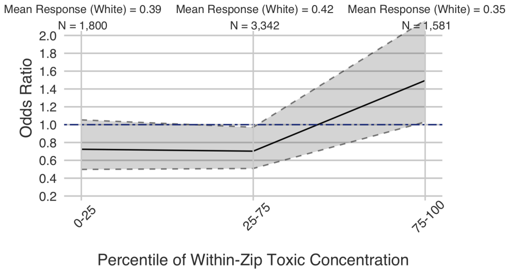


(b) Hispanic/LatinX

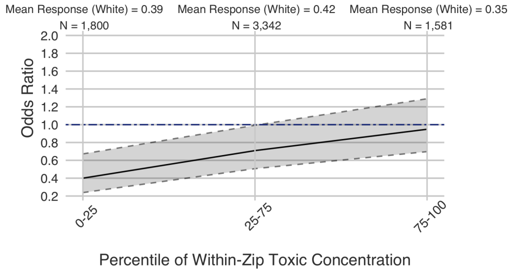
Note: Figure plots odds ratios relative to the White identity. Odds ratios are estimated using a within-property conditional logit assuming a random utility model described in Eq. (1). Standard errors are clustered at the ZIP code level using a score wild bootstrap proposed by Kline and Santos (2012) 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

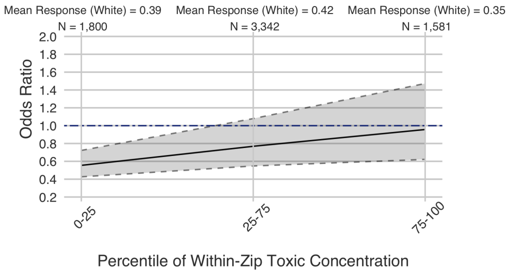


(A.1) Above Median Minority Share

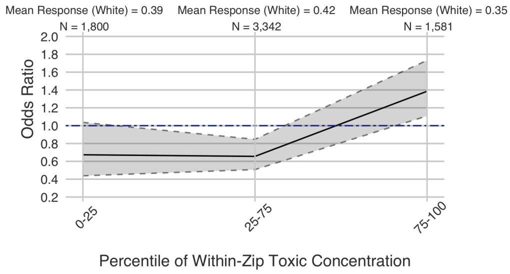


(A.2) Below Median Minority Share

Panel B: Above vs Below Median Rent

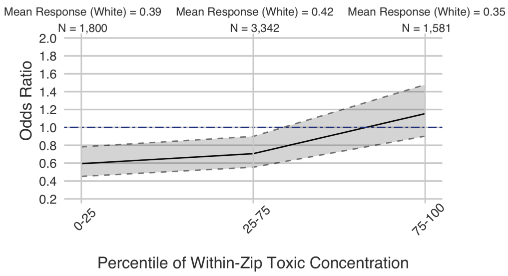


(B.1) Above Median Rent

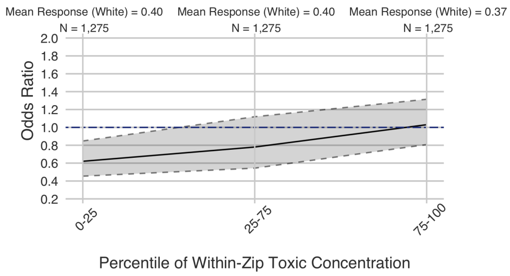


(B.2) Below Median Rent

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).

Appendix

A1 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. We use the 80th percentile of facilities to guarantee sufficient variation in toxic concentrations within a ZIP code and note that our findings are, therefore, representative of markets with major point sources of chemical toxics. 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

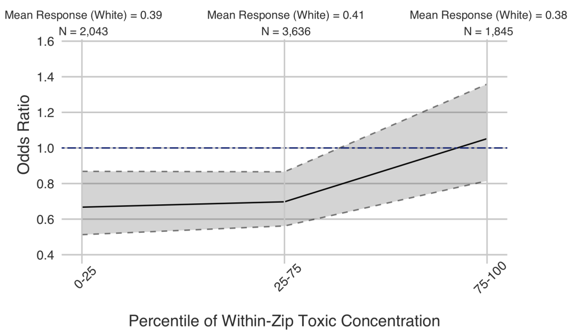
Zip code	City, State	Zip code	City, State	Zip code	City, State
35215	Birmingham, AL	60641	Chicago, IL	12866	Saratoga Springs, NY
85281	Tempe, AZ	60617	Chicago, IL	10012	New York, NY
85705	Tucson, AZ	60657	Chicago, IL	10009	New York, NY
92118	Coronado, CA	60617	Chicago, IL	10028	New York, NY
92672	San 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.

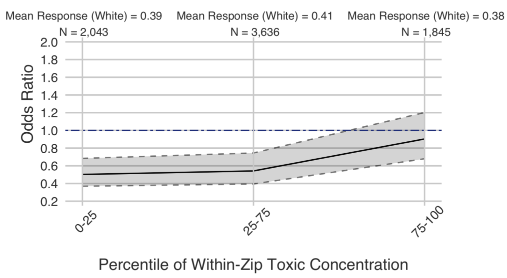
Figure 1 maps the ZIP codes with high emitting facilities. We select a random sample of ZIP codes from this set and compile the full set of property listings in each ZIP. We exclude ZIP codes that do not have at least 30% of listings within and at least 30% of listings beyond 1 mile of a facility, which 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. Odds Ratio by Within-ZIP Toxic Concentration
Full Set of Experimental ZIP Codes

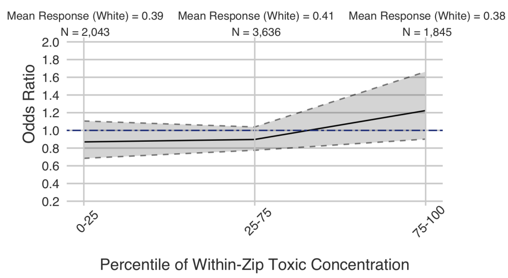
Panel A: Minority



Panel B: African American vs Hispanic/LatinX



(a) African American

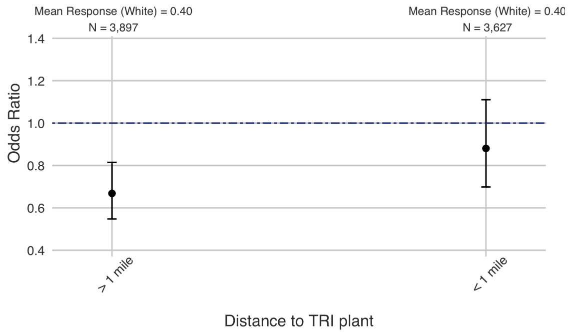


(b) Hispanic/LatinX

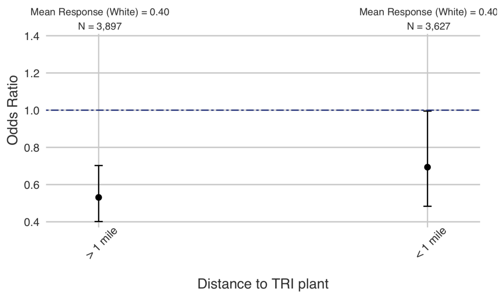
Note: The sample adds 3 ZIP code trials that where dropped as a result of small samples of listings when the trial was run (less than 30 listings) and 2 were dropped as a result of concern about rate limiting practices. The figure plots odds ratios relative to the White identity. Odds ratios are estimated 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.

Figure A2. Odds Ratio by Proximity to Closest TRI Plant
Full Set of Experimental ZIP Codes

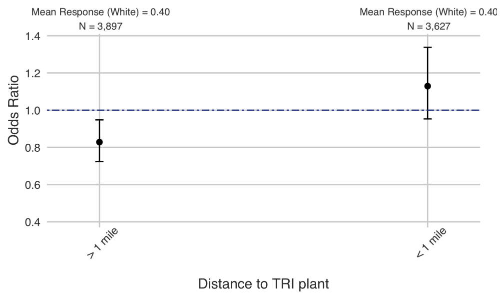
Panel A: Minority



Panel B: African American vs Hispanic/LatinX



(a) African American

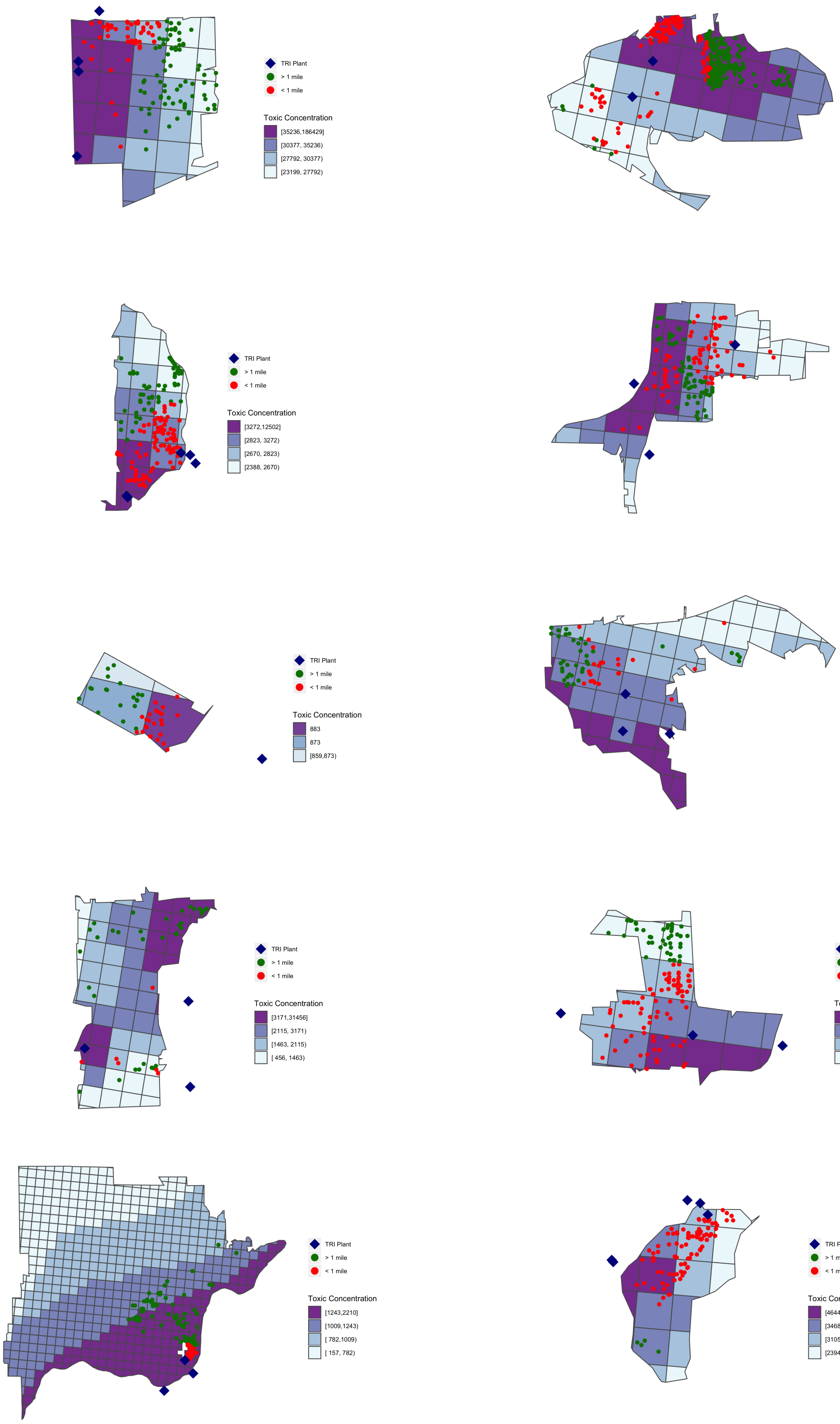


(b) Hispanic/LatinX

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 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. All estimates are robust to inclusion/omission of controls.

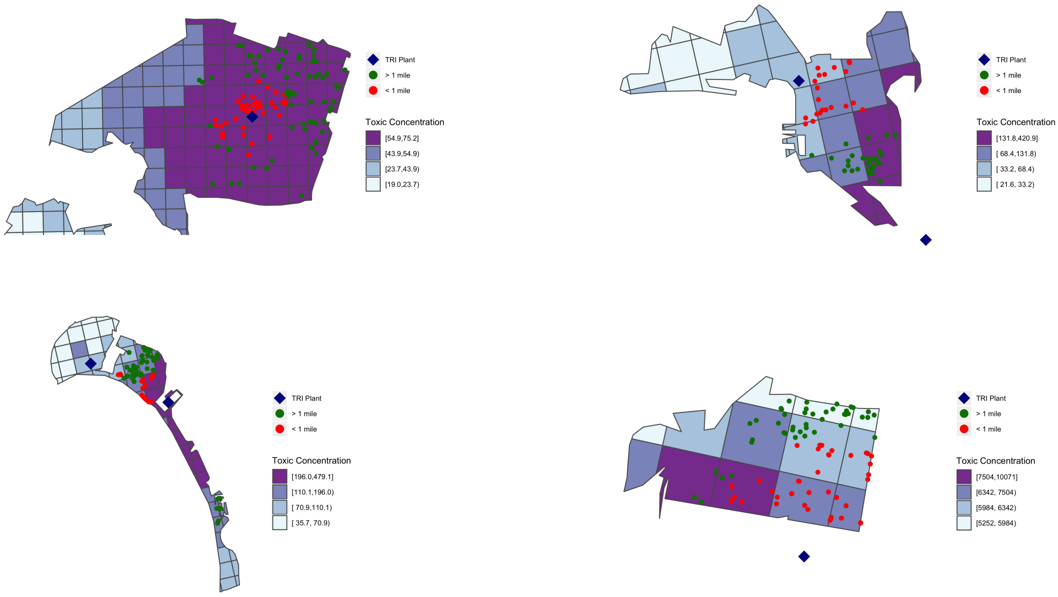
We define the level of exposure for each of the properties within the resulting sample based on their ambient concentrations of toxic pollutants using the Risk Screening Environmental Indicators (RSEI) measure developed by the US Environmental Protection Agency. Facilities report stack and fugitive air 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

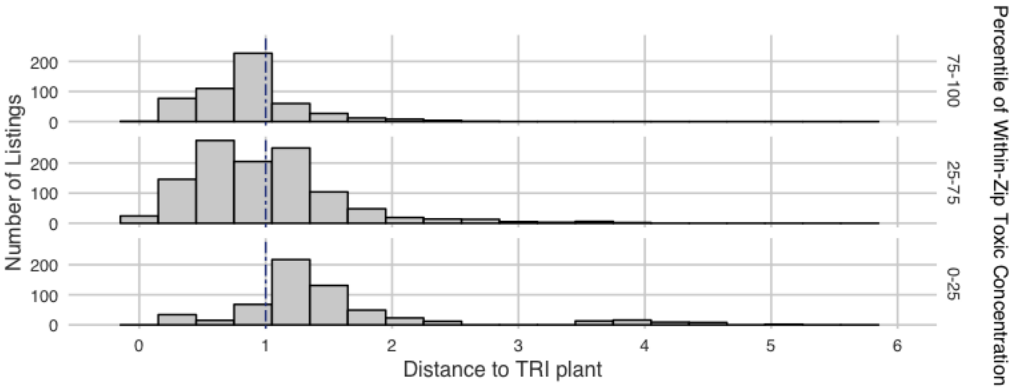


Note: Figure shows ZIP codes where the experiment was conducted. Shades of purple denote the quartiles of RSEI toxic concentration. The blue rhomboids denote the location of TRI plants. Circular markers illustrate property listings where the experiment was conducted, with red markers illustrating the 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 corresponds to TRI emissions in 2016, which is the most recent available data. The experiment was conducted during 2018-2019. To evaluate the time-consistency of RSEI estimates, we analyze 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. We find a correlation of over 90% across the 3-year period.

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 A4 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 A4. 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.[24] 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.

[24]Toxic concentration is the sum of the chemical concentrations in a grid cell weighted by inhalation toxicity. Toxic concentrations are modeled using AERMOD, which incorporates information about facilities (location, stack height, etc.), meteorology (wind, wind direction, and ambient temperature), chemical concentration, and specific decay rates. Inhalation toxicity weights are "a proportional system of numerical weights that reflect the toxicities of chemicals relative to one another. The toxicity weights of chemicals increase as the toxicological potential to cause chronic human health effects increases."(EPA, 2018) Toxic concentrations are particularly useful for "comparing levels of potential impact between geographic areas"(EPA, 2020b). Cancer and Non Cancer scores are unitless measures provided in RSEI. These measure the chemicals' toxicity, separately, for carcinogenic and noncarcinogenic effects. These also include the size and location of the exposed population. Toxic concentrations, unlike cancer and cancer scores, excludes population from the calculations, which allows identifying sparsely populated areas with high toxic concentrations.

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	2.787***	15.909***
	(11.987)	(23.091)	(46.262)	(0.495)	(0.569)
Cancer Score	5.759	7.871	10.361	1.212***	2.712***
	(9.591)	(11.310)	(15.157)	(0.227)	(0.260)
Non Cancer Score	3.231	5.791	6.273	3.589***	4.198***
	(10.368)	(13.041)	(12.170)	(0.263)	(0.303)
Rent (1000)	2.235	1.703	1.840	-0.313***	-0.279***
	(2.436)	(1.335)	(1.549)	(0.038)	(0.044)
Single Family Home	0.213	0.171	0.114	-0.049***	-0.102***
	(0.410)	(0.376)	(0.318)	(0.011)	(0.012)
Apartment	0.128	0.131	0.152	-0.008	0.028**
	(0.335)	(0.338)	(0.359)	(0.010)	(0.011)
Multi Family	0.490	0.523	0.577	0.024*	0.059***
	(0.500)	(0.500)	(0.494)	(0.013)	(0.015)
Other Bldg. Type	0.168	0.175	0.157	0.033***	0.015
	(0.374)	(0.380)	(0.364)	(0.009)	(0.010)
Bedrooms	2.435	2.267	2.331	-0.133***	-0.130***
	(1.129)	(0.981)	(0.934)	(0.029)	(0.033)
Bathrooms	1.540	1.425	1.485	-0.098***	-0.026
	(0.764)	(0.630)	(0.640)	(0.018)	(0.021)
Sqft.	716.327	749.188	694.330	-16.946	5.284
	(730.209)	(759.089)	(756.266)	(21.817)	(25.083)
Assault	220.546	183.757	253.292	-15.264***	4.610
	(319.979)	(272.190)	(387.808)	(4.140)	(4.756)
Groceries	31.926	25.144	28.438	-0.849**	-3.000***
	(44.011)	(22.791)	(35.535)	(0.366)	(0.420)
Share of Hispanics	0.101	0.131	0.089	0.022***	-0.031***
	(0.163)	(0.208)	(0.130)	(0.005)	(0.005)
Share of African American	0.208	0.233	0.299	0.026***	0.066***
	(0.271)	(0.286)	(0.337)	(0.007)	(0.008)
Share of Whites	0.687	0.643	0.612	-0.039***	-0.046***
	(0.274)	(0.270)	(0.316)	(0.006)	(0.007)
Poverty Rate	0.238	0.291	0.274	0.048***	0.026***
	(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	-0.011***	0.013***
	(0.155)	(0.149)	(0.182)	(0.004)	(0.004)
Share of Listings	0.263	0.497	0.244	0.229***	-0.018
	(0.122)	(0.212)	(0.103)	(0.071)	(0.071)
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.

A1.1 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 a 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 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).

A concern that arises in both audit and correspondence studies is the potential for those being audited to check the online profile of the tester or fictitious applicant. Nearly all correspondence studies rely on the assumption that online search tools will not affect the interpretation of results. The extent to which this assumption holds may vary across different settings. We highlight the following features of the present setting in this regard:
(1) Our correspondence design focuses on the first contact in a housing search, where the returns to learning about a respondent are low. We might expect online research to occur in later stages of contact.
(2) Our study utilizes names that are sampled from the highest percentiles of the distribution of each of three racial groups. By construction, these very common names will be linked to many possible online identities. For example, if a property manager were to conduct a google search of one of our fictitious identities, they would retrieve results like: this example. It is likely that a large fraction of the renter population also has a weak online presence. We assume that the likelihood that property managers will be affected by (the absence of) identifiable online information is low.

Name Selection

First names are taken from the work of Gaddis (2017a,b), which experimentally tests for congruence between the statistical distribution in birth records and the probability of external classification by survey respondents. Gaddis describes the selection procedure:

> "I selected names for this study using New York state birth record data for all births from 1994 to 2012 obtained from the New York State Department of Health to examine population-level race and SES characteristics. These data separately list the total number of births by (1) name and mother's race and (2) name and mother's education. This data structure allowed me, for example, to choose two names similar in terms of mother's race but different in terms of mother's education-in other words, a black lower-SES name and a black middle- to upper-SES name. Two examples used in this study are DaQuan and Jabari; 91.8 percent of children named DaQuan and 92.1 percent of children named Jabari are born to black mothers. These names are equal in blackness but vary by mother's education; only 12.8 percent of mothers who name their child DaQuan have some college or more education, whereas 56.8 percent of mothers who name their child Jabari have some college or more education. Additionally, when possible, I selected names that were used in previous or ongoing audit studies from different disciplines (e.g., Bertrand and Mullainathan 2004; Gaddis 2015; Milkman et al. 2012)."

Gaddis finds congruence rates of 75%, 75.5%, and 87.3%, respectively, for African American, Hispanic, and White first names. When last names are included, Gaddis finds that congruence rates increase to 82.5%, 97.3%, and 92.4% for African American, Hispanic, and White first-last name pairs, respectively. Gaddis also shows that congruence rates for all groups decline when first names are (mis)matched with last names from a different group. Based on this evidence, we select first-last name pairs that are shown to have a high probability of eliciting racially congruent perceptions. Panel A of Table A3 reports the identification rates from Gaddis (2017a,b) for the specific subset of first names that we use in the present study. In the study, we use the following first-last name pairs: Nia Harris, Jalen Jackson, Ebony James, Lamar Williams, Shanice Thomas, DaQuan Robinson, Isabella Lopez, Jorge Rodriguez, Mariana Morales, Pedro Sanchez, Jimena Ramirez, Luis Torres, Aubrey Murphy, Caleb Peterson, Erica Cox, Charlie Myers, Leslie Wood, Ronnie Miller. In every case, congruence rates increase with the inclusion of a correctly matched last name. Panel B reports the set of last names used in our study and examined in Gaddis (2017a,b), which were generated using the distribution from the 2010 Census. We note that imperfect ($< 100\%$) name-race congruence shown by Gaddis has implications for the interpretation of our results since names with lower levels of congruence will be less likely to induce discriminatory behavior. The fact that African American names are associated with lower congruence than LatinX names suggests that our results may understate discriminatory constraints facing the African American group relative to the LatinX group. We also note that heterogeneity in congruence by maternal education (lower congruence for the low maternal education group) may mean that our estimates understate constraints for renters with low maternal education.

The birth record data used in Gaddis (2017a) cover the years 1994 to 2012, making them relevant for renters under age 25 as of the time of our study. Gaddis (2017a) explains the choice to use the full set of NY birth data in his study, rather than constrain the dataset to an age range that is more likely to have entered the rental housing market or labor market (i.e. 18-25). Gaddis (2017a) does not provide an analysis of differences in the frequency of occurrence of names in early years (i.e. 1994-2001) and later years (i.e. 2002-2012) of birth records. Given that this study is designed to guide correspondence research, we assume that differences are not substantial. Gaddis (2017a) also discusses potential heterogeneity in names used across regions: "Although racial and SES-based naming practices may vary somewhat across regions, the question of importance is whether racial perceptions from names vary across regions. In supplemental analyses, I test whether respondents from New York vary from respondents in the rest of the United States. I find no substantive differences in these analyses, suggesting that the use of New York data likely has no significant bearing on the results (footnote 4, pp. 484-485)."

A1.2 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, 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.

Table A3. Identification Rates for First Names and Last Name Frequencies

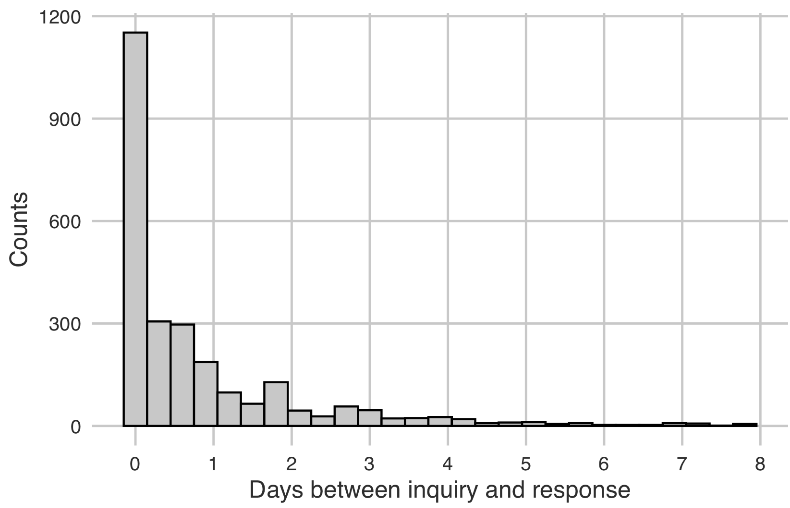
Panel A. Identification Rates from Gaddis (2017a,b) (%)				
Race	First Name	No Last Name	Last Name Included	Quartile mother's education
African American	Nia	41	65	High
African American	Jalen	63	71	High
African American	Ebony	91	95	Med
African American	Lamar	88	94	Med
African American	Shanice	93	92	Low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

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

Notes: In the study, we use the following first-last name pairs; Nia Harris, Jalen Jackson, Ebony James, Lamar Williams, Shanice Thomas, DaQuan Robinson, Isabella Lopez, Jorge Rodriguez, Mariana Morales, Pedro Sanchez, Jimena Ramirez, Luis Torres, Aubrey Murphy, Caleb Peterson, Erica Cox, Charlie Myers, Leslie Wood, Ronnie Miller.

Figure A5 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 A5. 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.

A1.3 Estimating the Magnitude of Housing Discrimination

Given the experimental setup described in Section 2 and Section 3, we model the response of a landlord listing property i as choosing to respond to a renter j as:

$$u_{ij}^* = \sum_k (\psi_k + \beta_{kj} Minority_j) Z_{i \in k} + \theta X_j + \delta_i + \epsilon_{ij} \quad j = 1, 2, 3 \tag{4}$$

where $\epsilon_{ij} \sim$ Logistic. A landlord chooses to respond to the inquiry $y_{ij} = 1$ if $u*_{ij} > 0$. Thus

$$P(y_{ij} = 1 | X, Z, \delta) = F(\sum_k (\psi_k + \beta_k Minority_j) Z_{i \in k} + \theta X_j + \delta_i) \tag{5}$$

$F(.) = \frac{exp(.)}{1+exp(.)}$ is the logistic cumulative distribution function. $Minority_j$ indicates whether the fictitious identity belongs to one of our minority groups: African American or Hispanic/LatinX, the White identity is the base group. X_j is a vector of renter-specific control variables: gender, education level and the order in which the inquiry was sent. δ_i is landlord-property specific fixed effect that controls for time invariant unobservable characteristics.$Z_{i \in k}$ are indicators denoting bin of within ZIP code percentile of pollution exposure of the listing. Either defined by within ZIP RSEI toxic concentrations: $k = 0 - 25\%, 25 - 75\%, 75 - 100\%$ or distance to nearest active TRI facilities ($k =< 1$ mile, > 1 mile). As shown by Hsiao (1986) the presence of an incidental parameter (δ_i) can lead to biased and inconsistent estimates. To avoid this problem we estimate a Chamberlain's (1980) conditional logit function, where $\sum_{j=1}^{J} y_{ij}$ is a minimal sufficient statistic. Then the conditional likelihood function is

$$L_c = \sum_i \frac{exp(\sum_j y_{ij}(\sum_k \beta_k Minority_j \times Z_{i\in k} + \theta X_j))}{\sum_{s\in S_i} exp(\sum_j s_j(\sum_k(\beta_k Minority_j \times Z_{i\in k} + \theta X_j))} \tag{6}$$

with $S_i = \{(s_1, \ldots, s_J)|s_j \in 0, 1and \sum_j s_j = \sum_j y_{ij}\}$. The likelihood is free of any unobserved fixed heterogeneity and invariant listing level characteristics. Note that in the cases that it does not respond to any identity or all of them then $\sum_{j=1}^{J} y_{ij}$ is 0 or 3, drop out from the likelihood because $lnL_c = 0$. These are 59% of the listings - i.e. 41% of listings have differential response as is indicated in the Appendix tables. Then $exp(\beta_k)$ then is the odds ratio, the odds that a minority identity receives a response relative to a White identity from a landlord-listing i in pollution exposure bin k:

$$\frac{P(y_{ij}=1|Minority_j=1,x,z,\delta)}{P(y_{ij}=0|Minority_j=1,x,z,\delta)} \Big/ \frac{P(y_{ij}=1|Minority_j=0,x,z,\delta)}{P(y_{ij}=0|Minority_j=0,x,z,\delta)} = exp(\beta_k) \tag{7}$$

Standard errors are clustered at the ZIP level. Robust standard errors require consideration of the *randomization design* and the *sampling design* (Abadie et al., 2017). In this study, randomization occurs at the level of a listing and sampling occurs at the level of a ZIP code (we sample from the set of ZIP codes located close to a toxic facility and then send inquiries to all available listings). When clustered at the listing level, estimates are slightly more precise though highly similar.

Table A4. 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 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 the odds of a response yielding a housing choice are 23% lower for an inquiry made for the average listed property 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 the relative response rate to inquiries made from

African American identities is 60% lower, there is no statistical difference in response to Hispanic/LatinX identities on average.

Table A5. 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 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 the 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 A6 report results with successive sets of controls and indicate that there is no difference in estimates that include or omit the maternal education or other controls. Column 5 reports estimates from a linear probability model that includes a listing fixed effect to capture within-listing differences in response rates. The magnitudes of estimates from the linear probability model are not statistically different from the conditional logit, though they are somewhat attenuated. This is consistent with prior work of Haggstrom (1983), who shows that the LPM estimates tend to be shrunken towards zero when compared to maximum likelihood estimates.

Table A6. Estimates of Discriminatory Constraint on Housing Choice: Robustness to Controls and Estimation Strategy

	Dependent variable: Response				
	Conditional Logit				*Linear Probability Model*
	(1)	(2)	(3)	(4)	(5)
Panel A: Quartiles of RSEI Tox. Conc.					
Panel A.1.: Minority					
Minority 0-25th perc. Tox. Conc.	0.5830***	0.5860***	0.5804***	0.5939***	0.7633***
	(0.4597,0.7395)	(0.4607,0.7454)	(0.4516,0.7458)	(0.4510,0.7820)	(0.6759,0.8507)
Minority 25-75th perc. Tox. Conc.	0.7033**	0.7124**	0.7114**	0.7059**	0.8177***
	(0.5464,0.9052)	(0.5601,0.9061)	(0.5617,0.9010)	(0.5541,0.8994)	(0.7202,0.9152)
Minority 75-100th perc. Tox. Conc.	1.1857	1.1850	1.1872	1.1542	1.0972
	(0.9182,1.5310)	(0.9323,1.5063)	(0.9398,1.4997)	(0.9014,1.4781)	(0.9505,1.2438)
Panel A.2.: By Race					
Af. American 0-25th perc. Tox. Conc.	0.4560***	0.4519***	0.4419***	0.4456***	0.6529***
	(0.3378,0.6154)	(0.3345,0.6106)	(0.3248,0.6012)	(0.3209,0.6187)	(0.5581,0.7476)
Af. American 25-75th perc. Tox. Conc.	0.5299**	0.5411**	0.5386***	0.5380***	0.6948***
	(0.3628,0.7739)	(0.3758,0.7792)	(0.3782,0.7670)	(0.3802,0.7614)	(0.5708,0.8188)
Af. American 75-100th perc. Tox. Conc.	1.0265	1.0273	1.0230	0.9912	0.9989
	(0.7436,1.4172)	(0.7545,1.3987)	(0.7584,1.3799)	(0.7392,1.3292)	(0.8316,1.1662)
Hispanic/LatinX 0-25th perc. Tox. Conc.	0.7399**	0.7515**	0.7487**	0.7771*	0.8854***
	(0.5946,0.9206)	(0.6029,0.9368)	(0.5909,0.9487)	(0.6066,0.9957)	(0.7951,0.9757)
Hispanic/LatinX 25-75th perc. Tox. Conc.	0.9228	0.9252	0.9251	0.9240	0.9545
	(0.7971,1.0683)	(0.8036,1.0652)	(0.7994,1.0705)	(0.7833,1.0901)	(0.8786,1.0305)
Hispanic/LatinX 75-100th perc. Tox. Conc.	1.3728*	1.3694*	1.3792*	1.3416	1.2036*
	(1.0224,1.8432)	(1.0323,1.8166)	(1.0411,1.8270)	(0.9831,1.8309)	(1.0164,1.3909)
Panel B: Proximity to TRI Plant					
Panel B.1.: Minority					
TRI less than 1 mile × Minority	0.8940	0.9056	0.9053	0.8877	0.9394
	(0.6981,1.1449)	(0.7153,1.1465)	(0.7149,1.1464)	(0.6897,1.1426)	(0.8230,1.0558)
TRI more than 1 mile × Minority	0.6576***	0.6581***	0.6554***	0.6618***	0.7944***
	(0.5235,0.8260)	(0.5293,0.8181)	(0.5245,0.8189)	(0.5275,0.8302)	(0.7257,0.8632)
Panel B.2.: By Race					
TRI less than 1 mile × African American	0.6999	0.7140	0.7099	0.6910	0.8127*
	(0.4727,1.0362)	(0.4851,1.0508)	(0.4821,1.0453)	(0.4626,1.0322)	(0.6543,0.9712)
TRI more than 1 mile × African American	0.5236***	0.5213***	0.5159***	0.5215***	0.6895***
	(0.3770,0.7273)	(0.3785,0.7180)	(0.3755,0.7089)	(0.3800,0.7157)	(0.6018,0.7773)
TRI less than 1 mile × Hispanic/LatinX	1.1435	1.1477	1.1515	1.1512	1.0810
	(0.9641,1.3564)	(0.9749,1.3511)	(0.9724,1.3637)	(0.9589,1.3821)	(0.9842,1.1778)
TRI more than 1 mile × Hispanic/LatinX	0.8184**	0.8214**	0.8208**	0.8271**	0.9090***
	(0.7050,0.9501)	(0.7171,0.9409)	(0.7079,0.9517)	(0.7085,0.9655)	(0.8525,0.9655)
Mean Response (White)	0.39	0.39	0.39	0.39	0.39
Gender		Yes	Yes	Yes	Yes
Education Level			Yes	Yes	Yes
Inquiry Order				Yes	Yes
Observations	6,723	6,723	6,723	6,723	6,723
Listings	2,241	2,241	2,241	2,241	2,241
% w. diff. response	0.41	0.41	0.41	0.41	0.41

Notes: Table reports odd ratios from a within-property conditional logit model with successive inclusion of controls in columns (1)-(4). In column (5) reports the odds ratio from a within-property linear probability model of the form $y_{ij} = \sum_k \beta_k \, Minority_j \times Z_{i \in k} + \theta X_j + \delta_i + \epsilon_{ij}$. The odds ratio are then constructed as $OR = {}^{((\mu_k+\beta_k)/(1-(\mu_k+\beta_k)))}/_{(\mu_k/(1-\mu_k))}$ where μ_k is the average response rate in bin k for the white identity. 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 clustered at Zip Code level. 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 A7 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 A7. 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	0.7406**	0.7178***	0.7822*
	(0.6006,0.9132)	(0.5983,0.8613)	(0.6275,0.9749)
Minority 25-75th perc. Toxic Concentration	0.8877	0.9238	0.8666
	(0.7495,1.0514)	(0.7903,1.0797)	(0.7322,1.0258)
Minority 75-100th perc. Toxic Concentration	1.1431	0.8287	0.8459
	(0.9000,1.4518)	(0.6821,1.0067)	(0.6582,1.0872)
Panel A.2.: By Race			
Af. American 0-25th perc. Toxic Concentration	0.5799***	0.6795***	0.6551**
	(0.4350,0.7730)	(0.5563,0.8301)	(0.4916,0.8730)
Af. American 25-75th perc. Toxic Concentration	0.7688	0.7789**	0.7360**
	(0.5750,1.0277)	(0.6561,0.9248)	(0.5964,0.9083)
Af. American 75-100th perc. Toxic Concentration	1.0022	0.6976**	0.8477
	(0.7643,1.3141)	(0.5426,0.8971)	(0.5891,1.2196)
Hispanic/LatinX 0-25th perc. Toxic Concentration	0.9364	0.7651*	0.8963
	(0.7338,1.1949)	(0.5932,0.9868)	(0.7150,1.1236)
Hispanic/LatinX 25-75th perc. Toxic Concentration	1.0086	1.1000	1.0150
	(0.8330,1.2212)	(0.8946,1.3526)	(0.8532,1.2074)
Hispanic/LatinX 75-100th perc. Toxic Concentration	1.3047	0.9690	0.8436
	(0.9456,1.8001)	(0.7370,1.2739)	(0.6099,1.1668)
Panel B: Proximity to TRI Plant			
Panel B.1.: Minority			
TRI plant less than 1 mile × Minority	1.0135	0.8882	0.9274
	(0.8447,1.2162)	(0.7723,1.0216)	(0.7926,1.0851)
TRI plant more than 1 mile × Minority	0.8067**	0.7999**	0.7603**
	(0.6963,0.9346)	(0.6817,0.9388)	(0.6330,0.9131)
Panel B.2.: By Race			
TRI plant less than 1 mile × African American	0.8779	0.7435**	0.8217
	(0.7167,1.0754)	(0.6155,0.8981)	(0.6566,1.0282)
TRI plant more than 1 mile × African American	0.6715***	0.7207**	0.6622***
	(0.5336,0.8451)	(0.5875,0.8842)	(0.5452,0.8043)
TRI plant less than 1 mile × Hispanic/LatinX	1.1583	1.0515	1.0499
	(0.8895,1.5083)	(0.8628,1.2816)	(0.8813,1.2509)
TRI plant more than 1 mile × Hispanic/LatinX	0.9587	0.8982	0.8541
	(0.8413,1.0925)	(0.7520,1.0727)	(0.6963,1.0477)
Gender	Yes	Yes	Yes
Education Level	Yes	Yes	Yes
Observations	2,241	2,241	2,241

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 A8 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 A8. 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 A9 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 characterize the level of discriminatory constraint facing prospective renters. The estimates in Table A9 estimates indicate that relative response rates from human-generated responses are somewhat lower than estimates 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 A9. 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: 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.

A2 Returns to Effort in Housing Search Across Zones

Our main focus throughout the paper is measuring the differential constraints that minorities face when searching for homes at different levels of pollution exposure. We measure constraints using estimates of differences in within-property response rates. These results have implications for returns to effort in search in different exposure zones, which become clear when we transform relative response rates ratios into inquires per response.[25]

Table A10 reports the returns to effort in housing search at different percentiles of within-zip toxic concentration and by distance to TRI plant. Minorities face higher search costs relative to Whites except in high-exposure locations, where Hispanic/LatinX renters receive the highest yield per inquiry (1 response per 2.4 inquiries). At low exposure locations, African Americans receive one expected response for 4.6 inquires. Hispanic/LatinX renters can expect one response per 3.2 inquiries. White renters can expect one response per 2.6 inquiries. African Americans face lower returns to their efforts everywhere, but

[25]See Table A10 for details calculations

also they bear a higher incremental cost of search in low exposure neighborhoods. The estimates in Table A10 indicate that African American renters must send 1.8 more inquires to receive an expected response in low-exposure locations than to receive an expected response in high-exposure locations. Hispanic/LatinX renters need to send 0.8 more inquiries per expected response in low-exposure locations than in high-exposure locations. These patterns are similar, albeit less stark, when using proximity to a facility as the measure of exposure.

Table A10. Returns to Effort in Housing Search Across Zones

	Inquiries Per Response			
	(1)	(2)	(3)	(4)
	Percentiles of Within-Zip Toxic Concentration			Differences
	0th-25th	25th-75th	75th-100th	(1)-(3)
White	2.55	2.41	2.83	-0.28
Minority	3.76	3.06	2.56	1.20
African American	4.61	3.76	2.79	1.82
Hispanic/LatinX	3.16	2.53	2.36	0.80
	Distance to TRI Plant			
	more 1 mile	less 1 mile		(1)-(2)
White	2.54	2.53		0.02
Minority	3.40	2.74		0.65
African American	4.01	3.28		0.73
Hispanic/LatinX	2.94	2.31		0.63

Notes: Inquiries per response are calculated first by taking the inverse of the mean response for Whites in the 0-25 percentile, e.g. 1/0.39 = 2.55, to obtain an estimate of the number of inquires per response for Whites. We then divide it by the relative response rates $\left(\frac{P(y_{ij}=1|Minority_j=1,x_j,z_{ik})}{P(y_{ij}=1|Minority_j=0,x_j,z_{ik})} = exp(\beta_k)\frac{(1+exp(\theta X_j))}{(1+exp(\beta_k+\theta X_j))}\right)$.

A3 Heterogeneity by Maternal Education

Table A11 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 A11. Estimates of Discriminatory Constraint on Housing Choice
Heterogeneity by Maternal Education

	Dependent variable: Response	
	(1)	(2)
Minority 0-25th perc. Toxic Concentration × Low	0.5196** (0.3247,0.8313)	
Minority 25-75th perc. Toxic Concentration × Low	0.6011** (0.4251,0.8500)	
Minority 75-100th perc. Toxic Concentration × Low	1.3016 (0.9306,1.8205)	
Minority 0-25th perc. Toxic Concentration × Medium	0.5478** (0.3707,0.8094)	
Minority 25-75th perc. Toxic Concentration × Medium	0.6208* (0.4097,0.9407)	
Minority 75-100th perc. Toxic Concentration × Medium	0.9094 (0.5665,1.4598)	
Minority 0-25th perc. Toxic Concentration × High	0.7466 (0.5498,1.0138)	
Minority 25-75th perc. Toxic Concentration × High	0.9276 (0.7260,1.1852)	
Minority 75-100th perc. Toxic Concentration × High	1.3728 (0.9977,1.8887)	
Af. American 0-25th perc. Toxic Concentration × Low		0.3079*** (0.1564,0.6061)
Af. American 25-75th perc. Toxic Concentration × Low		0.3818** (0.2090,0.6975)
Af. American 75-100th perc. Toxic Concentration × Low		1.3839 (0.8380,2.2857)
Af. American 0-25th perc. Toxic Concentration × Medium		0.4275** (0.2527,0.7231)
Af. American 25-75th perc. Toxic Concentration × Medium		0.4544** (0.2502,0.8251)
Af. American 75-100th perc. Toxic Concentration × Medium		0.6285 (0.3492,1.1314)
Af. American 0-25th perc. Toxic Concentration × High		0.6304* (0.4294,0.9253)
Af. American 25-75th perc. Toxic Concentration × High		0.8224 (0.6129,1.1035)
Af. American 75-100th perc. Toxic Concentration × High		1.2722 (0.7757,2.0867)
Hispanic/LatinX 0-25th perc. Toxic Concentration × Low		0.7995 (0.4729,1.3517)
Hispanic/LatinX 25-75th perc. Toxic Concentration × Low		0.8327 (0.6028,1.1502)
Hispanic/LatinX 75-100th perc. Toxic Concentration × Low		1.2244 (0.8246,1.8182)
Hispanic/LatinX 0-25th perc. Toxic Concentration × Medium		0.6615** (0.4949,0.8841)
Hispanic/LatinX 25-75th perc. Toxic Concentration × Medium		0.8758 (0.6538,1.1732)
Hispanic/LatinX 75-100th perc. Toxic Concentration × Medium		1.2670 (0.7204,2.2284)
Hispanic/LatinX 0-25th perc. Toxic Concentration × High		0.9398 (0.6470,1.3651)
Hispanic/LatinX 25-75th perc. Toxic Concentration × High		1.0790 (0.7153,1.6277)
Hispanic/LatinX 75-100th perc. Toxic Concentration × High		1.5104* (1.0747,2.1227)
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 A12. 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.