Housing Discrimination and the Pollution Exposure Gap in the United States

Peter Christensen, Ignacio Sarmiento-Barbieri and Christopher Timmins*

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Abstract

The choice of residential location is a critical economic decision for households in the United States. Recent research has shown that neighborhood pollution exposures can have significant effects on health outcomes, disproportionately affecting minority households. In this study, we combine experimental evidence on discrimination in the rental market for housing with observational evidence from a panel detailing the movements of 1.5 million renter households to study the extent to which discrimination constrains the housing choices of minorities and contributes to inequity in health outcomes. We find that renters with African American and Hispanic/LatinX names receive the exact same response rates to inquiries made for housing within a tight radius of plants that emit toxic pollutants (high exposure locations), while receiving up to 35% and 36% lower response rates at lower exposure locations in the same markets. We find that African American and Hispanic/LatinX renters in these markets move into high exposure neighborhoods at higher rates and move out at lower rates than similar white households, resulting in higher exposures to toxics and particularly during periods of pregnancy. These differences result in a 19% higher likelihood of in utero exposures to toxic emissions for children born in Hispanic/LatinX households and 16.6% higher likelihoods for children born in African American households.

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*Christensen: Department of Agricultural and Consumer Economics, University of Illinois, 431 Mumford Hall, 1301 W. Gregory Urbana Illinois 61801 (email: pchrist@illinois.edu); Sarmiento-Barbieri: Department of Economics, University of Illinois, 216 David Kinley Hall, 1407 W. Gregory, Urbana, IL 61801 (email: srmntbr2@illinois.edu); Timmins: 209 Social Sciences Building, P.O. Box 90097, Durham, North Carolina 27708 (email: christopher.timmins@duke.edu).We thank seminar participants at for excellent comments. Thanks to research assistants in the University of Illinois Big Data and Environmental Economics and Policy (BDEEP) Group and the Duke Environmental Justice Lab for excellent work. In particular, we acknowledge software development by Christopher Kim. We acknowledge generous support from the Russell Sage Foundation and the National Center for Supercomputing Applications. All errors are our own.

1 Introduction

A long-standing body of research has demonstrated that minority households in the United States are disproportionately exposed to a range of harmful pollutants. Related work has revealed that in utero exposures from toxic plants or traffic congestion in close proximity to a home residence has important effects on infant health and birth-weight (Currie and Neidell, 2005, Currie and Schmieder, 2009, Currie and Walker, 2011, Currie et al., 2015). Patterns of residential sorting have also been shown to be highly correlated with differences in chronic respiratory conditions such as asthma (Alexander and Currie, 2017). These facts elevate concern that differential location choices in US housing markets result in a persistent race-gap in a range of pollution-related health outcomes. However, it has been difficult to disentangle the impact of several different factors affecting the sorting behavior of minority households. No prior study has been able to provide evidence on the specific effect of housing discrimination on exposures and separate it from income disparities, housing or neighborhood preferences, or other types of differences underlying residential sorting behavior (Chetty et al., 2018). Understanding the role and impact of housing discrimination is critical for developing a clear understanding of the race-gap in pollution exposures, evaluating the full range of impacts of housing discrimination, and for refining fair housing policy to better protect the health of minority households.

This paper presents experimental evidence on the impact of discriminatory behavior on housing choices of renters using a correspondence study conducted on a major online rental housing platform in markets with major sources of exposure to chemical toxics. We combine the experimental estimates with evidence from a household panel that details the location choices of more than 1.5 million renters living in the same markets. We sample rental listings in zip codes that contain plants that emit toxic pollutants throughout the United States,[1] and we compare rates of discrimination within a tight radius (1 mile) of emitting facilities as well as rates at locations with lower levels of exposure but within the same market. This design allows us to examine the effect of discrimination on housing

[1]A market survey conducted in 2015 reports that 72% of housing searches were initiated on online platforms, suggesting that these platforms have now become the locus of housing search and increasing the potential impact of these technologies on discriminatory behavior (Apartments.com, 2015).

choice within high exposure locations throughout US cities and also analyze our results in direct relation to recent estimates of the long-run damages associated with these exposures (Currie et al., 2015, Currie and Neidell, 2005, Currie and Schmieder, 2009). The study therefore gains empirical traction with respect to the effect of housing discrimination on long-run health outcomes, which is a critical research and policy question that has remained virtually unanswered due to the methodological challenges involved.

The field experiment builds upon a growing literature that uses correspondence designs to detect racial discrimination in the housing market (Phillips, 2014, Gaddis and Ghoshal, 2015, Ewens et al., 2014, Carlsson and Eriksson, 2014, Ahmed and Hammarstedt, 2008, Ahmed et al., 2010, Hanson and Hawley, 2011, Hanson et al., 2011, Carpusor and Loges, 2006). While much of this literature has focused on estimating the incidence of discrimination for different groups and studying the behavioral mechanisms underlying discriminatory behavior, there has been a recent call for research that focuses on its impact (Phillips, 2017, Guryan and Charles, 2013). Researchers have long hypothesized that discrimination may be a factor that contributes to differential pollution exposures between race/ethnic groups in the US (Crowder and Downey, 2010, Logan and Alba, 1993).[2] This study provides the first empirical evidence of discriminatory behavior in housing markets with high pollution exposures. Our results indicate that renters face considerable discriminatory constraints when searching for housing in neighborhoods with low exposure to chemical toxics. Renters with African American and Hispanic/LatinX names receive the exact same response rates to inquiries made for housing at high exposure locations (within 1 mile of a plant), while receiving up to 35% and 36% lower response rates (respectively) to inquiries made for rental properties in low exposure neighborhoods in the same zip codes. By constraining the housing choices in safer neighborhoods relative to high exposure neighborhoods, housing discrimination distorts the search process of minority renters and likely results in an exposure gap.

After testing for effects of discrimination on rental housing available in markets with

[2] Crowder and Downey (2010) refer to this hypothesis as the *racial discrimination thesis*, which attributes differences in pollution exposures to housing market discrimination that constrains the location choices of minority households in a housing search.

large emissions sources, we examine the patterns of minority renter households relative to white households using a panel that details household-specific residential location decisions made in the same zip codes between 2012-2016. We build upon a literature that examines the behavior of movers with respect to major sources of pollution. While much of the existing literature has relied upon aggregate changes in the racial composition of neighborhoods to estimate changes in exposures by race group, the present study has the distinct advantage of following individual households as they make location decisions. Several papers argue that data on individual households is critical for valid inferences regarding the effects of location decisions on pollution exposures as well as identifying differences in income and preferences that also shape these decisions (Depro et al., 2015, Banzhaf and Walsh, 2013). Our panel identifies the original and final residences of households who are making choices about where to locate in these markets, allowing us to estimate the effect of those choices on exposures while conditioning on income and other important attributes such as family status and prior residence. The panel also identifies the timing of new children in the sample, allowing us to test for differences in the incidence of in utero exposures and examine location decisions during a pregnancy. We find that Hispanic/LatinX households are 17.6% more likely than white households to rent properties located within 1 mile of a toxic facility and are 19% more likely to have a pregnancy in a high exposure neighborhood. African American households are up to 8% more likely than white households to live in low exposure neighborhoods and 16.6% more likely to have a pregnancy in a high exposure neighborhood. Currie et al. (2015) show that in utero exposures raise the likelihood of low birthweight by 3%. Given this evidence, our estimates would imply that Hispanic and African American households in these markets are 3.5% more likely to have a low birthweight child.

Finally, we use the observational data to further decompose the results on differential exposures by examining differences in the probability of moving into or out of a high exposure neighborhood. Our estimates suggest that African American households are significantly more likely than white households to move into high exposure neighborhoods and both minority groups are substantially less likely in any given year to move out of high exposure neighborhoods. There is no evidence that minority households are more likely to move into high exposure neighborhoods preceding the birth of a child, although minority mothers are substantially less likely to move out during a pregnancy. These differences are especially pronounced for low income minority renters, even when compared to white renters in the same brackets of income.

This paper proceeds as follows. The following section summarizes a number of relevant literatures. Section 3 describes our experimental design and observational data. Section 4 reports and discusses results from the field experiment. Section 5 reports and discusses results from the observational analysis. Section 6 concludes.

2 Literature Review

In this section, we describe a number of relevant literatures. These include studies that use experimental techniques to study discrimination, as well as several strands of work in the area of environmental justice – the analysis of the correlations between pollution, race and class, how those correlations have developed, and the policies that can be used to deal with inequities, as was mandated under Executive Order 12898. See Banzhaf, Ma and Timmins (Forthcoming, *Journal of Economic Perspectives*) for a more general summary of the environmental justice literature.

2.1 Experimental Analysis of Discrimination

Our study uses a correspondence study design to elicit differential response rates to housing inquiries on a major online rental housing platform. A large and growing literature utilizes field experiment techniques for detecting discrimination. Bertrand and Duflo (2017) summarize this literature, focusing on the difference between audit and correspondence studies. In a correspondence study, fictitious applicants correspond only by mail or via online platform. One of the best known early studies used fictitious resumes sent in reply to help-wanted ads in Boston and Chicago newspapers, differing by racialized name (Bertrand and Mullainathan, 2004). Correspondence studies have subsequently been used to study numerous dimensions of discrimination in the labor market, including on the basis of race and ethnicity (McGinnity et al., 2009, Baert et al., 2013, Booth and Leigh, 2010, Maurer-Fazio, 2012, Galarza et al., 2014, Zussman, 2013), gender (Carlsson, 2011, Booth and Leigh, 2010), caste and religion (Banerjee et al., 2009, Wright et al., 2013), previous unemployment spells (Eriksson and Rooth, 2014, Ghayad, 2013), sexual orientation (Ahmed et al., 2013, Patacchini et al., 2015, Bailey et al., 2013), and obesity (Rooth, 2009). Consistent with prior correspondence studies, we elicit measures of discriminatory behavior using racial signaling based on a set of 18 names that are shown to have a high probability of classification in each of 3 racial categories throughout the United States: African American, LatinX/Hispanic, White. Our estimates of discriminatory constraints placed on different minority groups will be identified from within-property differences in responses that make housing available to an applicant or do not.

2.2 Environmental Justice: Pollution Exposures

Work in the environmental justice literature has considered a variety of types of pollution. The early literature focused on exposure to TSDFs (Treatment, Storage and Disposal Facilities) and found consistent evidence of correlations with race (Perlin et al. (1995), Centner et al. (1996), Ringquist (1997), Hird and Reese (1998) and Sadd et al. (1999)). Other papers have used alternative methodological approaches. Baden and Coursey (2002) focused attention on a particular city and explained exposure with a detailed demographic history. Burby and Strong (1997) utilized an interview protocol and explained exposure by race and class in terms of pollution perceptions. Rather than TSDFs, Davidson and Anderton (2000) considered RCRA (Resource Conservation and Recovery Act) facilities, finding some of the only contradictory evidence in this literature (i.e., higher exposure in working class neighborhoods with a *lower*percentage of minorities).

This initial focus on undesirable land uses was followed by a second generation of studies that analyzed air and water releases. This includes data on the presence of plants and those plants' emissions from the Toxic Release Inventory (TRI), which is our focus here. Other studies focused on measures of ambient pollution concentrations instead of emissions. For example, Clark et al. (2017) and Rosofsky et al. (2018) measure disparate impacts in criteria pollutants (i.e., NO2 and PM2.5). Another set of studies have used dispersion models to characterize the linkages between emissions and concentrations (Chakraborty and Armstrong (1997), Ash and Fetter (2004), Shapiro (2005)), while others have focused on a translation of exposure into lifetime cancer risk (Morello-Frosch et al. (2001), Morello-Frosch and Jesdale (2006), and Collins et al. (2015)). Emphasizing the role of cumulative impacts, other studies have analyzed the clustering of multiple nuisances in the same community and the extent to which harms might increase more than proportionally with increasing exposures (Morello-Frosch and Shenassa (2006)), Sadd et al. (2011), Su et al. (2009), Su et al. (2012), and Lerner (2010)).

2.3 Measuring the Impact of Residential Sorting on Exposure

The focus of our analysis is on the role of residential location decisions, and the role of discrimination in that process, on exposure to pollution. While not considering housing discrimination, papers in the environmental justice literature have analyzed the role of residential sorting in leading to disproportionate exposures. In particular, a number of studies have tested either for "coming to" or "fleeing from" environmental nuisances using longitudinal data. These studies have modeled dynamics directly by looking at changes in demographics following changes in environmental quality (Oakes et al. (1996), Yandle and Burton (1996), Been (1994), Been and Gupta (1997), Shaikh and Loomis (1999), Pastor et al. (2001), Baden and Coursey (2002), Morello-Frosch et al. (2002), Cameron and McConnaha (2006), Lambert and Boerner (1997), Noonan et al. (2007), Greenstone and Gallagher (2008), Banzhaf and Walsh (2008), Gamper-Rabindran and Timmins (2011), Mohai and Saha (2015), and Best and Rüttenauer (2017). Evidence from this literature in favor of a residential sorting explanation for inequitable exposure has been mixed at best.

The literature described above has primarily made use of data describing aggregate neighborhood demographics, rather than individual sorting decisions. Banzhaf and Walsh (2013) and Depro et al. (2015) have argued that finding evidence of residential sorting with such aggregate data is difficult if not impossible. Banzhaf and Walsh (2013) point out that changes in demographics must be compared to changes at "control sites," which themselves might be changing demographically in general equilibrium. Depro et al. (2015) underscore the fact that changes in pollution exposure depend upon both the starting and ending pollution levels associated with a particular move. We typically do not have access to data on large numbers of individual moves, and using aggregate data, the regression of the sort described above is not capable of uniquely identifying individual preferences. Depro et al. (2015) instead show how this identification problem can be solved by applying additional structure to the model of the sorting decision.

2.4 Short- and Long-Run Impacts of Pollution Exposures

Šrám et al. (2005) reviewed a large literature that has found evidence that exposures to environmental nuisances negatively affect birth outcomes (e.g., birth weight, gestation length, congenital abnormalities, and infant mortality). More recently, Currie (2011) demonstrated that exposure to pollution while in utero is decreasing in education but is higher for minority mothers and that the resulting differences in exposures to toxic releases can explain differences in low birth weight.

Other papers have subsequently demonstrated that neo-natal health can impact later health and socioeconomic status, supporting the so-called "fetal origins hypothesis" (Almond and Currie (2011), Almond et al. (2017)). The list of outcomes studied in this literature include adult health (e.g. diabetes), education, labor force outcomes, IQ, adult height and subsequent child birth weight, earnings and educational attainment, and adult poverty (Currie and Moretti (2007), Oreopoulos et al. (2008), Currie (2009), Almond et al. (2012), Barreca (2010), Black et al. (2007), Figlio et al. (2014), Currie et al. (2014)). Persico et al. (2016) use population-level data on those born in Florida between 1994 and 2002 to examine the impacts of prenatal exposure to nearby Superfund sites on schooling outcomes. Voorheis (2017) uses a unique combination of data linking responses to the American Community Survey to Social Security Administration data and the universe of IRS 1040 tax returns to measure the effect of particulate matter exposure at birth on incarceration rates and college attendance.

3 Field Experiment: Housing Discrimination

3.1 Experimental Design

Sample of Housing Markets and Rental Properties

This study brings together observational and experimental data to characterize the differential rates of sorting into high exposure neighborhoods and the mechanisms underlying those differences.[3] The study focuses on exposures to toxic emissions reported in the Toxic Release Inventory (TRI) database, which identifies the exact location of major point sources in housing markets throughout the United States.

In prior work on the damages of toxic plants reporting in the TRI, Currie et al. (2015) provide evidence that hazardous ambient pollution is highest near toxic plants and decays rapidly. They also find that on average emissions do not reach further than one mile. In order to study the relationship between housing discrimination in high/low exposure zones, we follow Currie et al. (2015) by defining a potential study area that consists of all zip codes that contain at least one high-emitting toxic facility that is within one mile of a residential neighborhood.[4] We select a random sample of zip codes from this set and compile the full set of 3br/2ba property listings for the neighborhood. For each listing, we collect information on the rent, address, apartment characteristics, and information on neighborhood amenities (crime, school ratings, local amenities). We define the level of exposure for each of the properties within the resulting sample based on their distance to the nearest toxic facility in the zip code. We begin with the definition of a high exposure area (within a mile of the toxic plant) from Currie et al. (2015) and then vary the distance measure in further tests. We cap the distance, however, up to four miles to focus the study on neighborhoods that fall within the vicinity of a toxic plant.

[3]The experiment was registered on the AEA RCT Registry as trial 3366 (Christensen et al., 2018) and the human subjects protocol for this research design was approved by the University of Illinois Institutional Review Board (IRB #18381) on 12/07/2017.

[4]We define a high-emitting toxic facility as above the 80th percentile of toxics emissions in the TRI.

Table 1 details the characteristics of listed properties in our sample. The average rent for a 3br/2ba rental property within 1 mile of a toxic plant in our sample is about $2,200. On average, the rental prices for properties located between 1-2 and 2-4 miles from the nearest plant are approximately $2,300 and $1,675, respectively. Properties located near plants are, on average, more likely to be multi-family and slightly smaller. The neighborhoods in closer proximity have somewhat higher assault rates, lower elementary quality elementary schools, and higher poverty rates. High exposure neighborhoods are on average closer in proximity to restaurants and grocery stores. We do not observe significant or substantial differences in the racial composition, unemployment rate, or share college educated households in the average neighborhood across the different distances.

Fictitious Renter Identities and Correspondence Design

Consistent with prior correspondence studies, we assign race using a set of 18 names that are shown to have a high probability of association with each of 3 racial categories throughout the United States: African American, LatinX/Hispanic, White. A question that has emerged in prior correspondence studies using racialized names is the possibility that any given name may signal race as well as other unobserved characteristics such as income (Guryan and Charles, 2013, Fryer Jr and Levitt, 2004). To test this empirically, we construct groups with each consisting of 3 male and 3 female names and stratify the sample of first names using statistical distribution of mother's educational attainment (low, medium, and high) from hospital birth records. The first name labels for this study are constructed using the work of Gaddis (2017a,b), which tested the racialized perceptions of first and last names for African American, LatinX/Hispanic, and White social groups. Last name labels were also taken from this work and tested for any geographic variability using (Crabtree and Chykina, 2018).[5]

[5] 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, particularly in markets where there is a high return to gathering such information (e.g., high skilled labor). To address this problem, one correspondence study created an online presence for their fictitious applicants in an analysis of discrimination in the labor market. In parallel analyses of labor and rental markets, another study created websites for applicants and kept track of how often they were accessed. Our study utilizes names that are sampled from the highest percentiles of the distribution of each of three racial groups. These are very common names and we view the likelihood that the responses from property managers will be affected by online information about these names as low.

Randomization Protocol and Response Coding

Immediately following 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).[6] 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.[7] 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 software architecture is designed to capture responses in any of these forms. The content of a message and time stamp are then extracted and coded. Phone, text, and email responses from property managers are recorded by a team of human coders to ensure the quality of the data.

4 Observational Data on Renter Households

We identify the location choices of renter households using a residential households dataset created by InfoUSA. The dataset provides the address history of people who were identified at a United States address at some point between 2012 and 2017. The data allows us to construct a sample of households living in any of the zip codes that we study between 2012-2017 and observe changes in address as well as other attributes. InfoUSA identifies movers using a combination of utility data, deed transfers (homeowners) and FRCA compliant magazine and credit sources.[8] Besides the address and household identifier,

[6] Phillips (2016) provides evidence of a within-trial impact when multiple inquiries sent in matched correspondence designs in competitive labor markets.

[7] As described below, our design simulates a housing search using all available listings in a Metropolitan Statistical Area at a given time and is therefore reflective of the true set of options available in an 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. Our research design has three important characteristics: (1) it minimizes the possibility of any suspicion among property managers, (2) it allows for empirical tests for the effect of competition on discriminatory response in the housing market, and (3) it allows for tests of within-property difference in response and a robust counterfactual in our welfare estimation.

[8] InfoUSA company reports a lag of approximately 2-3 days from connection for identifying new utility connections and 2-4 weeks for deed transfers. The company estimates a 90-95% coverage of deed transfers. The company reports that the database currently contains information on 120 million households and 292 million individuals in the US, which must be validated every 12-24 months. The company reports recording approximately 1 million moves per month.

the data contains information about their ownership status (owner or renter), ethnicity of the head of the household, his estimated income, age, marital status, if there are children present and the number of these children. The racial identities of households in the InfoUSA data are predicted using a proprietary algorithm that assigns a likelihood of racial/ethnic categories using first, middle and last names of individuals identified in the database.

We utilize the sample of more than 1.5 million renter households from InfoUSA to construct a panel of location choice by year for all renters that locate in any year within 4 miles of the toxic facilities in our sample from the TRI.[9] This panel observes households who move in, households who stay in, and households who move out of high exposure neighborhoods. Table 2 describes the characteristics of hoseuholds in the panel. 44.6% of the households in the panel are identified as white, while the shares of Hispanic/LatinX and African American households are 16.5% and 16.7%, respectively. The average income for households in the sample is $31,099, with substantial differences across the groups. The average income is $24,495 for Hispanic/LatinX households, $19,513 for African American, and $36,339 for white households. A Hispanic/LatinX households are somewhat more likely than white households to be married, while African American households are less likely than both groups to be married, though there are no significant difference between the groups. There are no significant differences in the share of households that are pregnant in any given year or in the number of children in any given year.

5 Experimental Results

This section reports experimental estimates of housing market discrimination in zip codes with zones of high exposure to airborne chemical toxics. Our main specification makes use of our matched-paired design to estimate the probability that an applicant i to listing j receives a response to an inquiry for rental housing, such that the estimates capture

[9] To increase the power of these tests, our main specifications utilize the full sample of neighborhoods located within 4 miles of the toxic facilities used in the experimental sample. However, we also restrict our analysis to renters that locate within in the same 178 zip codes where we collect experimental data, which are located in Atlanta GA., Houston TX., Philadelphia PA., New York, NY, Tempe AZ, Coronado CA. This is an ongoing project and additional zip codes will be added as the field experiment continues.

within-property differences in response rates between race groups:

$$P(response_{ij}|choice) = \sum_{\substack{Race \in \{Hispanic, \\ African\,American\}}} (\beta_{1,race} 1[d_j < 1] \times Race + \beta_{2,race} 1[d_j > 1] \times Race) + \theta X_i + \alpha_i + \epsilon_{ij} \quad (1)$$

where d denotes distance in miles to the closest TRI plant, e.g. $1[d_j < 1]$ indicates whether listing j is within 1 mile of a TRI plant, *Race* indicates the applicant race, i.e. Hispanic, African American. The left out category is the white identity. X_i is a vector of individual control variables: gender, education level and the order in which the inquiry was sent, and α_i is a listing fixed effect which allows for within listing comparisons.

Table 3 presents odds ratios from Equation 1 that reflect the probability of a response to an inquiry from a Hispanic or African American renter identity relative to a white identity. The first row for each race group provides the odds ratio in the high exposure neighborhood (within 1 mile) while the row below presents the odds ratio in the high exposure neighborhood. Columns 1-4 report estimates from specifications that include (1) no controls, (2) a control for the gender associated with the name, (3) a control for the education level associated with the name, (4) the inquiry order. Column 5 reports estimates for odds ratios for the 1st inquiry alone, which does not reflect a within-property difference and is estimated with 1/3 the sample.

The odds ratios suggest an equivalent response rate between renters with Hispanic names and a white counterpart in high exposure neighborhoods (within 1 mile of a toxic plant), but that the response rate for Hispanic renters is 25-30% lower in low-exposure neighborhoods in the same zip code (between 1-4 miles). The difference is less pronounced for African American renters, though there is some evidence of a difference in matched models with the full set of controls.

While there is evidence that exposures dissipate within 1 mile on average, less is known about the heterogeneity in that decay function between plants and it is likely that exposures are not limited to 1 mile for all facilities. Table 4 examines how discrimination rates change as a function of distance to the nearest toxic plant. Odds ratios in this table show evidence of increasing discrimination rates for both minority groups at greater distances from the nearest plant.[10] Hispanic renters have a greater than 36% lower probability of a response to an inquiry made for a homes between 2-4 miles of a toxic source. African American renters have about a 35% lower probability. Tables 6 reports estimates from tests that examine heterogeneity in discrimination rates by sex and level of mother's education (which affects first name selection). These tests involve multiple interactions, which substantially reduces statistical power. Overall, they provide some evidence that male renters face rates of higher discrimination when they are searching for housing in low exposure areas. Differences by education level suggest that minority renters with first names signalling both a high or low level of maternal education face discriminatory constraints.

The experimental evidence presented above indicates that minority renters face discriminatory constraints when searching for housing in low exposure neighborhoods in housing markets (zip codes) that contain high emissions of chemical toxics. On the other hand, minority renters do not appear to face the same constraints in neighborhoods in high exposure zones. These neighborhoods vary along other dimensions as well. Table 5 reports the tests for differences in the racial composition and rental prices of homes in these neighborhoods. These tests involve multiple interactions and generally lack the statistical power to make clear inferences about differences in discrimination rates in low/high exposure neighborhoods that also differ in rental prices and racial composition. However, the odds ratios provide suggestive evidence that minority households are more likely to be excluded from low exposure neighborhoods when rental prices are lower and when the share of white households is higher.

[10] An exception to this is the odds ratios for homes within .5 miles of a plant, which are lower for minorities than those within 1 mile. However, given the geography, these are estimates are based on small samples and are not different from zero in either case or from each other.

6 Location Choice and Toxic Exposures by Race

6.1 Estimates of the Race-Gap in Toxics Exposures

We begin by estimating the race-gap in toxics exposures for the renter population in our study area. We define the race-gap using differences in the likelihood of renting in high exposure areas conditional on having ever rented in any of the neighborhoods in our study area (i.e., 0-4 miles of a toxic plant). This specification provides descriptive evidence of differences in location choice for minority versus white households in the exact markets sampled for our experiment.

Our model takes the following form:

$$P(High\,Exposure_{ijt}) = \beta_H Hispanic_i + \beta_{AA} Af.\,American_i + \theta X_{it} + \delta_{jt} + u_{ijt} \qquad (2)$$

where $High\,Exposure_{ijt}$ equals one if the renter lives in the high exposure area (within one mile of a toxic plant) of the neighborhood j and 0 if she lives in the low exposure area. $Hispanic_i$ and $Af.\,American_i$ are indicators for the race of the head of the household, the omitted category are White households, and X_{it} includes controls for income, age of the household, marital status, and number of children. We include zip code by year fixed effects, δ_{jt}, which ensures that our estimates are based on within neighborhood-year differences.

Panel A in Table 7 reports odds ratios that describe the likelihood that an African American or Hispanic household locates within a high exposure neighborhood. Odds ratios are estimated relative to a white household as in equation (2). The first column reports differences in the odds of living within 1 mile relative to outside 1 mile of a facility, whereas the second column reports differences in the odds of living within 1 miles versus outside 2 miles of a facility. These estimates indicate that Hispanic households are 17.6% more likely than white households to live in high exposure neighborhood when low exposure is defined as beyond 1 mile and and 20.7% more likely when low exposure is defined as beyond 2 miles. African American households appear to be slightly (1.2%)

less likely to live in a high exposure area when using the 1-4 mile definition, but become 7.9% more likely when using the more conservative 2-4 mile definition.

6.2 Estimates of the Race-Gap in In Utero Exposures

Using information on changes in the number of children as identified by InfoUSA, we identify in utero exposures to toxics for each of the three race groups in our sample.[11] We define a probable in utero exposure as a change in the number of children identified in a household that coincides with a residential location in a high exposure zone. Since we observe each household only once each year, we adopt the most conservative definition of the timing of pregnancy. If a household is observed with zero children in 2012 and with one child in 2013, then we count them as potentially pregnant in both 2012 and 2013.[12] If that household resides in a high exposure neighborhood in 2012 and 2013, then they are identified as having in utero exposure for both of those years. If the household resides in a high exposure neighborhood for 2012, then the household is identified with an in utero exposure in 2012 but not 2013.

Panel B in Table 7 provides estimates of differences in the likelihood of exposure for minority households relative to a white counterpart. These estimates indicate that in utero exposure is 20.8% more likely for Hispanic households using the 1-4 mile definition for low exposure and 19.1% more likely using the 2-4 mile definition. African American households are not significantly more likely to have in utero exposures (3.8% more likely, though not significant) if using the 1-4 mile definition of low exposure but become 16.6% more likely if using the 2-4 mile definition.

[11] InfoUSA uses direct

[12] The actual timing of pregnancy with respect to these two years depends upon the timing of the birth relative to the timing of observation in 2013. Lack of information on the exact timing of a birth introduces some measurement error in our data (for all race groups), but we do not find that our estimates are sensitive to alternate definitions.

6.3 Movers and Stayers

Moving Into and Out of Exposure

In the prior section, we provided evidence that minority households are more likely to live in neighborhoods that result in high exposures to chemical toxics and are also more likely than white households to sustain damaging in utero exposures during their pregnancies. These results do not propose or test a particular mechanism, but rather estimate size of the pollution-exposure gap.

In this section, we utilize the household panel to capture the location choices of households who are moving to examine how these choices relate to toxic exposures in our sample. We classify a family as a mover if we observe them in two different addresses in any two consecutive years. We then restrict the sample to focusing on families that are moving into neighborhoods with toxic plants by estimating the following model:

$$P(Y_{ijt}) = \beta_H Hispanic_i + \beta_{AA} Af.\,American_i + \theta X_{it} + \delta_{jt} + u_{ijt} \tag{3}$$

where Y_{ijt} equals one if the renting household moves into the high exposure neighborhood j and 0 if it moves into the low exposure neighborhood in year $t = 1$. As before, $Hispanic_i$ and $Af.\,American_i$ are indicators for the race of the head of the household indicates the race of the head of the household, and X_{it} includes flexible controls for income, age of the household, marital status, and number of children. We include zip code-by-year fixed effects δ_{jt} based on the renting household's new address.

We then utilize equation (3) to estimate differences in the likelihood that households move out of a high exposure neighborhood. In this model, the sample is the set of renting households who are observed in a high exposure neighborhood during the period 2012-2016. Y_{ijt} equals one if the renting household moves out of a high exposure area (in year $t = 1$) of neighborhood j and 0 if it stays at the same address in consecutive years.[13]

[13]Renting households are classified as movers if a move is observed from a high exposure zone to any other neighborhood in the United States. Moves are not restricted to final addresses observed within the study area. In some cases, renting households may move to a high exposure neighborhood in a zip code that is not contained in the study area. These households will be classified as having moved out of high exposures, which would lead to some possible attenuation bias in our estimates assuming that minority

$Race_i$ indicates the race of the head of the household, and X_{it} includes flexible controls for income, age of the household, marital status, and number of children. We include zip code-by-year fixed effects δ_{jt} based on the renting household's initial address.

Figure 3 reports the results on movers and stayers. Results from panel 3a indicate that African American households are 15-18% more likely than white households to move into high exposure neighborhoods in our sample. Odds ratios suggest that Hispanic renters are 4-9% more likely to move into high exposure neighborhoods, though the estimates are not different from zero. Results from panel 3b indicate that African American households living in high exposure neighborhoods are 10% less likely than white households to move out of high exposure neighborhoods in any given year and that Hispanic households are 30% less likely.

In Figure 3, panels 3c and 3d use the definition of pregnancy defined above to test for differences in the location decisions of households that we identify as likely pregnant. Panel 3c suggests that differences in the likelihood of moving into a high exposure neighborhood disappear for pregnant mothers, which provides some evidence that all mothers avert pollution exposures when making location choices. However, panel 3d indicates that African American and Hispanic households are substantially less likely than white households to move out of high exposure neighborhoods during a pregnancy. Odds ratios indicate a 40% lower likelihood for African American and a 45% lower likelihood for Hispanic/LatinX households. These results indicate that differences in the rates of exposure in this sample can be explained by the combination of an increased likelihood among minority households to move into high exposure neighborhoods when they are not pregnant and a substantially lower likelihood of moving out of these neighborhoods just preceding or during a pregnancy. These differences cannot be explained by differences in the likelihood of locating in a high exposure neighborhood during a pregnancy.

In Figure 3, panels 3e-3h explore heterogenity in the results for movers and stayers. We define five income quintiles using the income distributions for each of the minority

households are more likely to move into high exposure neighborhoods when moving to locations falling outside our set of TRI facilities. Future versions of this paper will control for such cases, though we expect the number to be small.

samples. We then estimate differences relative to white households in the same income bracket. While imprecisely estimated, these tests suggest that differences in the likelihood of moving in and staying are more pronounced for low income, minority households. There may also be differences at the highest income levels. We further examine these differences using a survival analysis that estimates differences in the likelihood of moving out of a high exposure property over a period of up to 5 years. Figure 4a reports these results. During the period 2012-2016, white renters who are observed in a high exposure residence have an 80.4% likelihood of remaining in a high exposure location 5 years later, whereas the likelihoods for African American and Hispanic/LatinX households are 86.2 and 89.4%, respectively. The differences become even more stark for households that have a pregnancy during the sample period. In this sample, white renters who are observed in a high exposure residence have an 41.4% likelihood of remaining in a high exposure location 5 years later, whereas the likelihoods for African American and Hispanic/LatinX households are 55.3 and 51.1%, respectively.

7 Conclusion

For over two decades, researchers have advanced and discussed a *Racial Discrimination Thesis* as an important part of the explanation for the well-established disparity in exposures to chemical toxics and other harmful pollutants in the United States. However, it has been difficult to isolate the effect of disparities income, preferences, and information from the direct effect of discrimination in these markets. As a result, this thesis has remained untested and a large literature on race-specific sorting in US housing markets has failed to account for the effect of discriminatory constraints on pollution exposures. This paper provides the first empirical evidence that racial discrimination constrains a housing search by eliminating choices in low exposure neighborhoods of markets with polluting facilities. While the experiment provides evidence substantial discriminatory behavior in low exposure neighborhoods, we find no evidence of the same constraints operating in neighborhoods characterized by high exposures.

By constraining the set of choices available in less polluted neighborhoods relative to more polluted ones, housing market discrimination shapes the location choices of renters in these markets and very likely exacerbates the race-gap in exposure to toxics. Our analysis of this gap using a large sample of renting households from 2012-2016 confirms the presence of a substantial race-gap in exposures in these markets and indicates important effects on in utero exposures for both of the minority populations that we study. Importantly, we find evidence that while minority households are more likely than white households to move into high exposure neighborhoods, this difference disappears when we look specifically at households with pregnant mothers. We interpret this as suggestive of averting behavior on the part of all pregnant households, which likely involves substantial additional investment in search for minority households given the housing discrimination that they face. Our analysis also suggests that, having located in a high exposure neighborhood, minority households are always more likely than white households to stay. This difference is substantially larger than differences in the likelihood of moving in, is present across all levels of income, and persists even through pregnancies. We interpret the evidence of differences in the likelihood to stay in a high exposure location, which could also be exacerbated by the effect of discriminatory constraints on the productivity of a housing search, as a very likely component of the race-gap in cumulative exposures to airborn toxics.

By providing direct evidence of the link between housing discrimination and the race-gap in pollution exposures, this study points to a key role for fair housing policy in addressing environmental health and justice concerns. However, the study is also limited in several respects. First, our experimental results are limited to listings that appear on a rental housing platform. While this is an important platform in the market (and there is evidence that online search is utilized in the majority of rental housing searches more generally), it certainly does not capture the full set of listings available and may miss key sub-markets that are relevant in a study of toxics exposures. Second, we utilize a small sample of names and rely heavily on the signal that they produce. We go beyond prior studies to examine potential heterogeneity in the effects produced along multiple dimensions, but these names are not representative of the population of renters in our markets. Third, the correspondence design used in this study does not capture the full effect of discriminatory constraints on the likelihood of signing a lease. We can be reasonably confident that minority applicants with these names would not have access to the listings that are made unavailable to them, but we cannot say whether further contact with property managers would lead to larger effects.[14] Fourth, because we do not directly observe the decisions made by minorities in the presence of discriminatory constraints, we cannot make direct inferences about the precise effect of the discriminatory constraints that we study on final exposures.[15]

[14]It is also conceivable that the effects on a final lease would become smaller if the property managers who do respond to minority inquiries are more likely to select minority candidates.

[15]It is worth noting that fully addressing the last two limitations in an experimental setting would require involving actual renters in a search for housing and subjecting them to real-life discrimination.

References

Ahmed, A. M., Andersson, L., and Hammarstedt, M. (2010). Can Discrimination in the Housing Market be Reduced by Increasing the Information about the Applicants? *Land Economics*, 86(1):79–90.

Ahmed, A. M., Andersson, L., and Hammarstedt, M. (2013). Are Gay Men and Lesbians Discriminated Against in the Hiring Process? *Southern Economic Journal*, 79(3):565–585.

Ahmed, A. M. and Hammarstedt, M. (2008). Discrimination in the Rental Housing Market: A Field Experiment on the Internet. *Journal of Urban Economics*, 64(2):362–372.

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

Almond, D. and Currie, J. (2011). Killing me softly: The fetal origins hypothesis. *Journal of economic perspectives*, 25(3):153–72.

Almond, D., Currie, J., and Duque, V. (2017). Childhood circumstances and adult outcomes: Act ii. Technical report, National Bureau of Economic Research.

Almond, D., Currie, J., and Herrmann, M. (2012). From infant to mother: Early disease environment and future maternal health. *Labour Economics*, 19(4):475–483.

Apartments.com (2015). Online Search Behavior and Trends of Apartment Renters: A Joint Study by Apartments.com and Google.

Ash, M. and Fetter, T. R. (2004). Who lives on the wrong side of the environmental tracks? evidence from the epa's risk-screening environmental indicators model. *Social Science Quarterly*, 85(2):441–462.

Baden, B. M. and Coursey, D. L. (2002). The locality of waste sites within the city of chicago: a demographic, social, and economic analysis. *Resource and Energy Economics*, 24(1-2):53–93.

Baert, S., Cockx, B., Gheyle, N., and Vandamme, C. (2013). Do Employers Discriminate Less if Vacancies are Difficult to Fill? Evidence from a field experiment. Working Paper.

Bailey, J., Wallace, M., and Wright, B. (2013). Are Gay Men and Lesbians Discriminated Against When Applying for Jobs? A four-city, internet-based field experiment. *Journal of Homosexuality*, 60(6):873–894.

Banerjee, A., Bertrand, M., Datta, S., and Mullainathan, S. (2009). Labor Market Discrimination in Delhi: Evidence from a Field Experiment. *Journal of Comparative Economics*, 37(1):14–27.

Banzhaf, H. S. and Walsh, R. P. (2008). Do people vote with their feet? an empirical test of tiebout. *American Economic Review*, 98(3):843–63.

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

Barreca, A. I. (2010). The Long-Term Economic Impact of In Utero and Postnatal Exposure to Malaria. *Journal of Human Resources*, 45(4):865–892.

Been, V. (1994). Locally undesirable land uses in minority neighborhoods: Disproportionate siting or market dynamics? *Yale Law Journal*, pages 1383–1422.

Been, V. and Gupta, F. (1997). Coming to the nuisance or going to the barrios? a longitudinal analysis of environmental justice claims. *Ecology law quarterly*, 24(1):1–56.

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

Bertrand, M. and Mullainathan, S. (2004). Are Emily and Greg More Employable than Lakisha and Jamal? *American Economic Review*, 94(4):991–1013.

Best, H. and Rüttenauer, T. (2017). How selective migration shapes environmental inequality in germany: Evidence from micro-level panel data. *European Sociological Review*, 34(1):52–63.

Black, S. E., Devereux, P. J., and Salvanes, K. G. (2007). From the cradle to the labor market? the effect of birth weight on adult outcomes. *The Quarterly Journal of Economics*, 122(1):409–439.

Booth, A. and Leigh, A. (2010). Do Employers Discriminate by Gender? A field experiment in female-dominated occupations. *Economics Letters*, 107(2):236–238.

Burby, R. J. and Strong, D. E. (1997). Coping with chemicals: blacks, whites, planners, and industrial pollution. *Journal of the American Planning Association*, 63(4):469–480.

Cameron, T. A. and McConnaha, I. T. (2006). Evidence of environmental migration. *Land Economics*, 82(2):273–290.

Carlsson, M. (2011). Does Hiring Discrimination Cause Gender Segregation in the Swedish Labor Market? *Feminist Economics*, 17(3):71–102.

Carlsson, M. and Eriksson, S. (2014). Discrimination in the Rental Market for Apartments. *Journal of Housing Economics*, 23:41–54.

Carpusor, A. G. and Loges, W. E. (2006). Rental Discrimination and Ethnicity in Names. *Journal of Applied Social Psychology*, 36(4):934–952.

Centner, T. J., Kriesel, W., and Keeler, A. G. (1996). Environmental justice and toxic releases: establishing evidence of discriminatory effect based on race and not income. *Wis. Envtl. LJ*, 3:119.

Chakraborty, J. and Armstrong, M. P. (1997). Exploring the use of buffer analysis for the identification of impacted areas in environmental equity assessment. *Cartography and Geographic Information Systems*, 24(3):145–157.

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

Christensen, P., Sarmiento-Barbieri, I., and Timmins, C. (October 09, 2018). The impact of housing discrimination on the pollution exposure gap in the united states. aea rct registry. october 09. http://www.socialscienceregistry.org/trials/3366/history/35504. AEA RCT Registry.

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

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

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

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

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

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

Currie, J. and Moretti, E. (2007). Biology as destiny? short-and long-run determinants of intergenerational transmission of birth weight. *Journal of Labor economics*, 25(2):231–264.

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

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

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

Currie, J., Zivin, J. G., Mullins, J., and Neidell, M. (2014). What do we know about short-and long-term effects of early-life exposure to pollution? *Annu. Rev. Resour. Econ.*, 6(1):217–247.

Davidson, P. and Anderton, D. L. (2000). Demographics of dumping ii: a national environmental equity survey and the distribution of hazardous materials handlers. *Demography*, 37(4):461–466.

Demidenko, E. (2007). Sample size determination for logistic regression revisited. *Statistics in medicine*, 26(18):3385–3397.

Demidenko, E. (2008). Sample size and optimal design for logistic regression with binary interaction. *Statistics in medicine*, 27(1):36–46.

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

Eriksson, S. and Rooth, D.-O. (2014). Do Employers use Unemployment as a Sorting Criterion When Hiring? Evidence from a field experiment. *American Economic Review*, 104(3):1014–39.

Ewens, M., Tomlin, B., and Wang, L. C. (2014). Statistical Discrimination or Prejudice? A large sample field experiment. *Review of Economics and Statistics*, 96(1):119–134.

Figlio, D., Guryan, J., Karbownik, K., and Roth, J. (2014). The effects of poor neonatal health on children's cognitive development. *American Economic Review*, 104(12):3921–55.

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

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

Gaddis, S. M. (2017b). Racial/Ethnic Perceptions from Hispanic Names: Selecting names to test for discrimination. *Socius*, 3:2378023117737193.

Gaddis, S. M. and Ghoshal, R. (2015). Arab American Housing Discrimination, Ethnic Competition, and the Contact Hypothesis. *The ANNALS of the American Academy of Political and Social Science*, 660(1):282–299.

Galarza, F., Kogan, L., and Yamada, G. (2014). ¿ Existe discriminación en el mercado laboral limeño?: Un análisis experimental. *Lima: Universidad del Pacco.*

Gamper-Rabindran, S. and Timmins, C. (2011). Hazardous waste cleanup, neighborhood gentrification, and environmental justice: Evidence from restricted access census block data. *American Economic Review*, 101(3):620–24.

Ghayad, R. (2013). The Jobless Trap. Unpublished Manuscript.

Greenstone, M. and Gallagher, J. (2008). Does hazardous waste matter? evidence from the housing market and the superfund program. *The Quarterly Journal of Economics*, 123(3):951–1003.

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

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

Hanson, A., Hawley, Z., and Taylor, A. (2011). Subtle Discrimination in the Rental Housing Market: Evidence from e-mail correspondence with landlords. *Journal of Housing Economics*, 20(4):276–284.

Hird, J. A. and Reese, M. (1998). The distribution of environmental quality: An empirical analysis. *Social Science Quarterly*, pages 693–716.

Lambert, T. and Boerner, C. (1997). Environmental inequity: Economic causes, economic solutions. *Yale J. on Reg.*, 14:195.

Lerner, S. (2010). *Sacrifice zones: the front lines of toxic chemical exposure in the United States*. Mit Press.

Logan, J. R. and Alba, R. D. (1993). Locational returns to human capital: Minority access to suburban community resources. *Demography*, 30(2):243–268.

Maurer-Fazio, M. (2012). Ethnic Discrimination in China's Internet Job Board Labor Market. *IZA Journal of Migration*, 1(1):12.

McGinnity, F., Nelson, J., Lunn, P., and Quinn, E. (2009). Discrimination in Recruitment: Evidence from a field experiment. Unpublished Manuscript.

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

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

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

Morello-Frosch, R., Pastor Jr, M., Porras, C., and Sadd, J. (2002). Environmental justice and regional inequality in southern california: implications for future research. *Environmental health perspectives*, 110(Suppl 2):149.

Morello-Frosch, R. and Shenassa, E. D. (2006). The environmental "riskscape" and social inequality: implications for explaining maternal and child health disparities. *Environmental health perspectives*, 114(8):1150.

Noonan, D. S., Krupka, D. J., and Baden, B. M. (2007). Neighborhood dynamics and price effects of superfund site clean-up. *Journal of Regional Science*, 47(4):665–692.

Oakes, J. M., Anderton, D. L., and Anderson, A. B. (1996). A longitudinal analysis of environmental equity in communities with hazardous waste facilities. *Social Science Research*, 25(2):125–148.

Oreopoulos, P., Stabile, M., Walld, R., and Roos, L. L. (2008). Short-, medium-, and long-term consequences of poor infant health an analysis using siblings and twins. *Journal of human Resources*, 43(1):88–138.

Pastor, M., Sadd, J., and Hipp, J. (2001). Which came first? toxic facilities, minority move-in, and environmental justice. *Journal of urban affairs*, 23(1):1–21.

Patacchini, E., Ragusa, G., and Zenou, Y. (2015). Unexplored Dimensions of Discrimination in Europe: Homosexuality and physical appearance. *Journal of Population Economics*, 28(4):1045–1073.

Perlin, S. A., Setzer, R. W., Creason, J., and Sexton, K. (1995). Distribution of industrial air emissions by income and race in the united states: an approach using the toxic release inventory. *Environmental Science & Technology*, 29(1):69–80.

Persico, C., Figlio, D., and Roth, J. (2016). Inequality Before Birth: The Developmental Consequences of Environmental Toxicants. National Bureau of Economic Research, Working paper No. w22263.

Phillips, D. C. (2014). Getting to Work: Experimental evidence on job search and transportation costs. *Labour Economics*, 29:72–82.

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

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

Ringquist, E. J. (1997). Equity and the distribution of environmental risk: The case of tri facilities. *Social science quarterly*, pages 811–829.

Rooth, D.-O. (2009). Obesity, Attractiveness, and Differential Treatment in Hiring: A Field Experiment. *Journal of Human Resources*, 44(3):710–735.

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

Sadd, J. L., Pastor, M., Morello-Frosch, R., Scoggins, J., and Jesdale, B. (2011). Playing it safe: Assessing cumulative impact and social vulnerability through an environmental justice screening method in the south coast air basin, california. *International Journal of Environmental Research and Public Health*, 8(5):1441–1459.

Sadd, J. L., Pastor Jr, M., Boer, J. T., and Snyder, L. D. (1999). "every breath you take...": the demographics of toxic air releases in southern california. *Economic Development Quarterly*, 13(2):107–123.

Shaikh, S. L. and Loomis, J. B. (1999). An investigation into the presence and causes of environmental inequity in denver, colorado. *The Social Science Journal*, 36(1):77–92.

Shapiro, M. D. (2005). Equity and information: Information regulation, environmental justice, and risks from toxic chemicals. *Journal of Policy Analysis and Management: The Journal of the Association for Public Policy Analysis and Management*, 24(2):373–398.

Šrám, R. J., Binková, B., Dejmek, J., and Bobak, M. (2005). Ambient air pollution and pregnancy outcomes: a review of the literature. *Environmental health perspectives*, 113(4):375.

Su, J. G., Jerrett, M., Morello-Frosch, R., Jesdale, B. M., and Kyle, A. D. (2012). Inequalities in cumulative environmental burdens among three urbanized counties in california. *Environment international*, 40:79–87.

Su, J. G., Morello-Frosch, R., Jesdale, B. M., Kyle, A. D., Shamasunder, B., and Jerrett, M. (2009). An index for assessing demographic inequalities in cumulative environmental hazards with application to los angeles, california.

Voorheis, J. (2017). Air quality, human capital formation and the long-term effects of environmental inequality at birth.

Wright, B. R., Wallace, M., Bailey, J., and Hyde, A. (2013). Religious Affiliation and Hiring Discrimination in New England: A field experiment. *Research in Social Stratification and Mobility*, 34:111–126.

Yandle, T. and Burton, D. (1996). Reexamining environmental justice: a statistical analysis of historical hazardous waste landfill siting patterns in metropolitan texas. *Social science quarterly*, pages 477–492.

Zussman, A. (2013). Ethnic Discrimination: Lessons from the Israeli Online Market for Used Cars. *The Economic Journal*, 123(572):F433–F468.

8 Tables and Figures

Table 1. Property and Neighborhood Descriptive Statistics

	Distance to Toxic Plant		
	Less than 1 mile	Between 1 and 2 miles	Between 2 and 4 miles
Rent	2198.85	2304.01	1673.47
	(2658.64)	(2710.91)	(1042.74)
Single Family Home	0.58	0.63	0.85
	(0.49)	(0.48)	(0.36)
Apartment	0.08	0.05	0.05
	(0.28)	(0.22)	(0.21)
Multi Family	0.26	0.23	0.08
	(0.44)	(0.42)	(0.27)
Other Bldg. Type	0.07	0.08	0.03
	(0.26)	(0.28)	(0.17)
Bedrooms	2.77	2.83	2.92
	(0.7)	(0.67)	(0.39)
Bathrooms	1.87	1.91	1.97
	(0.48)	(0.42)	(0.25)
Sqft	1565.4	1599.76	1605.84
	(937.33)	(544.07)	(382.86)
Assaults	93.19	107.84	63.82
	(160.75)	(183.99)	(86.38)
Restaurants	223.6	205.88	25
	(503.55)	(469.28)	(31.56)
Supermarkets/Grocery Stores	27.76	23.17	1.78
	(71.23)	(63.78)	(1.98)
Share of Hispanics	0.23	0.23	0.22
	(0.23)	(0.2)	(0.19)
Share of African American	0.23	0.22	0.24
	(0.25)	(0.24)	(0.27)
Share of Whites	0.61	0.6	0.62
	(0.26)	(0.25)	(0.27)
Poverty Rate	0.18	0.16	0.12
	(0.14)	(0.13)	(0.11)
Unemployment Rate	0.07	0.07	0.07
	(0.06)	(0.07)	(0.06)
Share of College Educated	0.22	0.23	0.22
	(0.13)	(0.13)	(0.12)
Number of Properties	671	638	466

Notes: Table shows mean and standard deviation (in parentheses) of property and neighborhood characteristics for the experimental data for listings by distance to TRI plant. Share of Hispanics, African American, Whites, Poverty Rate, Unemployment Ratea and Share of College Educated are measured at the block group level and come from the ACS 2015.

Table 2. Descriptive Statistics: InfoUSA Sample

	All (1)	Hispanic (2)	African American (3)	White (4)
Share of Hispanic	0.165	-	-	-
	(0.371)			
Share of African American	0.167	-	-	-
	(0.373)			
Share of White	0.446	-	-	-
	(0.497)			
Share of Other Race	0.222	-	-	-
	(0.415)			
Income	31,099.50	24,495.88	19,513.31	36,339.05
	(30326.51)	(23592.16)	(20298.04)	(33011.48)
Age Household Head	40.725	39.591	41.289	40.985
	(14.858)	(13.7)	(15.241)	(15.279)
Share Married	0.087	0.116	0.051	0.087
	(0.281)	(0.32)	(0.221)	(0.282)
Share Pregnancies	0.079	0.087	0.095	0.081
	(0.27)	(0.282)	(0.294)	(0.272)
Number of Children	0.081	0.096	0.105	0.081
	(0.381)	(0.414)	(0.433)	(0.386)
Nbr. of Households	1,524,185	252,296	251,522	656,985
Observations	3,118,888	3,118,888	3,118,888	3,118,888

Notes: Table shows mean and standard deviation (in parentheses) of demographic characteristics for InfoUSA data for years 2012-2017

Table 3. Estimates of Discriminatory Constraint on Housing Choice
Proximity to Toxic Plant

	Dependent variable: Property Availability				
	(1)	(2)	(3)	(4)	(5)
					1st Inquiry
Toxic Plant less than 1 mile × Hispanic	1.0445	1.0320	0.9877	0.9819	1.0871
	(0.2000)	(0.2009)	(0.1829)	(0.1834)	(0.1963)
Toxic Plant more than 1 mile × Hispanic	0.7595*	0.7534*	0.7496**	0.7074**	0.7886
	(0.1135)	(0.1125)	(0.1042)	(0.1002)	(0.1189)
Toxic Plant less than 1 mile × African American	1.0445	1.0392	1.0359	1.0267	0.8787
	(0.2285)	(0.2296)	(0.2315)	(0.2165)	(0.1691)
Toxic Plant more than 1 mile × African American	0.9721	0.9628	0.9755	0.8798	1.0599
	(0.1433)	(0.1426)	(0.1474)	(0.1329)	(0.1570)
Gender		Yes	Yes	Yes	Yes
Education Level			Yes	Yes	Yes
Inquiry Order				Yes	Yes
Observations	5,325	5,325	5,325	5,325	1,775

Notes: Standard errors clustered at Zip Code level reported in parentheses.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 4. Estimates of Discriminatory Constraint on Property Availability
Proximity to Toxic Plant

	Dependent variable: Property Availability			
	Distance to Toxic Plant:			
	<1 mile	>1 mile	>1.5 miles	>2 miles
	(1)	(2)	(3)	(4)
Hispanic	0.9819	0.7074**	0.5509***	0.6379*
	(0.1834)	(0.1002)	(0.0966)	(0.1696)
African American	1.0267	0.8798	0.7715	0.6509*
	(0.2165)	(0.1329)	(0.1314)	(0.1534)
Gender	Yes	Yes	Yes	Yes
Education Level	Yes	Yes	Yes	Yes
Inquiry Order	Yes	Yes	Yes	Yes

Notes: Table reports odds ratio of regression 1 and reflect the odds of a response to an inquiry from a Hispanic or African American renter identity relative to a White renter identity. Odds ratio result from the exponentiation of the coefficients in 1, and standard errors have been adjusted accordingly. Standard errors clustered at Zip code level reported in parentheses. Stars reflect the significance of the test of $H_0 : \beta_{race} = 0$ $race \in \{Hispanic, AfricanAmerican\}$ which is equivalent to testing that the odds are different than one ($H_0 : exp(\beta_{race}) = 1$). * Significant at 10% level; ** significant at 5% level; *** significant at 1% level. 95% Confidence Intervals for Odds Ratios are reported in Appendix Table A.1

Table 5. Estimates of Discriminatory Constraint on Housing Choice
Heterogeneity by Rent and Neighborhood White Share

	Dependent variable: Property Availability		
	Distance to Toxic Plant:		
	<1 mile	>1 mile	>2 miles
	(1)	(2)	(3)
Panel A: Heterogeneity by Rent			
Hispanic × Low Rent	1.3287	0.8069	0.5882
	(0.3509)	(0.1514)	(0.2491)
Hispanic × High Rent	0.7604	0.6025**	0.6768
	(0.1747)	(0.1316)	(0.2033)
African American × Low Rent	1.2896	1.1971	0.9429
	(0.3518)	(0.2369)	(0.2933)
African American × High Rent	0.8421	0.6112**	0.4466**
	(0.2240)	(0.1223)	(0.1673)
Panel B: Heterogeneity by Share of Whites			
Hispanic × Low Share of Whites	0.8817	0.7931	0.7329
	(0.2310)	(0.1422)	(0.3313)
Hispanic × High Share of Whites	1.0747	0.6164**	0.5662
	(0.2746)	(0.1466)	(0.1977)
African American × Low Share of Whites	1.3015	0.9968	0.7229
	(0.4041)	(0.2191)	(0.2725)
African American × High Share of Whites	0.8687	0.7605	0.6005
	(0.2178)	(0.1807)	(0.2156)
Gender	Yes	Yes	Yes
Education Level	Yes	Yes	Yes
Inquiry Order	Yes	Yes	Yes
Observations	5,325	5,325	5,325

Notes: High(Low) Rent indicates that the rental unit is above(below) the 50th percentile of the Zip code rent distribution. High(Low) Share of Whites indicates that the rental unit is in a block group with above(below) the 50th percentile of the Share of White Population in the Zip Code. Standard errors clustered at Zip Code level reported in parentheses.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 6. Estimates of Discriminatory Constraint on Housing Choice
Heterogeneity by Gender and Education

	Dependent variable: Property Availability		
	Distance to Toxic Plant:		
	<1 mile	>1 mile	>2 miles
	(1)	(2)	(3)
Panel A: Heterogeneity by Gender			
Hispanic × Male	0.8136	0.5396***	0.5221*
	(0.1647)	(0.1020)	(0.1828)
Hispanic × Female	1.1899	0.9223	0.7686
	(0.3692)	(0.1746)	(0.2674)
African American × Male	0.9747	0.6525**	0.7120
	(0.3000)	(0.1256)	(0.2158)
African American × Female	1.0864	1.1681	0.5811*
	(0.2369)	(0.2347)	(0.1704)
Panel B: Heterogeneity by Education			
Hispanic × Low Education	1.2084	0.5447***	0.6205
	(0.2619)	(0.1098)	(0.2874)
Hispanic × Medium Education	0.8950	1.1262	0.8274
	(0.3017)	(0.2257)	(0.2703)
Hispanic × High Education	0.9644	0.4943***	0.4461**
	(0.3896)	(0.1163)	(0.1519)
African American × Low Education	1.2122	1.5330*	1.0351
	(0.4253)	(0.3364)	(0.3372)
African American × Medium Education	0.9845	0.5982	0.5649
	(0.3257)	(0.2048)	(0.2018)
African American × High Education	0.9138	0.7363	0.4205**
	(0.2395)	(0.1414)	(0.1440)
Gender	Yes	Yes	Yes
Education Level	Yes	Yes	Yes
Inquiry Order	Yes	Yes	Yes
Observations	5,325	5,325	5,325

Notes: High(Low) Rent indicates that the rental unit is above(below) the 50th percentile of the Zip code rent distribution. High(Low) Share of Whites indicates that the rental unit is in a block group with above(below) the 50th percentile of the Share of White Population in the Zip Code. Standard errors clustered at Zip Code level reported in parentheses.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 7. Likelihood of Renting in High Exposure Neighborhood (relative to white). All Households and Households with Pregnancies

	Dependent variable: Renting in High Exposure Area relative to a Low Exposure Area Outside:	
	1 Mile	2 Miles
	(1)	(2)
Panel A: All Households		
Hispanic	1.176***	1.307***
	(0.005)	(0.011)
African American	0.988*	1.079***
	(0.007)	(0.013)
Observations	3,118,888	1,848,797
Panel B: Households with Pregnancies		
Pregnant × Hispanic	1.208***	1.191***
	(0.026)	(0.055)
Pregnant × African American	1.038	1.166***
	(0.028)	(0.056)
Observations	1,091,104	640,890

Notes: *Panel A* shows the odds ratio respect to white renters of the likelihood of renting in high exposure areas vs renting in low exposure areas. *Panel B* shows odd ratios of pregnant minorities respect to white pregnant renters of the likelihood of renting in high exposure areas vs renting in low exposure areas. High exposure areas are those within 1 mile of a toxic plant. Column (1) takes as a low exposure areas as everything beyond one mile, up to 4 miles. Column (2) does it for everything beyond 2 miles up to 4 miles. Regressions control linearly for income, age, marital status of household head, and number of children in the household. We also include year by Zip code fixed effects.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Figure 1. Zip Codes in Sample

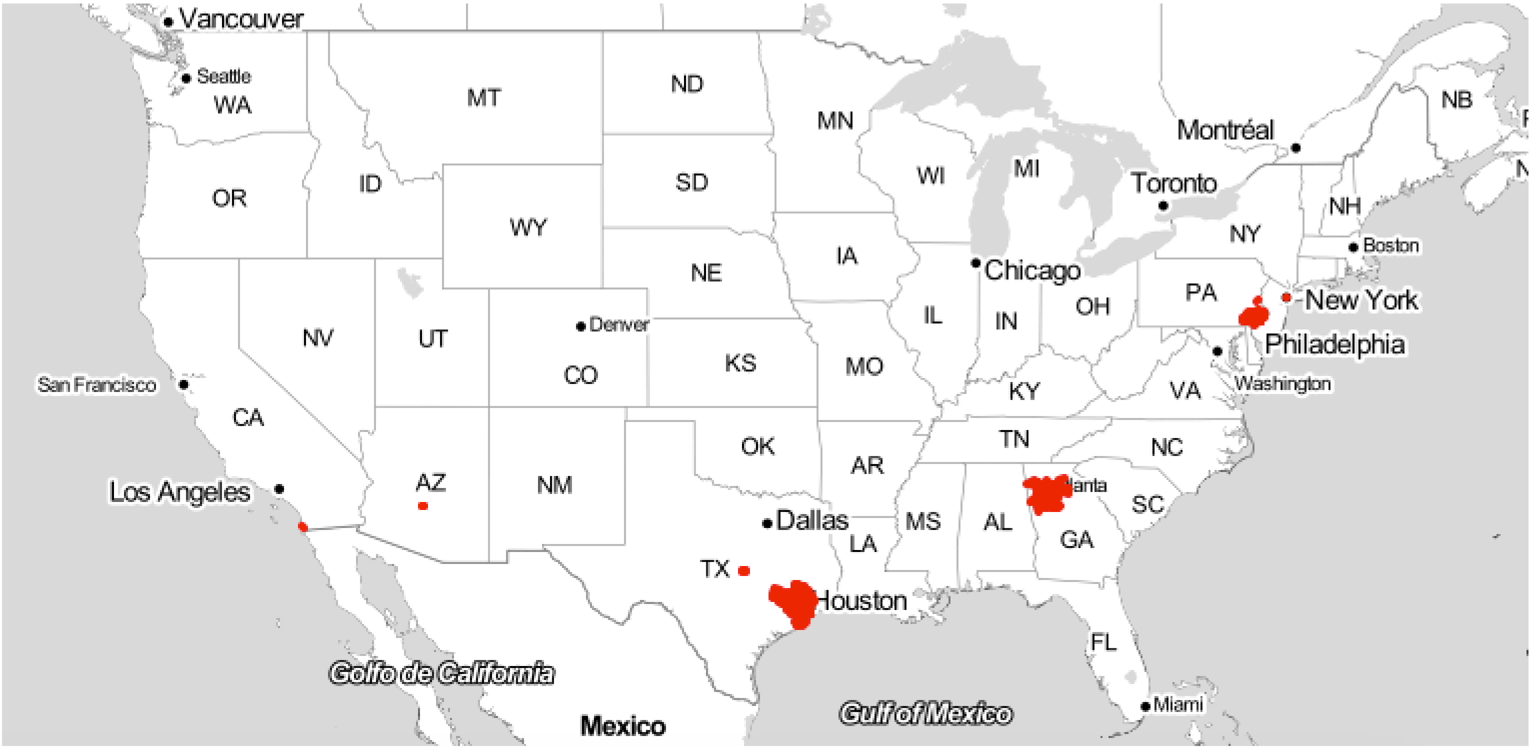
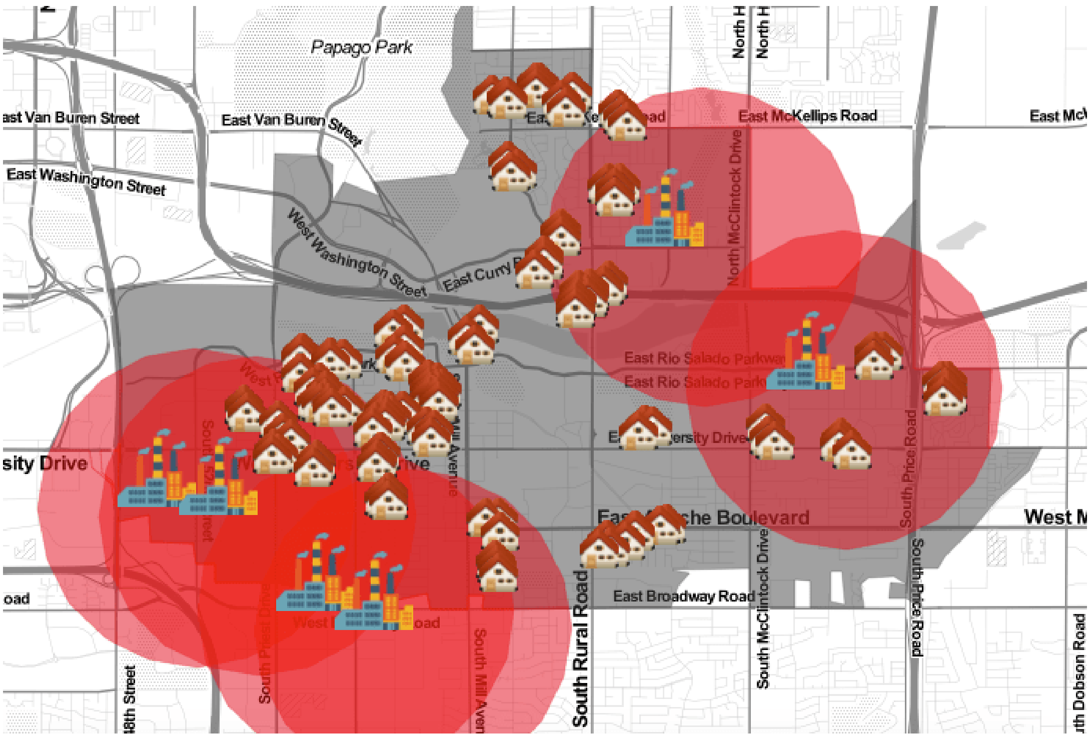


Figure 2. Experimental Sample Illustration

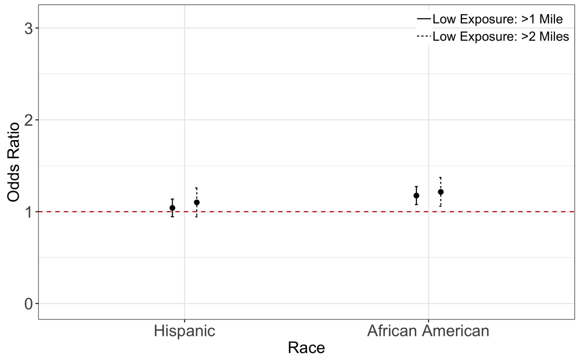
(a) Killeen, TX



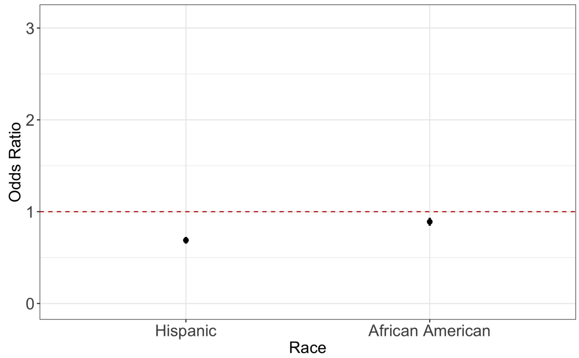
(b) Tempe, AZ

Note: Figures show the area within one mile of a toxic plant in red and the zip code in that area in grey. Markers denote the approximate locations of rental property listings in those zip codes.

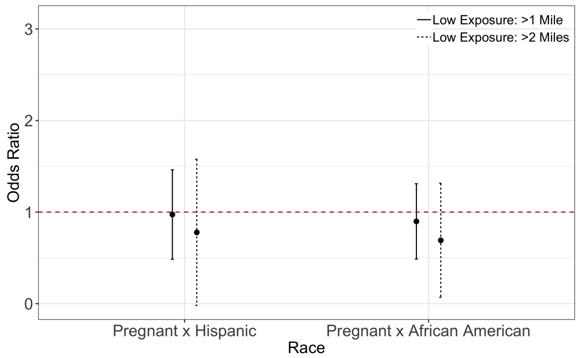
Figure 3. Odds Ratios: Movers and Stayers in High Exposure Locations



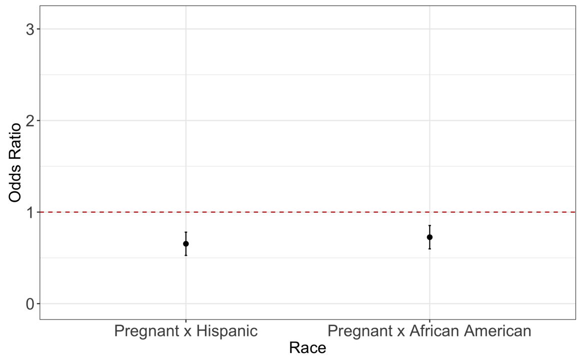
(a) Moving In (all renters)



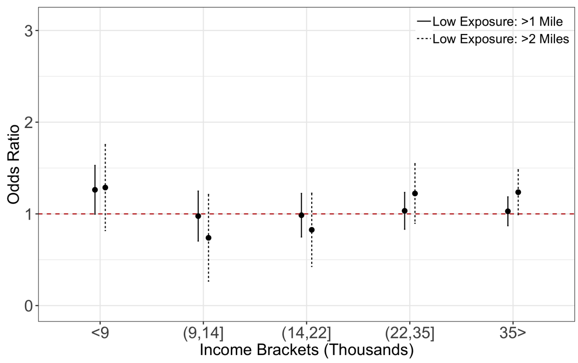
(b) Moving Out (all renters)



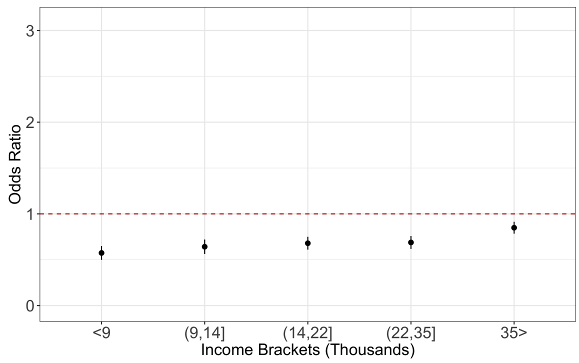
(c) Moving In (pregnant)



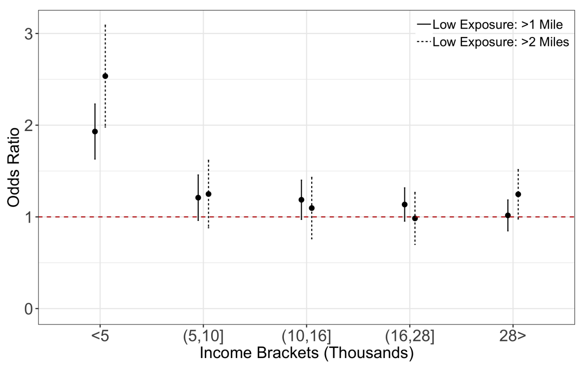
(d) Moving Out (pregnant)



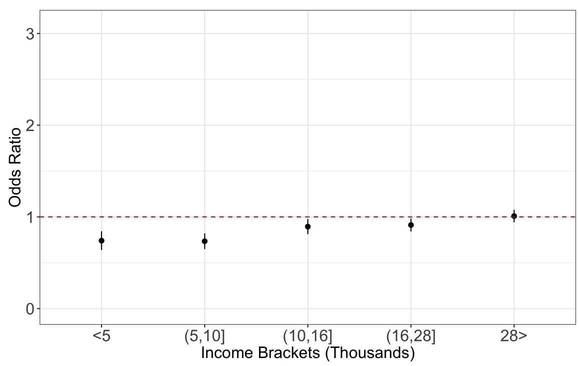
(e) Moving In (Hispanic Income Quintiles)



(f) Moving Out (Hispanic Income Quintiles)



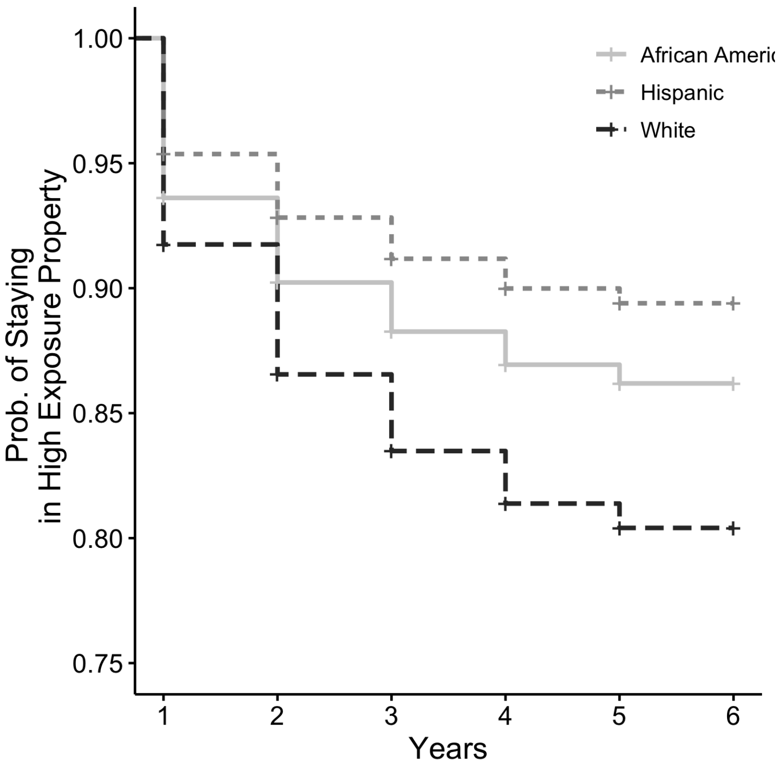
(g) Moving In (African Amer. Inc Quintiles)



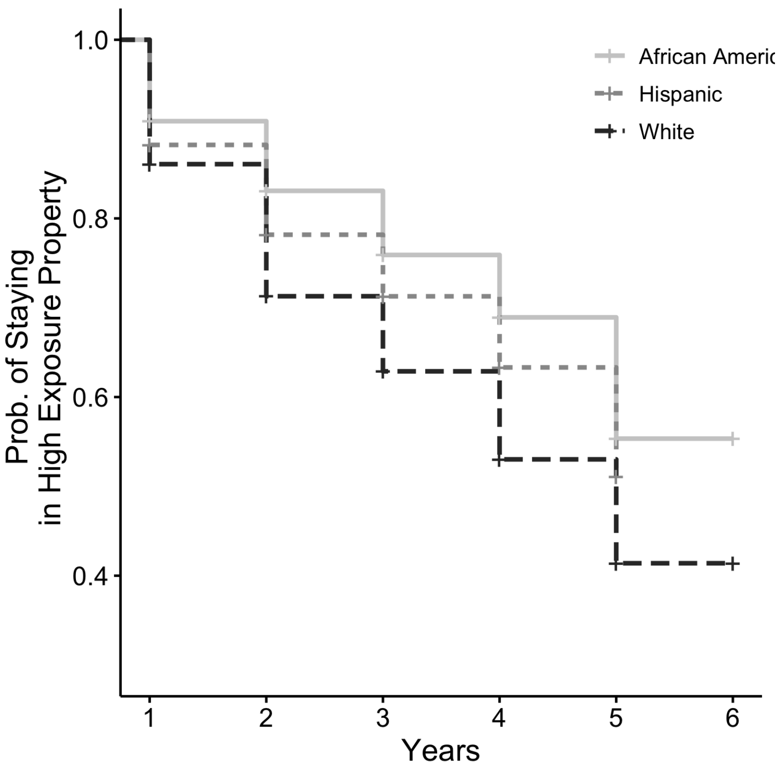
(h) Moving Out (African Amer. Inc Quintiles)

Notes: Results generated from the sample of renters in all zip codes within 1 mile of toxic plants (TRI facilities) sampled in the experimental design.

Figure 4. Move Out Rates



(a) All Renters



(b) Pregnant Renters

Notes: Kaplan-Meier estimate of the likelihood of moving out of a high exposure neighborhood using the full sample of movers observed in high exposure neighborhoods during the period 2012-2016 and the timing of their moves.

Appendices

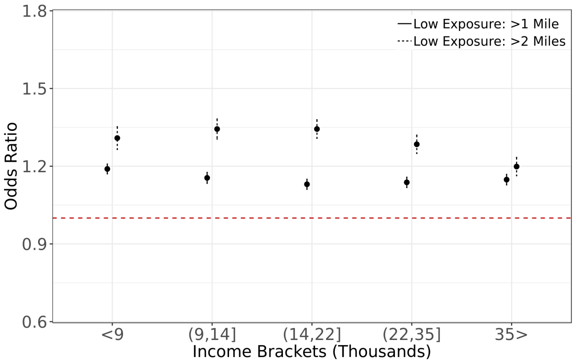
A Additional Results

Table A.1. Estimates of Discriminatory Constraint on Housing Choice Availability
Proximity to Toxic Plant

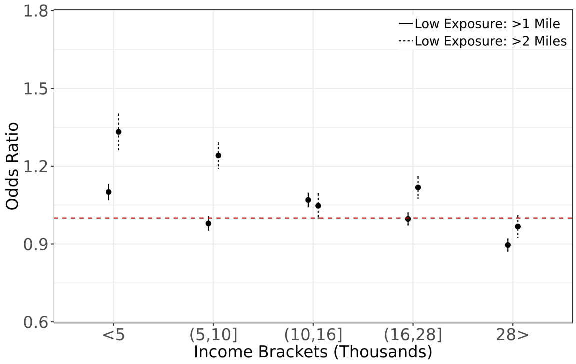
	Dependent variable: Property Availability			
	Distance to Toxic Plant:			
	<1 mile	>1 mile	>1.5 miles	>2 miles
	(1)	(2)	(3)	(4)
Hispanic	0.9819	0.7074**	0.5509***	0.6379*
	(0.6809 - 1.4158)	(0.5359 - 0.9337)	(0.3907 - 0.7769)	(0.3788 - 1.0742)
African American	1.0267	0.8798	0.7715	0.6509*
	(0.6792 - 1.5521)	(0.6544 - 1.1829)	(0.5525 - 1.0772)	(0.4102 - 1.0329)
Gender	Yes	Yes	Yes	Yes
Education Level	Yes	Yes	Yes	Yes
Inquiry Order	Yes	Yes	Yes	Yes

Notes: Zip code Cluster Standard errors reported in parentheses. P-values in brackets, and 95% Confidence Intervals
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

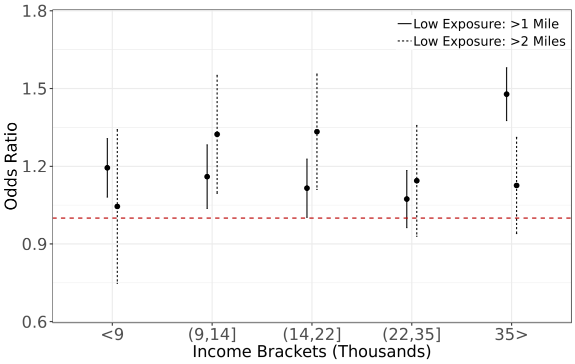
Figure A.1. Likelihood of Renting in High Exposure Neighborhood (relative to white).All Households and Households with Pregnancies by Income Quantiles



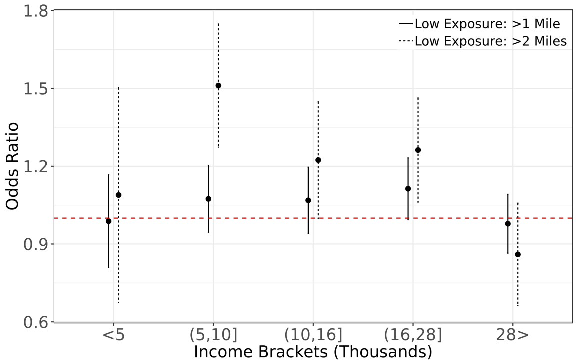
(a) All Households
(Hispanic Inc Quintiles)



(b) All Households
(African Amer. Inc Quintiles)



(c) Households with Pregnancies
(Hispanic Inc Quintiles)



(d) Households with Pregnancies
(African Amer. Inc Quintiles)

B Balance Statistics

B.1 Balance Table

Table B.1 reports the results of tests for balance in the sample by sequence of inquiry, day of week, and characteristics of renter names (gender and mother's education level). Estimates do not suggest any differences aside from a smaller number of inquiries sent from high education Hispanic/LatinX names, which is the result of data loss related to one of the renter identities. Our tests suggest that these names tend to get lower response rates than the other Hispanic/LatinX identities, so imbalance would result in conservative estimates of discrimination for the Hispanic/LatinX group as a whole. We control for Mother's education in all specifications and have test for any differences in a re-balanced panel.

Table B.1. Balance Statistics

Panel A: Inquiry Order					
	Dependent variable: Inquiry Sent				
	First	Second	Third		
Hispanic	−0.0017	0.0118	−0.0101		
	(0.0583)	(0.0581)	(0.0581)		
African American	0.0101	0.0017	−0.0118		
	(0.0581)	(0.0583)	(0.0581)		
Panel B: Evidence of Differential Choices by Weekday					
	Mon	Tue	Wed	Thurs	Fri
Hispanic	−0.0742	−0.0200	0.0091	0.0788	−0.0314
	(0.1456)	(0.1414)	(0.0779)	(0.0702)	(0.0723)
African American	−0.1661	0.1559	0.0622	0.0376	−0.0501
	(0.1492)	(0.1357)	(0.0770)	(0.0709)	(0.0726)
Panel C: Gender and Mother's Education Level					
	Gender		Mother's Education		
	Male	Female	Low	Medium	High
Hispanic	−0.0580	0.0580	0.1647**	0.1775**	−0.3649***
	(0.0681)	(0.0681)	(0.0707)	(0.0698)	(0.0729)
African American	−0.0395	0.0395	0.0634	−0.0760	0.0123
	(0.0681)	(0.0681)	(0.0712)	(0.0712)	(0.0700)
Observations	5,325	5,325	5,325	5,325	5,325

Notes: Standard errors clustered at the census tract level reported in parentheses.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

C Alternate Samples

C.1 Results for Restricted Sample of Zip Codes

This Appendix presents our main observational results using a restricted set of zip codes that exactly match the sample in the experimental study. In preferred estimates reported in the main text, we utilize all properties located within 0-4 miles of a TRI facility that also appears in the experiment. That results in a larger sample of households than this subset of zip codes sampled for the field experiment, increasing the statistical power of the tests.

Table C.1. Likelihood of Renting in High Exposure Neighborhood (relative to white)

	Dependent variable: *Renting in High Exposure Area*	
	(1)	(2)
	More than	
	1 Mile	2 Miles
Hispanic	1.196	1.326
	(0.007)	(0.019)
African American	0.951	1.030
	(0.008)	(0.019)
Observations	1,506,926	844,908

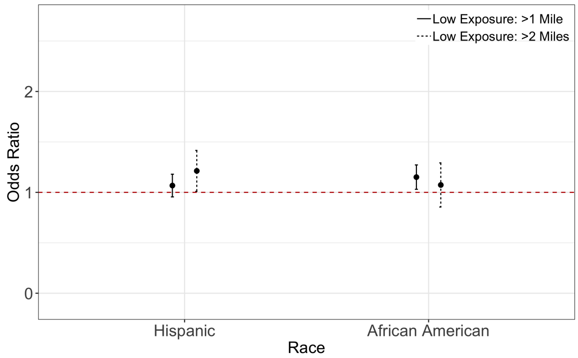
Notes: Regressions show the odds ratio respect to white renters of the likelihood of renting in high exposure areas vs renting in low exposure areas. High exposure areas are those within 1 mile of a toxic plant. Column (1) takes as a low exposure areas as everything beyond one mile, up to 4 miles. Column (2) does it for everything beyond 2 miles up to 4 miles. Regressions control linearly for income, age, marital status of household head, and number of children in the household. We also include year by Zip code fixed effects.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table C.2. Likelihood of Renting in High Exposure Neighborhood (relative to white) Households with Pregnancies

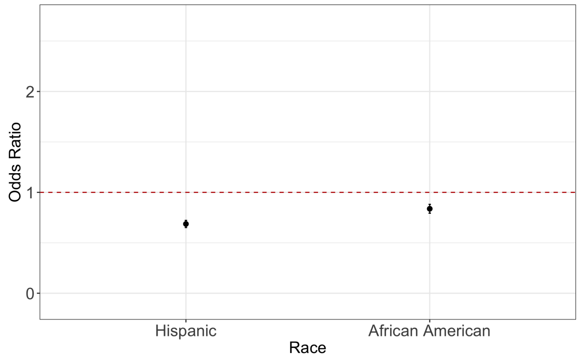
	Dependent variable:	
	Renting in High Exposure Area	
	(1)	(2)
		More than
	1 Mile	2 Miles
Pregnant × Hispanic	1.217***	1.220*
	(0.031)	(0.074)
Pregnant × African American	0.950	0.948*
	(0.034)	(0.073)
Observations	532,698	292,294

Notes: Table shows odd ratios of pregnant minorities respect to white pregnant renters of the likelihood of renting in high exposure areas vs renting in low exposure areas. High exposure areas are those within 1 mile of a toxic plant. Column (1) takes as a low exposure areas as everything beyond one mile, up to 4 miles. Column (2) does it for everything beyond 2 miles up to 4 miles. Regressions control linearly for income, age, marital status of household head, and number of children in the household. We also include year by Zip code fixed effects.ld. We also include year by Zip code fixed effects.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

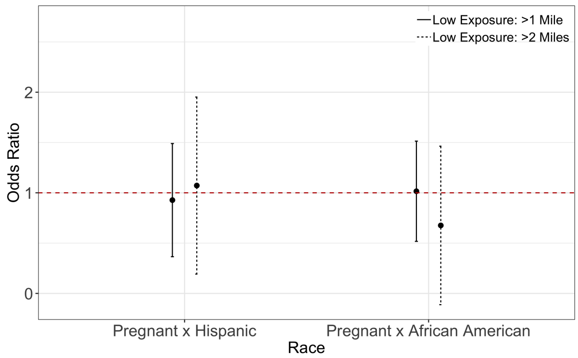
Figure C.1. Movers



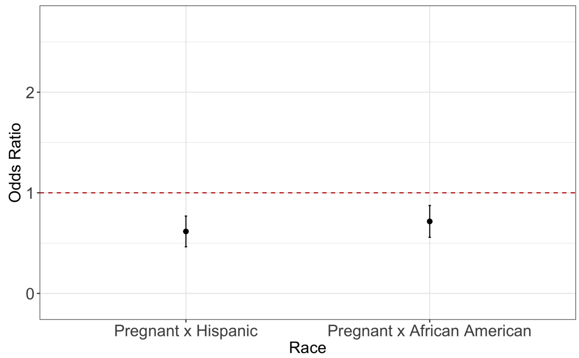
(a) Moving In (all renters)



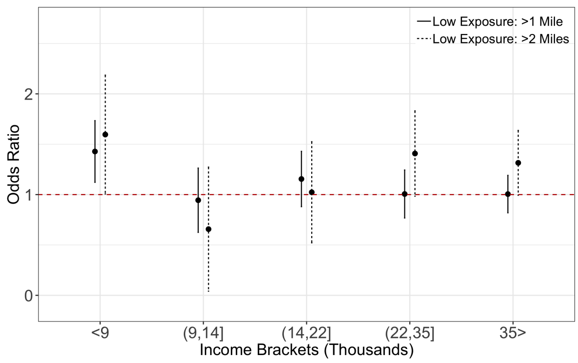
(b) Moving Out (all renters)



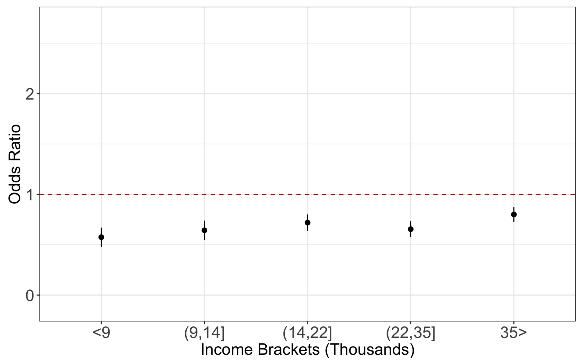
(c) Moving In (pregnant)



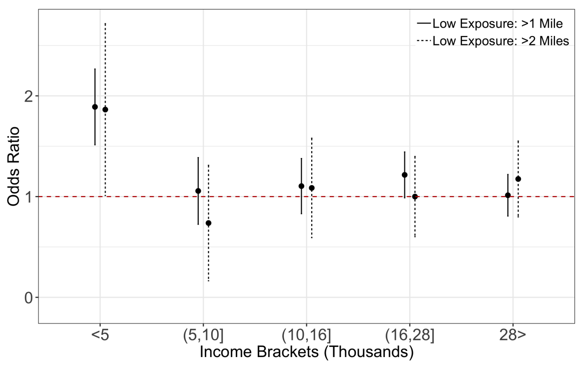
(d) Moving Out (pregnant)



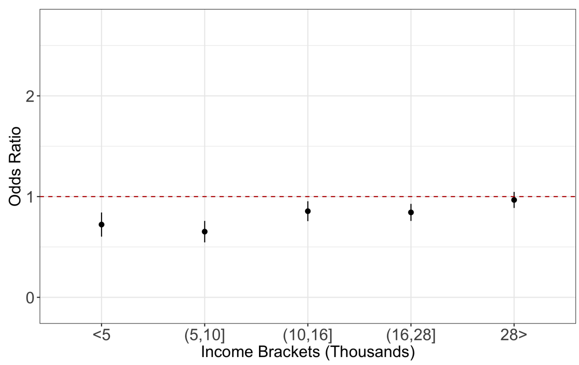
(e) Moving In (Hispanic Income Quintiles)



(f) Moving Out (Hispanic Income Quintiles)



(g) Moving In (African Amer. Inc Quintiles)



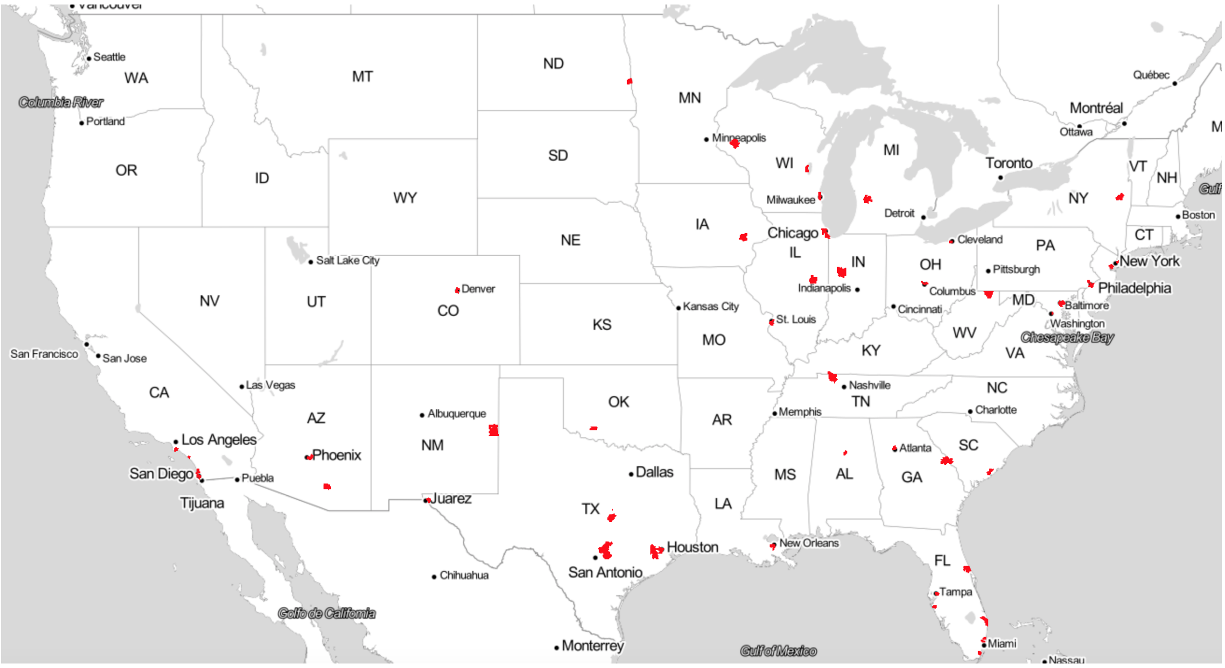
(h) Moving Out (African Amer. Inc Quintiles)

D Zip Codes with Major Emitters (TRI Facilities)

Table D.1. Zip Codes within One Mile of a Toxic Plants

Zipcode	City	State	Zipcode	City	State
35215	Birmingham	AL	21230	Baltimore	MD
85281	Tempe	AZ	21229	Baltimore	MD
85705	Tucson	AZ	49503	Grand Rapids	MI
92118	Coronado	CA	63118	Saint Louis	MO
92672	San Clemente	CA	63118	Saint Louis	MO
92101	San Diego	CA	58103	Fargo	ND
92037	La Jolla	CA	88101	Clovis	NM
90802	Long Beach	CA	10002	New York	NY
80210	Denver	CO	11211	Brooklyn	NY
80211	Denver	CO	11101	Long Island City	NY
20002	Washington	DC	11217	Brooklyn	NY
20001	Washington	DC	11222	Brooklyn	NY
20009	Washington	DC	10022	New York	NY
33021	Hollywood	FL	11201	Brooklyn	NY
33025	Hollywood	FL	11205	Brooklyn	NY
33312	Fort Lauderdale	FL	10065	New York	NY
33404	West Palm Beach	FL	10003	New York	NY
33410	West Palm Beach	FL	10314	Staten Island	NY
32169	New Smyrna Beach	FL	12866	Saratoga Springs	NY
33418	West Palm Beach	FL	10012	New York	NY
33602	Tampa	FL	10009	New York	NY
33178	Miami	FL	10028	New York	NY
33179	Miami	FL	10010	New York	NY
34243	Sarasota	FL	10016	New York	NY
33019	Hollywood	FL	11206	Brooklyn	NY
33018	Hialeah	FL	10021	New York	NY
33301	Fort Lauderdale	FL	11238	Brooklyn	NY
33480	Palm Beach	FL	43201	Columbus	OH
33033	Homestead	FL	44107	Lakewood	OH
33407	West Palm Beach	FL	73505	Lawton	OK
33316	Fort Lauderdale	FL	19146	Philadelphia	PA
33020	Hollywood	FL	19147	Philadelphia	PA
30906	Augusta	GA	19128	Philadelphia	PA
30309	Atlanta	GA	19148	Philadelphia	PA
52240	Iowa City	IA	19145	Philadelphia	PA
60614	Chicago	IL	29403	Charleston	SC
60608	Chicago	IL	37040	Clarksville	TN
60641	Chicago	IL	37042	Clarksville	TN
60617	Chicago	IL	37042	Clarksville	TN
60657	Chicago	IL	76549	Killeen	TX
60617	Chicago	IL	78666	San Marcos	TX
60616	Chicago	IL	79938	El Paso	TX
60623	Chicago	IL	79936	El Paso	TX
61820	Champaign	IL	77007	Houston	TX
60618	Chicago	IL	76543	Killeen	TX
60615	Chicago	IL	78130	New Braunfels	TX
60613	Chicago	IL	77479	Sugar Land	TX
60624	Chicago	IL	77450	Katy	TX
60647	Chicago	IL	77054	Houston	TX
60651	Chicago	IL	77479	Sugar Land	TX
60619	Chicago	IL	54751	Menomonie	WI
47906	West Lafayette	IN	54901	Oshkosh	WI
70118	New Orleans	LA	53202	Milwaukee	WI
70115	New Orleans	LA	53211	Milwaukee	WI
21224	Baltimore	MD	26505	Morgantown	WV
21201	Baltimore	MD			

Figure D.1. Zip Codes Within One Mile of a Toxic Plant



Note: Figure shows in red zip codes that are within one mile of a toxic emitting plant.

E Pilot Study and Power Calculations

E.1 Pilot Study

This section reports the results of a pilot study that we conducted in Houston. The purpose of the pilot was to test our experimental design and confirm power calculations. The pilot was conducted during June/July of 2018 and generated a set of matched estimates for 1031 3br/2ba properties in the Metropolitan Statistical Area of Atlanta–Sandy Springs–Roswell, GA. We conducted within-property tests for 1031 properties.[16] Our preliminary results show that inquiries sent from names associated with African American identities are 25.5% and Hispanic/LatinX identities are 37.4% less likely than a white counterpart to receive a response that indicates an available housing option. A test of differences using the first inquiry only suggests that the matched design yields within-property estimates that are comparable to those made in the context of a single inquiry.[17] Results suggested that discrimination against minority renters may be stronger in neighborhoods that do not contain toxic-emitting plants, have lower poverty rates, higher school quality (based on property-specific district), and higher levels of amenities (access to public transit, grocery stores, and cafes).

E.1.1 Power Calculations based on Pilot Study

We use existing apartment listing data from the same online platform in a pre-trial in Houston, TX to identify the sample size requirements for statistical power. The pre-trial yielded a 17.9% response rate to white names and 16.7% to names associated with African American or LatinX/Hispanic names (non white names). It also yielded a relatively balanced sample with respect to proximity to TRI facilities: 45% of the rental properties where in the neighborhood of a toxic plant (within 1 mile). To compute the sample sizes and the minimum detectable effects of the interaction of race and proximity to toxic plant we assume 90% test power and .05 significance level. Using simulations based on our pre-trial in Houston, TX with a conditional logit model based on paired inquiries we estimate that we should have power to detect an interaction effect with an odds ratio of 1.54 at 3017 properties. Figures E.1 and E.2 in our supporting materials shows simulation results for different sample sizes, for odds ration and p-values. Alternatively, if we use the Demidenko (2007, 2008) approach to calculate the number of listings it yields that we need about 2,433 properties to obtain for that detectable odds ratio. Phillips (2016) provides evidence of a within-trial impacts when multiple inquiries sent in matched correspondence designs in competitive labor markets. In a sample restricted to responses to the first inquiry and based on a simple logit model, our simulations show that we should be able to detect an effect with an odds ratio of 1.43 at 3676 properties. Figures E.3 and E.4 shows the results of these simulations.

[16] Results from the tests indicate that matched inquiries sent in the Atlanta pilot are balanced on inquiry order, gender, and mother's education.

[17] We note that the statistical power of the pilot was not sufficient to detect differences within subsets of the Atlanta sample and we report these results to illustrate suggestive evidence of heterogeneity found in discriminatory response by neighborhood attributes.

Figure E.1. Power Calculations Simulations Based on Paired Inquiries

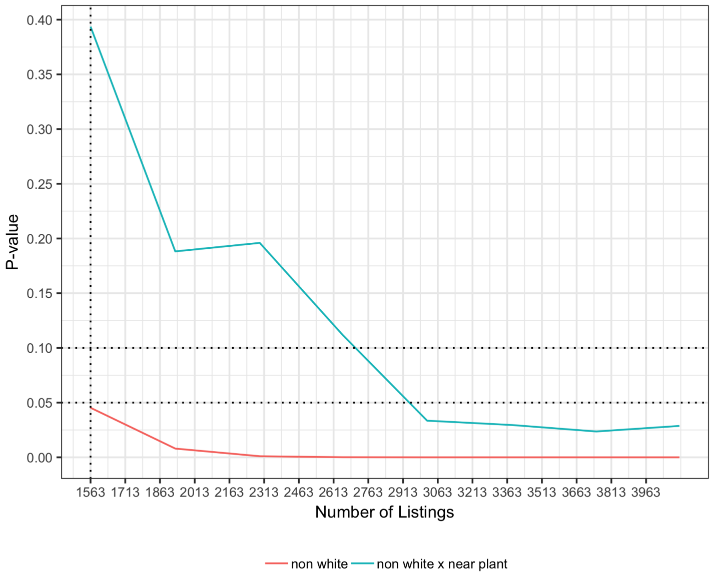


Figure E.2. Odds Ratio Simulations Based on Paired Inquiries

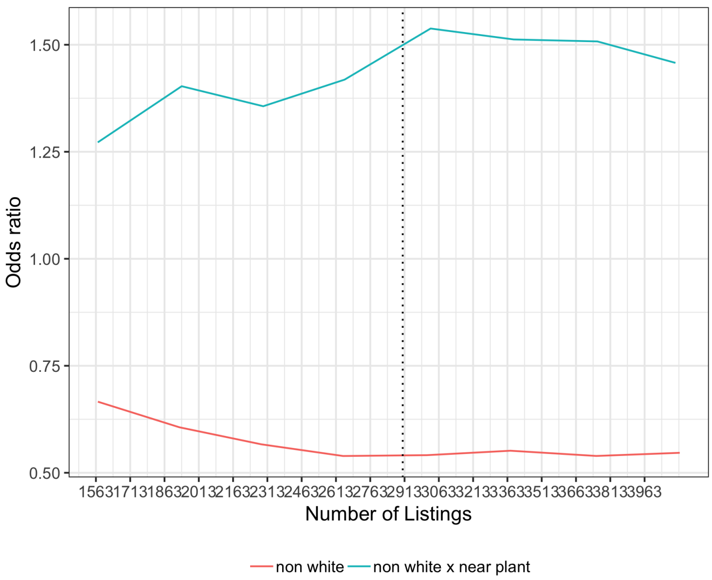


Figure E.3. Power Calculations Simulations Based on First Inquiries

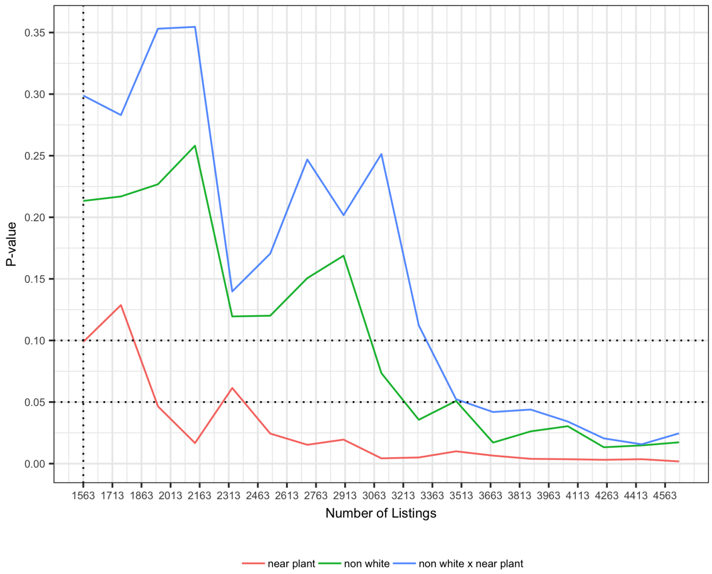


Figure E.4. Odds Ratio Simulations Based on First Inquiries