Housing Discrimination and the Pollution Exposure Gap in the United States

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Abstract

Neighborhood pollution exposures can have significant effects on health outcomes, disproportionately affecting minority households. In this study, we combine experimental evidence on discrimination from a correspondence design in the rental housing market with observational evidence from a panel detailing the movements of 1.9 million renter households to study the extent to which discrimination constrains the housing choices of minorities in ways that contribute to a race gap in pollution exposures. 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 19% and 26% 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 23% higher likelihood of in utero exposures to toxic emissions for children born in Hispanic/LatinX households and 14.4% higher likelihoods for children born in African American households.

Key words: Housing Discrimination, Paired Tester Study, Housing Audit, Neighborhood Effects, Environmental Justice
JEL Classification: Q51, Q53, R310

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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). 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, including chronic respiratory conditions such as asthma (Alexander and Currie, 2017). For over two decades, researchers have hypothesized that discrimination may be an important factor in explaining the exposure gap in the US (Crowder and Downey, 2010, Logan and Alba, 1993).[1] However, no prior study has provided an empirical test of this *racial discrimination thesis*, which in observational data requires disentangling discriminatory constraints from income disparities, housing/neighborhood preferences, and other differences underlying residential sorting behavior (Graham, 2018, Logan, 2011). Isolating the specific role of housing discrimination is critical for understanding the race-gap in pollution exposures and the long-run impacts of housing discrimination.

This paper presents experimental evidence on the incidence of discriminatory constraints in the rental housing markets with major sources of exposure to chemical toxics using a correspondence study conducted on a major online rental housing platform. We sample rental listings in zip codes that contain plants that emit toxic pollutants throughout the United States and 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 zip code.[2] This design allows us to examine the effect of discriminatory constraints on housing choices available to minority households in high/low exposure zones

[1] 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.

[2] 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).

and analyze them in relation to recent estimates of the long-run damages from the associated exposures (Currie et al., 2015, Currie and Neidell, 2005, Currie and Schmieder, 2009). The study gains empirical traction on the link between 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 research 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 (Guryan and Charles, 2013). 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 19% and 26% 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 exacerbates the race gap in exposures to chemical toxics in the United States.

Our correspondence study provides critical evidence on discriminatory constraints, but does not provide specific evidence on how these constraints interact with the sorting behavior of actual renters. In order to better understand the relationship between discrimination and the resulting location decisions, we examine the patterns of minority renter households relative to white households using a panel that details household-specific residential location choices made in the same sample of zip codes between 2012-2016. This analysis builds 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 advantage of following individual households as they make location decisions, which is important for valid inferences regarding the effects of location decisions on pollution exposures (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 that enter the households 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 20.5% more likely than white households to rent properties located within 1 mile of a toxic facility and are 23.3% more likely to have a pregnancy in a high exposure neighborhood. African American households are up to 8.4% more likely than white households to live in high exposure neighborhoods and 14.4% more likely to have a pregnancy in a high exposure neighborhood.

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 indicate 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. Differences in move out rates are 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 provides background on the link between housing discrimination and the pollution exposure gap in the empirical literature.

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 Discrimination and the Pollution Exposure Gap

In this section, we merge three mostly distinct strands of empirical evidence on: (1) the race-gap in pollution exposures, (2) experimental evidence on housing discrimination, and (3) the implications of (differential) exposures for long-run inequality.

2.1 The Pollution Exposure Gap in the US

For over three decades, large-scale research efforts have focused on documenting and examining correlations between pollution levels and the racial composition of neighborhoods across the United States. Much of this work has attempted to explain 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 et al. (2018) for a recent review of this environmental justice literature).

Early research 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, Sadd et al., 1999). The 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 the focus of the present study. 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, 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, 2012, Lerner, 2010).

With respect to location decisions, researchers 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, 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 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.[3] Researchers 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.

While identifying the exact combination of mechanisms that underpin the pollution exposure gap remains an open and active area of research, evidence of the gap itself is

[3]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.

robust. This has elevated concern that disproportionate pollution exposures among minority households may result not only from disparities that underlie location choices, but also from behavior that directly constrains the choices of minority households in US markets. The most prominent hypothesis has been the *racial discrimination thesis*: housing discrimination may constrain the housing choices of minority households in ways that result in differential sorting patterns with respect to pollution exposures. The distinction between constraints that are internal to the decisions of a household (i.e. budget constraint) versus external constraints facing minority households (i.e. discrimination) is crucial for understanding the nature of the exposure gap and for the design of effective policy instruments. In particular, the racial discrimination thesis implies that households do not have free locational choice in the housing market, which has far-reaching implications not only for fair housing policy, but also for efficient pollution abatement and a rapidly growing literature that uses revealed preference methods to estimate the willingness to pay for pollution avoidance.[4] Discriminatory constraints introduce a distortion that will directly bias estimates of the value that different communities place on local pollution and, as a result, economists and public policymakers may tend to understate a minority group's willingness to pay for its abatement.

2.2 Experimental Analysis of Housing Discrimination

To the best of our knowledge, the racial discrimination thesis has not been tested experimentally and has been subject to very little empirical examination. In observational settings, such as test would require the ability to identify discriminatory constraints and isolate them from disparities in income, housing or neighborhood preferences, and other differences underlying residential sorting behavior (Logan, 2011). However, audit and

[4]A long-standing literature in public economics has illustrated how the aggregation of individual locational choices made in housing markets influences the provision of local public goods such as pollution abatement, policing/public safety, and the quality of public education. See Champ et al. (2003) or Palmquist (2005) for a review of the hedonics literature, and the survey of the sorting literature in Kuminoff et al. (2013). A key assumption underlying these models is free locational choice, a feature that dates back to the work of Tiebout (1956), who first showed that households express their demand for and thus affect the supply of local public goods by "voting with their feet." In order to express our demand for local services and influence the level of their provision by our local governments, households must be free to choose from all available housing options in a local housing market.

correspondence studies continue to provide evidence that housing discrimination imposes (general) constraints on minority households (Bertrand and Duflo, 2017).

In a correspondence study, fictitious applicants correspond only by mail or via online platform. Correspondence designs give researchers more control than traditional audit studies over the exact traits of minority applicants that are varied in an experimental trial. Although correspondence research designs have been used to detect discrimination for more than 50 years, they have begun to proliferate in the past decade. 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., 2015, 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). In rental housing markets, correspondence studies have documented discrimination on the basis of race and ethnicity (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), LGBT status (Ahmed and Hammarstedt, 2009), and immigrant status (Baldini and Federici, 2011, Bosch et al., 2010).

The majority of correspondence research has focused on the use of racially distinct names as the trait used to elicit discriminatory behavior. While there are limitations associated with the use of any one particular trait, the consistent use of this design has enabled researchers to learn about racial perceptions of names across studies as well as in the general population. Multiple randomized experiments have focused exclusively on the alignment between perceived associations with an ethnic/racial group and self-identified racial identity (Crabtree and Chykina, 2018, Gaddis, 2017a,b). Recent advances in this literature yield three important insights: (1) racialized perceptions of first names in the general population are, on average, 73-75% congruent with the observed racial/ethnic identity of names drawn from samples of birth record data when mothers from a given racial/ethnic group constitute the majority (ex. names for which >50% of children are born to black/white/Hispanic mothers), (2) congruence between perceived and observed race/ethnicity increases (to 82% for black and 92% white) with the addition of a last name that is consistent with the racial/ethnic population in birth records (congruence falls sharply when the last name is selected from a different group), (3) congruence is somewhat higher for white names drawn from mothers with high educational attainment and higher for black names when associated with a mother with low educational attainment (Gaddis, 2017a,b).[5] We study discriminatory behavior using a set of 18 first-last name pairs 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.

2.3 Short- and Long-Run Impacts of Pollution Exposures

If housing discrimination differentially constrains the location choices of minority households and induces disproportionate levels of exposure to harmful pollutants, then a rapidly growing body of evidence indicates that discriminatory behavior could have important impacts on the birth outcomes (e.g., birth weight, gestation length, congenital abnormalities, and infant mortality) as well as on a variety of adult health and economic outcomes for affected minority households (Almond et al., 2018).[6] If pre-natal and early life exposures to harmful pollutants contribute to persistent inequity in the United States, as described by Currie (2011), then this could suggest a channel through which housing

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

[6]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, Isen et al., 2017, Voorheis, 2017).

discrimination affects perpetuates inequality.

Currie et al. (2015) and Currie and Schmieder (2009) provide direct evidence that exposure to chemical toxics has important effects on gestation and birth-weight. Currie (2011) also demonstrate 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. Alexander and Currie (2017) show that differences in neighborhood location choices explain a large part of the black-white gap in chronic respiratory conditions such as asthma. While these studies provide compelling evidence of the link between the location decisions of minority households and disparities in health outcomes, it is not clear from the existing work whether minority households made different decisions with an equivalent set of options or had access to a constrained set of choices. The present study is designed to test for evidence of choice set constraints.

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 experimentally test the *racial discrimination thesis*.[7] 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

[7]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.

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.[8]

Figure 1 maps the zip codes with high emitting facilities in the United States. We select a random sample of zip codes from this set and compile the full set of 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.

Table 1 details the characteristics of listed properties in our sample. The average rent for a rental property within 1 mile of a toxic plant in our sample is about $2,280. On average, the rental prices for properties located between 1-2 and 2-4 miles from the nearest plant are approximately $2,700 and $1,720, respectively. Properties located near plants are, on average, more likely to be multi-family and slightly smaller. The neighborhoods in closer proximity have somewhat lower assault rates, and higher poverty rates. High exposure neighborhoods are on average closer in proximity to grocery stores. The share of white households in the block group of the average property is higher in high exposure zones, while the share of minority households is is higher in lower exposure zones. However, we show below that the sign of these correlations flips when we look within zip codes. We do not observe significant or substantial differences in the unemployment rate or share college educated households in the average property's neighborhood within 2 miles of a facility, though the unemployment rate increases while the share of college educated households declines outside 2 miles.

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

Fictitious Renter Identities and Correspondence Design

Consistent with prior correspondence studies, we assign a racial/ethnic identity using a set of 18 names that are shown to have a high probability of association with each of 3 racial categories throughout the United States: African American, 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).[9]

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).[10] 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.[11] Responses from property managers are transmitted via email (gmail address

[9] 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.

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

[11] 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

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.[12] Besides the address and household identifier, 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. We note that several variables identified in the InfoUSA data are not directly observed, but are rather estimated or predicted using ancillary data collected at the address level and proprietary algorithms.[13] In particular, the racial/ethnic 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.

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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.

[12]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.

[13]In ongoing work, we examine the consistency between observations provided in InfoUSA and external sources of the same variables, including the US Census and ACS, Home Mortgage Disclosure Act (HMDA), and home transaction/loan data from CoreLogic.

We utilize the sample of more than 1.9 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.[14] 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. 50.2% of the households in the panel are identified as white, while the shares of Hispanic/LatinX and African American households are 14.1% and 13.5%, respectively. The average income for households in the sample is $41,736, with substantial differences across the groups. The average income is $29,360 for Hispanic/LatinX households, $20,589 for African American, and $48,784 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 within-property differences in response rates between race groups:

[14]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.

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

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.

Odds ratios from the within-property tests 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 21-26% lower in low-exposure neighborhoods in the same zip code (between 1-4 miles). Point estimates suggest a smaller 12-18% difference for African American renters that is only significant in the specification with all 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 suggest some evidence of increasing discrimination rates for both minority groups at greater distances from the nearest plant. Estimates are noisier at these distances and sample sized are reduced, though point estimates suggest renters have a 30% 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 27% lower probability.

5.1 Heterogeneity by Renter Characteristics (names)

Table 5 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. However, they provide some evidence that minority male renters face disproportionately higher rates of discrimination when they are searching for housing in low exposure areas. The estimates suggest that minority females get *higher* response rates than white counterparts in high exposure zones, though the odds for females also decline with distance the nearest TRI facility and associated exposures. Differences by maternal education level suggest that maternal education may not be associated with names that signal higher incomes, at least not in ways that result in lower rates of discrimination. If anything, these results suggest the clearest evidence of differential constraints facing minority renters with high maternal education, though there is some evidence that both high and low levels of maternal education face stronger discriminatory constraints.

5.2 Heterogeneity by Racial Composition and Price

Prior work has demonstrated that discriminatory constraints tend to be stronger in neighborhoods with a higher share of non-minority (white) households and higher prices (Christensen and Timmins, 2018). Panel A of Figure 3 plots the share of White, Black and Hispanic/LatinX households in the block group of a listed property as a function of distance from a TRI facility in the same zip code. This figure shows that high exposure neighborhoods tend also to be minority neighborhoods. On average, the share of white households in a low exposure neighborhood is 2.5 percentage points lower than the share in high exposure neighborhoods in the same zip code. Conversely, the share of African American and Hispanic/LatinX households is 2.25-2.5 percentage points lower than in high exposure neighborhoods.

Can the link between housing discrimination and pollution exposures be explained by existing segregation or differential constraints in white neighborhoods, which are correlated with lower exposures? We examine this question by comparing neighborhoods within each zip code that vary in levels of exposure, but do not vary in their demographic composition. Specifically, we restrict the sample to properties located in block groups where the share of white households is within 5 percentage points of the zip code median and the share of Black/Hispanic shares is within 2 percentage points of the zip code median.[15] Panel B of Figure 3 plots the share of White, Black and Hispanic/LatinX households as a function of distance from a TRI facility, illustrating that there is essentially no variation in racial/ethnic composition of neighborhoods in the restricted sample.

Panel A of Table 6 reports estimates from our primary tests using the restricted sample. Discriminatory constraints appear to become stronger and the variation as a function of exposure becomes more pronounced when holding neighborhood racial composition constant. We note that other attributes could be shifting in the restricted sample, but we interpret this as evidence that the link between housing discrimination and pollution exposures is not explained by variation in the existing demographic composition of neighborhoods.[16] In Panel B of Table 6, we report estimates from Model 1 but restrict tests to properties within the same quartile of price in a given zip code. While these tests are not fully powered, point estimates generally suggest stronger constraints in low exposure neighborhoods.

[15]We impose a tighter restriction on Black/Hispanic shares because they reflect deviations from a lower base.

[16]In Table A.1, we examine discrimination rates by racial composition irrespective of exposures to toxics. These estimates do not suggest that minorities face lower rates of discrimination in neighborhoods where they have higher group representation.

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 20.5% more likely than white households to live in high exposure neighborhood when low exposure is defined as beyond 1 mile and and 25.7% more likely when low exposure is defined as beyond 2 miles. African American households are 8.4% more likely to live in a high exposure area when using the 1-4 mile definition and 15.3% more likely when using the 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. 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.[17] 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 in utero exposure for minority households relative to a white counterpart. These estimates indicate that in utero exposure is 23.3% more likely for Hispanic households using the 1-4 mile definition for low exposure and 17.3% more likely using the 2-4 mile definition. African American households are also more likely to have in utero exposures, 14.4% more likely, if using the 1-4 mile definition of low exposure and 33.7% more likely if using the 2-4 mile definition.

6.3 Movers and Stayers

Moving Into and Out of Exposure

Results in the prior section provide evidence that minority households are more likely to live in neighborhoods that result in high exposures to chemical toxics and are also more

[17]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.

likely than white households to sustain damaging in utero exposures during their pregnancies. In this section, we utilize the household panel to capture the location choices of households who are moving (or not) 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.[18]

Figure 4 reports the results on movers and stayers. Results from panel 4a indicate that African American households are 21-29% more likely than white households to move into high exposure neighborhoods in our sample. Odds ratios suggest that Hispanic renters are 1.5-3% more likely to move into high exposure neighborhoods, though the estimates are

[18] 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 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.

not different from zero. Results from panel 4b indicate that African American households living in high exposure neighborhoods are 16% less likely than white households to move out of high exposure neighborhoods in any given year and that Hispanic households are 32% less likely.

In Figure 4, panels 4c and 4d use the definition of pregnancy defined above to test for differences in the location decisions of households that we identify as likely pregnant. Panel 4c 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 4d 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 34% lower likelihood for African American and a 33% 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 4, panels 4e-4h explore heterogenity in the results for movers and stayers. We define five income quintiles using the income distributions for each of the minority 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 5a reports these results. During the period 2012-2016, white renters who are observed in a high exposure residence have an 75.4% likelihood of remaining in a high exposure location 5 years later, whereas the likelihoods for African American and Hispanic/LatinX households are 87.2% and

84.2%, 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 a 17% likelihood of remaining in a high exposure location 5 years later, whereas the likelihoods for African American and Hispanic/LatinX households are 37% and 34.8%, 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, prior studies have not provided empirical tests for evidence of discriminatory constraints that control for other differences in income, preferences, and information in markets that are characterized by high pollution exposures. As a result, this thesis has remained untested and a large literature on race-specific sorting in US housing markets has been unable 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. Using a correspondence study, we provide experimental evidence of substantial discriminatory behavior in low exposure neighborhoods of housing markets with major sources of chemical toxics. We find no evidence of discriminatory constraints operating in high exposures neighborhoods of the same markets. These results appear across different brackets of housing price and when we restrict the sample to control for differences in the racial composition of neighborhoods at different levels of exposure.

By constraining the set of choices available in less polluted neighborhoods relative to more polluted ones, housing market discrimination constrains 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. We find that exposures are higher for Hispanic/LatinX households, which is consistent with the evidence of stronger discriminatory constraints facing that group. We also find evidence that while minority households are more likely than white households to move into high exposure neighborhoods, this difference in mover behavior appears to become much smaller 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 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.[19] 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.[20]

[19]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.

[20]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.

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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	2281.72	2693.89	1723.58
	(2632.31)	(4050.44)	(1403.15)
Single Family Home	0.4	0.48	0.74
	(0.49)	(0.5)	(0.44)
Apartment	0.13	0.07	0.07
	(0.33)	(0.26)	(0.25)
Multi Family	0.38	0.32	0.15
	(0.48)	(0.47)	(0.36)
Other Bldg. Type	0.09	0.12	0.04
	(0.29)	(0.33)	(0.19)
Bedrooms	2.6	2.72	2.81
	(0.9)	(0.93)	(0.57)
Bathrooms	1.73	1.81	1.91
	(0.57)	(0.54)	(0.43)
Sqft	1469.79	1508.24	1568.04
	(952.21)	(598.61)	(455.88)
Assault	89.45	124.12	69.4
	(142.93)	(190.62)	(73.38)
Supermarkets/Grocery Stores	34.34	32.96	2.45
	(72.36)	(67.86)	(3.12)
Share of Hispanics	0.18	0.18	0.21
	(0.19)	(0.18)	(0.19)
Share of African American	0.21	0.20	0.28
	(0.24)	(0.23)	(0.28)
Share of Whites	0.64	0.64	0.58
	(0.26)	(0.25)	(0.26)
Poverty Rate	0.22	0.19	0.14
	(0.21)	(0.18)	(0.11)
Unemployment Rate	0.07	0.07	0.09
	(0.06)	(0.06)	(0.06)
Share of College Educated	0.27	0.26	0.21
	(0.17)	(0.15)	(0.11)
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	0.141	-	-	-
	(0.348)			
Share of African American	0.135	-	-	-
	(0.341)			
Share of White	0.502	-	-	-
	(0.5)			
Share of Other Race	0.222	-	-	-
	(0.416)	-	-	-
Income	41736.33	29360.40	20589.61	48720.86
	(50212.27)	(35144.72)	(23235.74)	(53784.27)
Age Household Head	41.46	39.87	41.30	42.08
	(15.16)	(13.69)	(15.23)	(15.67)
Share Married	0.128	0.126	0.059	0.15
	(0.334)	(0.331)	(0.236)	(0.357)
Share Pregnancies	0.087	0.088	0.102	0.092
	(0.282)	(0.283)	(0.303)	(0.289)
Number of Children	0.102	0.102	0.12	0.114
	(0.44)	(0.429)	(0.471)	(0.471)
Nbr. of Households	1,904,647	281,914	267,249	897,071
Observations	4,321,996	593,802	565,655	2,109,949

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	1.1391	1.1133	1.0988	1.1339	1.1053
	(0.9116 - 1.4233)	(0.8913 - 1.3905)	(0.8792 - 1.3732)	(0.8832 - 1.4557)	(0.7932 - 1.5403)
Toxic Plant more than 1 mile × Hispanic	0.7834**	0.7710**	0.7699**	0.7378***	0.8509
	(0.6564 - 0.9350)	(0.6468 - 0.9190)	(0.6496 - 0.9125)	(0.6168 - 0.8825)	(0.6778 - 1.0683)
Toxic Plant less than 1 mile × African American	1.0774	1.0600	1.0613	1.0720	0.8176
	(0.8738 - 1.3284)	(0.8575 - 1.3104)	(0.8576 - 1.3135)	(0.8638 - 1.3305)	(0.6262 - 1.0675)
Toxic Plant more than 1 mile × African American	0.8768	0.8560	0.8604	0.8100*	1.0032
	(0.7343 - 1.0471)	(0.7177 - 1.0210)	(0.7207 - 1.0271)	(0.6763 - 0.9702)	(0.7949 - 1.2662)
Gender		Yes	Yes	Yes	Yes
Education Level			Yes	Yes	Yes
Inquiry Order				Yes	Yes
Observations	5,217	5,217	5,217	5,217	1,739

Notes: Standard errors clustered at Zip Code level. 90% Confidence Intervals reported in parentheses.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 4. 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	1.1339	0.7378***	0.6181***	0.7022
	(0.8832 - 1.4557)	(0.6168 - 0.8825)	(0.4832 - 0.7906)	(0.4864 - 1.0138)
African American	1.0720	0.8100*	0.8243	0.7284
	(0.8638 - 1.3305)	(0.6763 - 0.9702)	(0.6465 - 1.0509)	(0.5186 - 1.0231)
Gender	Yes	Yes	Yes	Yes
Education Level	Yes	Yes	Yes	Yes
Inquiry Order	Yes	Yes	Yes	Yes
Observations	5,217	5,217	5,217	5,217
Observations With Differential Response	2,262	2,262	2,262	2,262

Notes: 90% Confidence Intervals in parenthesis. Standard errors clustered at Zip code level.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table 5. 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	0.9583	0.6322***	0.5812*
	(0.7234 - 1.2694)	(0.5020 - 0.7962)	(0.3554 - 0.9504)
Hispanic × Female	1.3757	0.8793	0.8645
	(0.9458 - 2.0011)	(0.6933 - 1.1153)	(0.5415 - 1.3802)
African American × Male	0.7593	0.6364***	0.7715
	(0.5363 - 1.0750)	(0.4947 - 0.8187)	(0.5033 - 1.1826)
African American × Female	1.5290**	1.0418	0.6767
	(1.1399 - 2.0509)	(0.8193 - 1.3247)	(0.4464 - 1.0256)
Panel B: Heterogeneity by Education			
Hispanic x Low Education	1.3073	0.5213***	0.6011
	(0.8827 - 1.9363)	(0.3762 - 0.7223)	(0.3050 - 1.1846)
Hispanic x Medium Education	0.9678	1.0608	1.0052
	(0.6270 - 1.4939)	(0.8118 - 1.3860)	(0.6277 - 1.6097)
Hispanic x High Education	1.2889	0.5848***	0.4559***
	(0.9044 - 1.8368)	(0.4271 - 0.8007)	(0.2787 - 0.7458)
African American x Low Education	1.2242	1.4376*	1.2333
	(0.7480 - 2.0035)	(1.0249 - 2.0166)	(0.7329 - 2.0755)
African American x Medium Education	0.9496	0.6066**	0.6895
	(0.6666 - 1.3529)	(0.4125 - 0.8921)	(0.4192 - 1.1339)
African American x High Education	1.1260	0.7239**	0.4249**
	(0.8112 - 1.5630)	(0.5647 - 0.9281)	(0.2441 - 0.7395)
Gender	Yes	Yes	Yes
Education Level	Yes	Yes	Yes
Inquiry Order	Yes	Yes	Yes
Observations	5,217	5,217	5,217

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. 90% Confidence Intervals 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 Rent and Restricted Sample

	Dependent variable: Property Availability		
	Distance to Toxic Plant:		
	<1 mile	>1 mile	>2 miles
	(1)	(2)	(3)
Panel A: Restricted Sample			
Hispanic	0.6689	0.4469**	0.2448**
	(0.3831 - 1.1678)	(0.2649 - 0.7540)	(0.0881 - 0.6798)
African American	0.6334	0.4327***	0.3623**
	(0.4002 - 1.0026)	(0.3014 - 0.6212)	(0.1637 - 0.8019)
Observations	873	873	873
Panel B: Heterogeneity by Rent			
Hispanic x Q1 Rent	1.7446**	0.6677	0.4202*
	(1.1540 - 2.6377)	(0.4360 - 1.0225)	(0.2019 - 0.8744)
Hispanic x Q2 Rent	0.8540	0.6522	0.5771
	(0.5276 - 1.3825)	(0.4134 - 1.0288)	(0.2962 - 1.1243)
Hispanic x Q3 Rent	1.0875	0.9141	0.8729
	(0.6588 - 1.7952)	(0.6313 - 1.3235)	(0.4522 - 1.6849)
Hispanic x Q4 Rent	0.8455	0.6674	1.4630
	(0.5266 - 1.3576)	(0.4306 - 1.0344)	(0.6470 - 3.3081)
African American x Q1 Rent	1.0736	0.7726	0.5118*
	(0.6969 - 1.6540)	(0.5038 - 1.1848)	(0.2661 - 0.9844)
African American x Q2 Rent	0.9888	1.0158	1.0768
	(0.6306 - 1.5504)	(0.6443 - 1.6014)	(0.6078 - 1.9078)
African American x Q3 Rent	1.0781	0.8537	0.5773
	(0.6591 - 1.7634)	(0.5275 - 1.3817)	(0.2389 - 1.3951)
African American x Q4 Rent	1.1441	0.5743**	0.7794
	(0.6827 - 1.9173)	(0.3914 - 0.8427)	(0.3531 - 1.7204)
Observations	5,196	5,196	5,196
Gender	Yes	Yes	Yes
Education Level	Yes	Yes	Yes
Inquiry Order	Yes	Yes	Yes

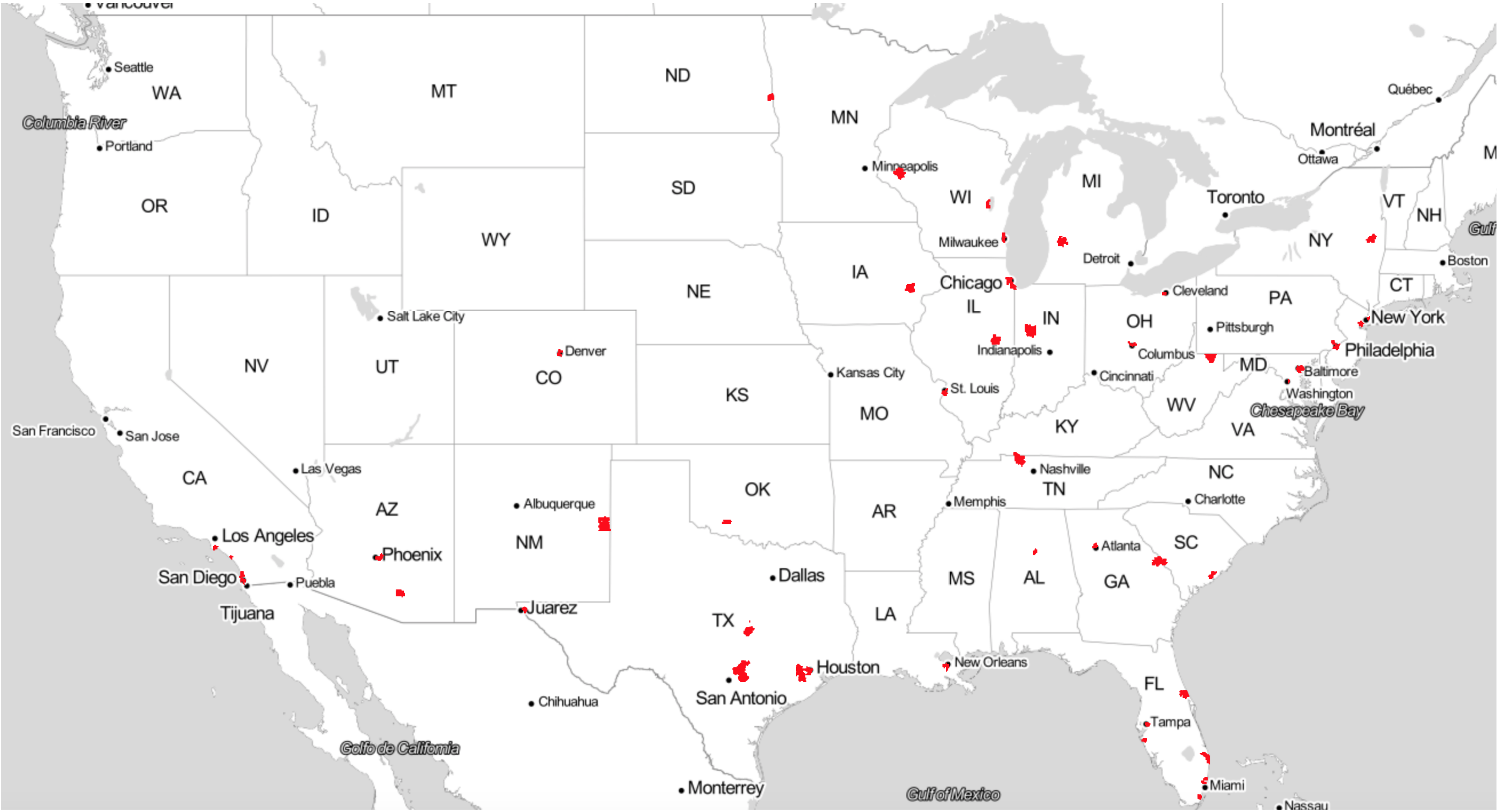
Notes: 90% Confidence Intervals in parenthesis. Standard errors clustered at Zip code level.*Panel A* restricts the sample to properties that are in block groups that their share of white population in within 2% of the median share of white population in the Zip code, and within 5% for Hispanics and African Americans. *Panel B* Shows heterogeneity by rent quartiles. Q1,(Q2,...) denote the first (second...) quartile of the rent distribution within a Zip Code.
* 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	1.205***	1.257***
	(1.197-1.214)	(1.241-1.274)
African American	1.084***	1.153***
	(1.073-1.094)	(1.132-1.176)
Observations	3,991,233	2,391,078
Panel B: Households with Pregnancies		
Pregnant × Hispanic	1.233***	1.173***
	(1.194-1.274)	(1.099-1.251)
Pregnant × African American	1.144***	1.337***
	(1.101-1.189)	(1.244-1.436)
Observations	1,548,857	922,321

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. . Standard errors clustered at Zip Code. 90% Confidence Intervals reported in parentheses.
* Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

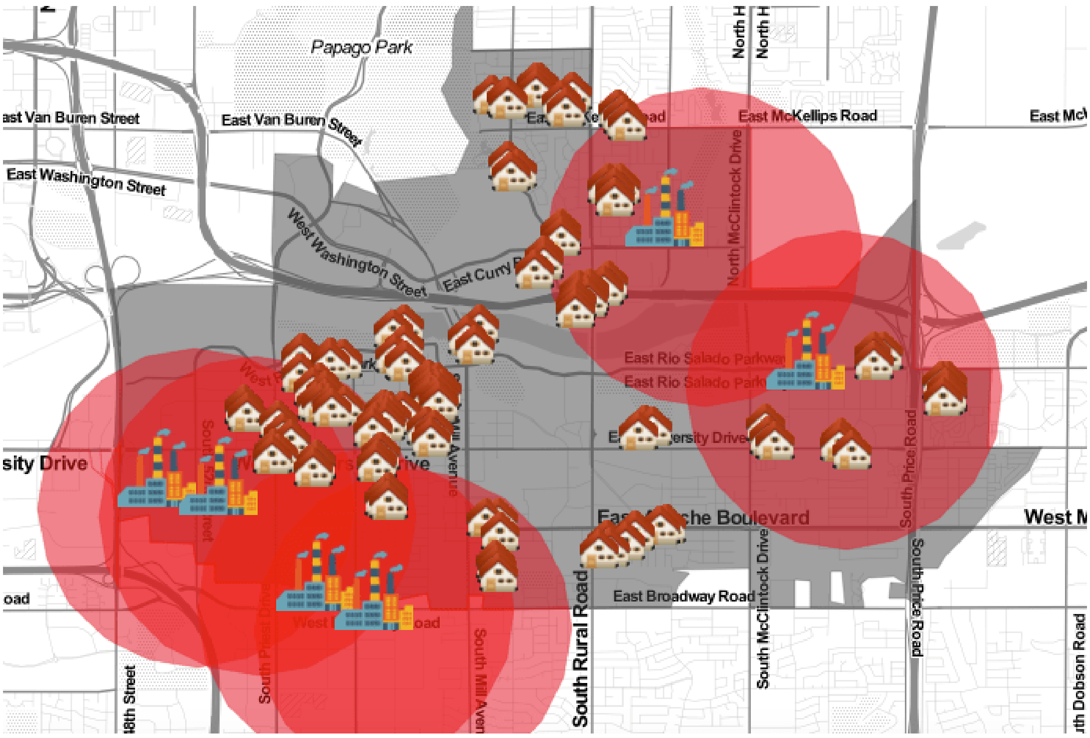
Figure 1. Zip Codes Within One Mile of a Toxic Plant



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

Figure 2. Experimental Sample Illustration

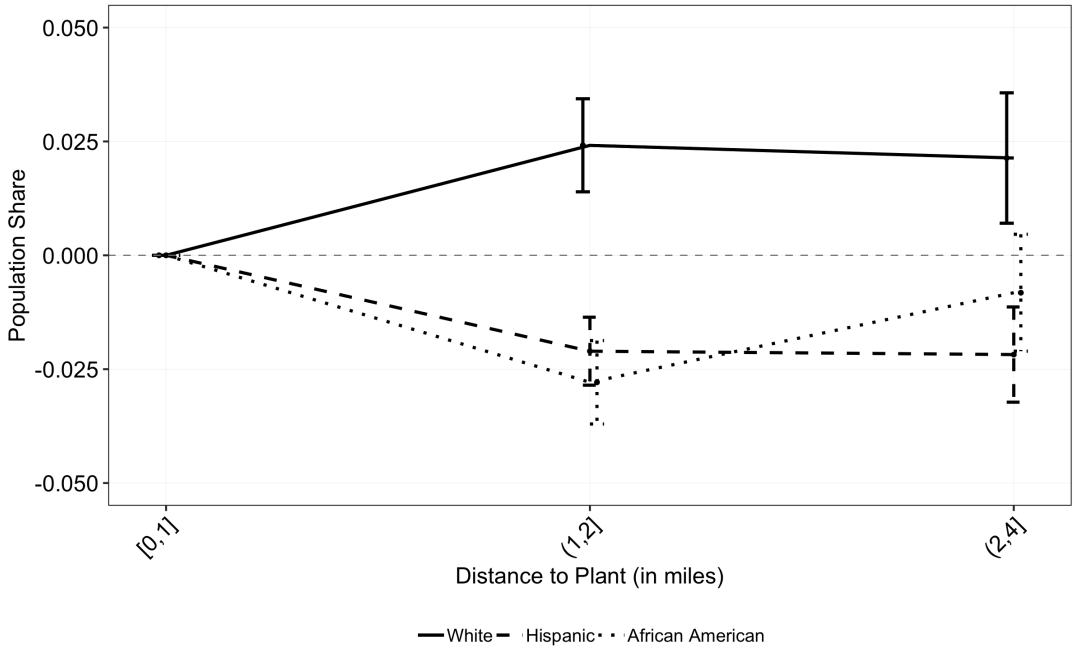
(a) Killeen, TX



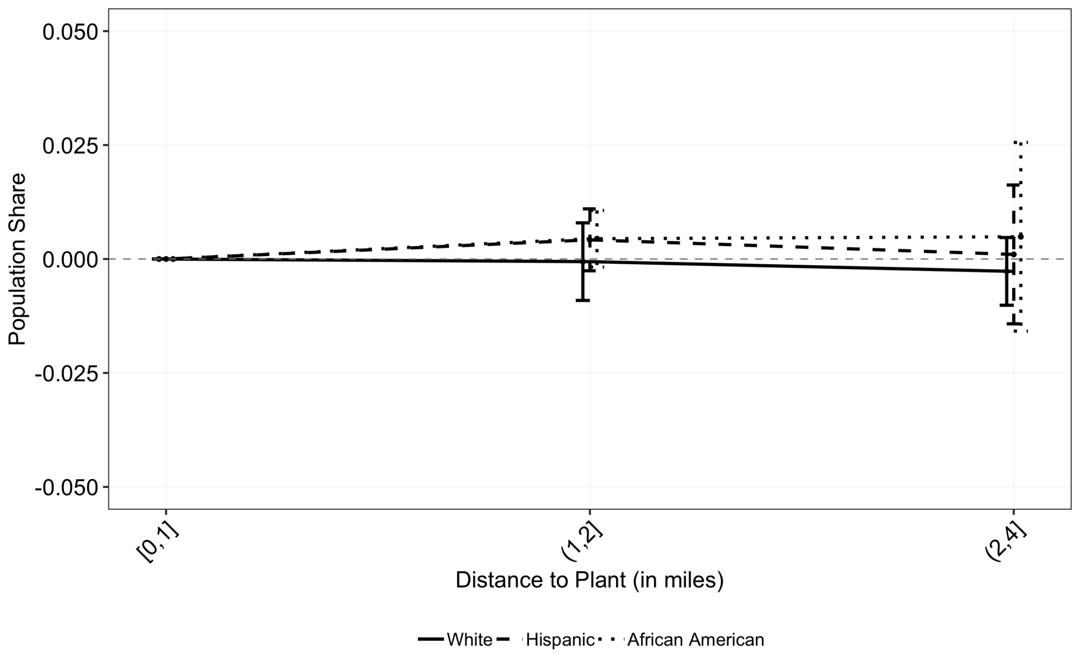
(b) Tempe, AZ

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. Race Share by Distance



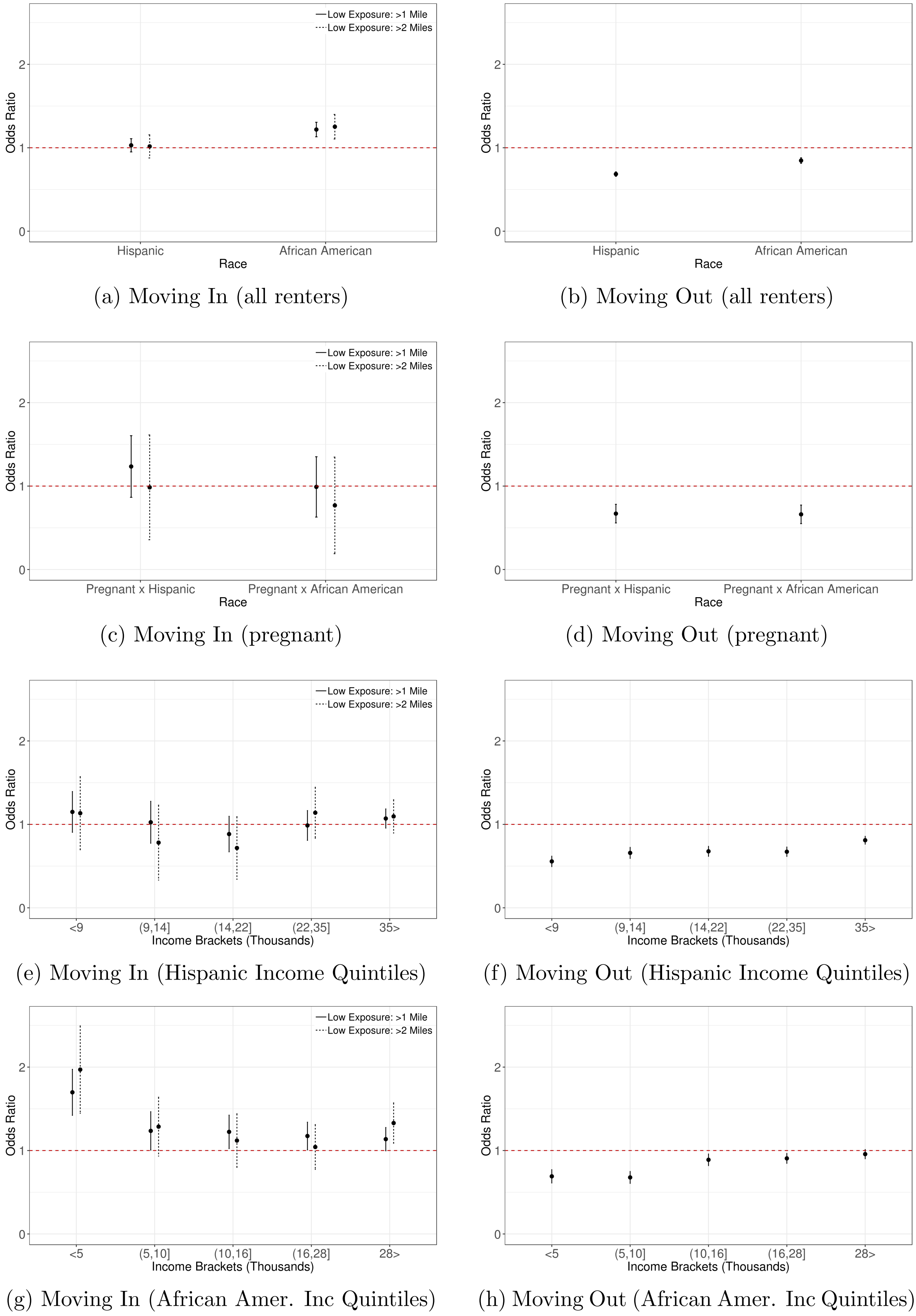
(a) Full Sample



(b) Restricted Sample

Notes: *Panel A* shows the relative difference of population share by distance to TRI facility respect to block groups within a mile of the facility. *Panel B* restricts the sample to block groups that their share of white population in within 2% of the median share of white population in the Zip code, and within 5% for Hispanics and African Americans

Figure 4. 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)

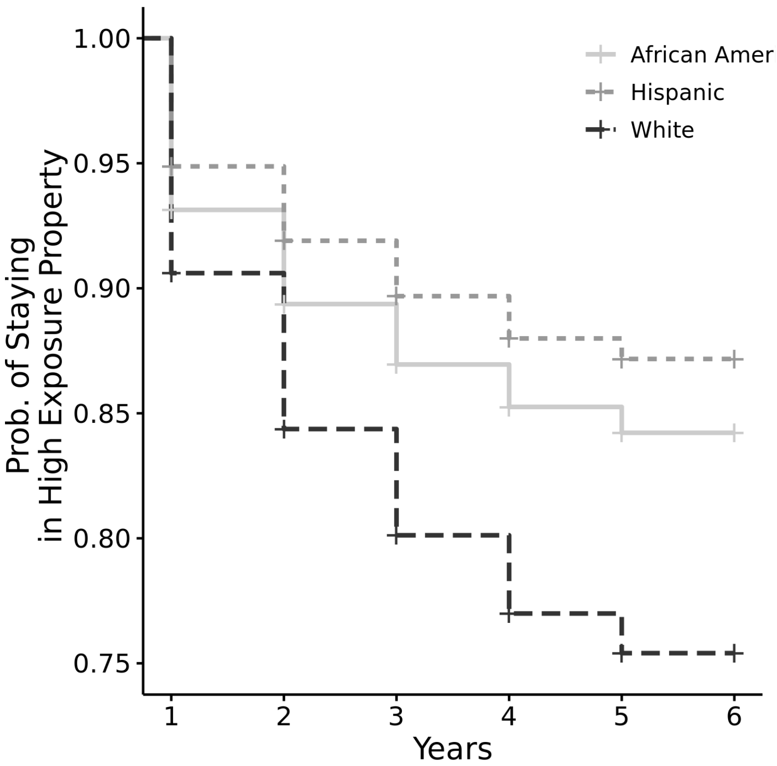
(f) Moving Out (Hispanic Income Quintiles)

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

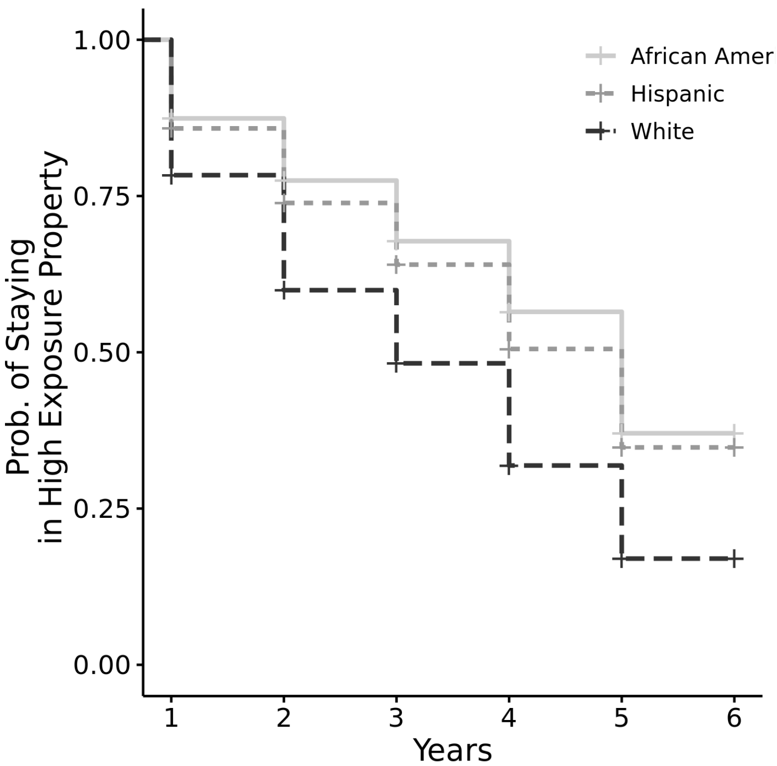
(h) Moving Out (African Amer. Inc Quintiles)

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 5. 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
Quartiles of Racial Composition

	Dependent variable: Property Availability			
	Quartiles			
	Q1	Q2	Q3	Q4
	(1)	(2)	(3)	(4)
Quartiles Shares of Whites				
Hispanic	0.8617	0.8287	0.9298	0.8170
	(0.6736 - 1.1022)	(0.6097 - 1.1264)	(0.7575 - 1.1414)	(0.5771 - 1.1564)
African American	0.9758	0.8686	1.0000	0.9354
	(0.7584 - 1.2556)	(0.6404 - 1.1783)	(0.8038 - 1.2441)	(0.6732 - 1.2997)
Observations	1,743	1,242	2,271	972
Quartiles Shares of African American				
Hispanic	0.9170	0.7790	0.9277	0.7598
	(0.7157 - 1.1748)	(0.5338 - 1.1367)	(0.7082 - 1.2152)	(0.5312 - 1.0869)
African American	0.9786	0.7790	1.0000	1.0225
	(0.7590 - 1.2616)	(0.5379 - 1.1280)	(0.7618 - 1.3127)	(0.7570 - 1.3811)
Observations	1,926	1,083	2,052	948
Quartiles Shares of Hispanics				
Hispanic	0.8105	1.1176	0.9809	0.7397*
	(0.6245 - 1.0519)	(0.7846 - 1.5919)	(0.7706 - 1.2484)	(0.5602 - 0.9767)
African American	1.0131	0.8374	0.9345	1.0615
	(0.7547 - 1.3600)	(0.6404 - 1.0951)	(0.7257 - 1.2032)	(0.7869 - 1.4318)
Observations	1,743	1,302	2,304	933

Notes: Each column are separate regressions dividing the sample by quartiles of racial composition per Zip code, e.g. Q1 of Panel A is the sample of listings in block groups in the first quartile of the share of whites in the Zip code.
90% Confidence Intervals reported in parentheses. * Significant at 10% level; ** significant at 5% level; *** significant at 1% level.

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 confirm that there is no evidence of differences in the timing or sequence of inquiries. We note that the experiment is ongoing and that there is some imbalance in names used for each group (gender and maternal education), which result from a data loss in a small number of trials. Paired trials with data loss are excluded from the present analysis and are currently being re-run. In the current analysis, we note that this results in a smaller number of inquiries sent from male names for both minority groups, a smaller number of high education Hispanic/LatinX names, and a higher number of high education African American names. All tests report estimates from paired trials and control for these attributes in estimates of average effects. We also note that tests by gender suggest that, if anything, male names tend to get lower response rates, so imbalance would result in conservative estimates of discrimination for the Hispanic/LatinX group as a whole.

Table B.1. Balance Statistics

	Panel A: Inquiry Order				
	Dependent variable: Inquiry Sent				
	First	Second	Third		
Hispanic	−0.0052	−0.0069	0.0121		
	(0.0587)	(0.0588)	(0.0588)		
African American	−0.0121	0.0052	0.0069		
	(0.0588)	(0.0587)	(0.0588)		
	Panel B: Evidence of Differential Choices by Weekday				
	Mon	Tue	Wed	Thurs	Fri
Hispanic	−0.1154	0.0679	−0.0127	0.0714	0.0057
	(0.1133)	(0.1303)	(0.0796)	(0.0772)	(0.0754)
African American	−0.1845	0.1845	0.0553	0.0273	−0.0115
	(0.1151)	(0.1270)	(0.0784)	(0.0779)	(0.0757)
	Panel C: Gender and Mother's Education Level				
	Gender		Mother's Education		
	Male	Female	Low	Medium	High
Hispanic	−0.1925***	0.1925***	0.0516	0.1511**	−0.2061***
	(0.0690)	(0.0690)	(0.0803)	(0.0699)	(0.0728)
African American	−0.1426**	0.1426**	−0.0858	−0.0648	0.1308*
	(0.0690)	(0.0690)	(0.0813)	(0.0706)	(0.0710)
Observations	5,217	5,217	5,217	5,217	5,217

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 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			

D Pilot Study and Power Calculations

D.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.[21] 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.[22] 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).

D.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.

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

[22] 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

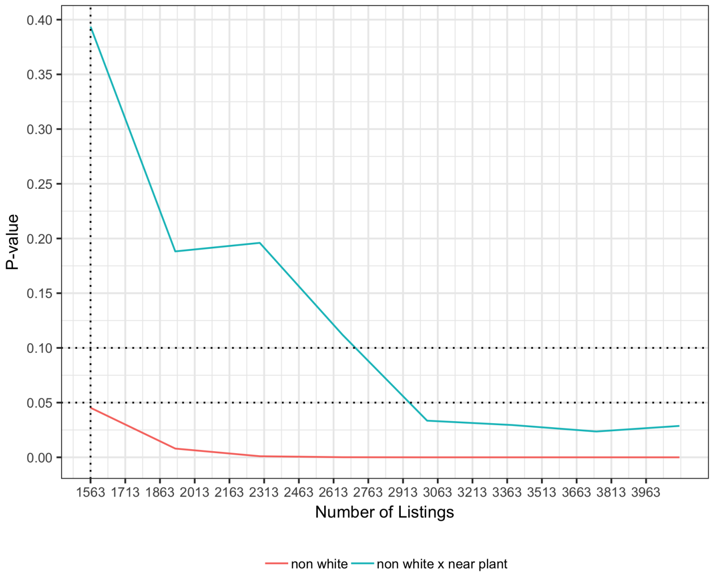


Figure E.2. Odds Ratio Simulations Based on Paired Inquiries

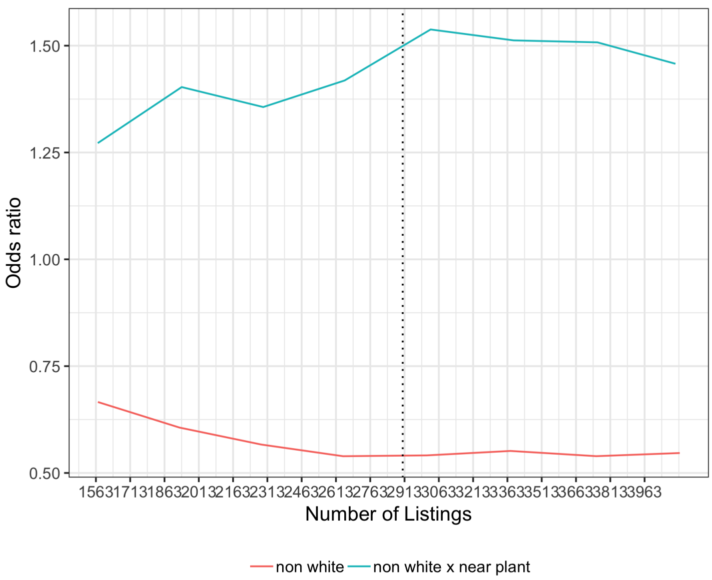


Figure E.3. Power Calculations Simulations Based on First Inquiries

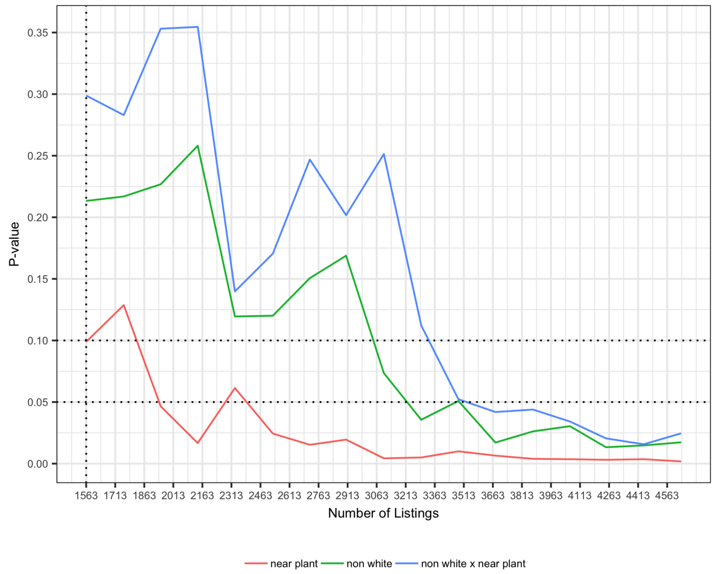


Figure E.4. Odds Ratio Simulations Based on First Inquiries