Does Racial Bias Distort Neighborhood Choice? The Impacts of Discrimination on Welfare and Revealed Preference in the Rental Housing Market

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Abstract

By constraining an individual's choice during a search, housing discrimination distorts sorting decisions away from true preferences and results in a ceteris paribus reduction in renters' welfare. This study combines a large-scale field experiment with a residential sorting model to derive utility-theoretic measures of renter welfare associated with the constraints imposed by discrimination in the rental housing market. In the 5 major metropolitan markets we study, we find that key amenities such as lower air toxicity and better schools are associated with higher levels of discrimination. We estimate welfare costs to renters from constraints during a search in these 5 cities to be equivalent to 4.5% and 3.8% of the annual incomes for the average African American and Hispanic/LatinX households, respectively. These costs increase substantially at higher levels of income. African American renters face damages greater than 10% of income at income levels above $100,000 per year. Strong preferences for housing in own-race neighborhoods can partially mitigate these effects at higher income levels, indicating that discriminatory constraints might induce higher income minority renters to trade off amenities for neighborhoods with other minority households. Finally, we study the effects of discrimination on revealed preferences for urban amenities. We find that discrimination drives a wedge between true preferences for key neighborhood amenities and those revealed in markets with discriminatory constraints. A naive model that ignores discriminatory constraints understates African American and Hispanic/LatinX amenity preferences by nearly 10% and significantly overstates African American preferences for own-race neighbors.

Key words: Housing Discrimination, Experimental Design, Correspondence Study, Consideration Sets, Neighborhood Effects, Environmental Justice
JEL Classification: Q51, Q53, R310

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1 Introduction

By constraining an individual's choice during a search, housing discrimination distorts purchase decisions away from true preferences and results in a *ceteris paribus* reduction in welfare. Decades after the passage of the Fair Housing Act, evidence from both audit and correspondence studies indicates that housing market discrimination continues to constrain the choices of people of color in the United States (Ewens et al., 2014, Carlsson and Eriksson, 2014, Hanson and Hawley, 2011, Ahmed and Hammarstedt, 2008) and steer them into disadvantaged neighborhoods (Christensen and Timmins, 2018, Christensen et al., 2020). However, most experimental research on discrimination has isolated the effect of discriminatory behavior without consideration for the role of housing search, making it difficult to understand the impacts of discriminatory actions on economic outcomes. This study combines a large-scale field experiment with structural methods to measure the effects of discrimination in a housing search process and estimate damages to renters in the United States.

A primary contribution of this paper is the integration of a correspondence experiment and a welfare-theoretic framework for modeling housing search. We present experimental evidence on the effects of discrimination on the location choices of renters using the behavior of property managers on a major online rental housing platform. Our study samples the entire set of listings for three-bedroom, two-bathroom units in each of five different major U.S. metropolitan housing markets: Atlanta, Houston, Philadelphia, Cleveland, and San Jose.[1] We first provide reduced form evidence on discriminatory constraints using variation in within-property differences in responses to housing inquiries about whether a housing unit is available to an applicant or not. We find that minority identities in our sample have a 31% lower likelihood of response indicating that a rental property is available for lease. Discriminatory constraints vary substantially by race group and across MSAs, with the lowest relative response rates found in Philadelphia (52.7%)

[1]Specifically, markets are defined using the Metropolitan Statistical Area definition and are sampled from the list of 28 metro areas used in recent paired-actor research by HUD/Urban Institute (Turner et al., 2013). Metropolitan Statistical Areas: Atlanta-Sandy Springs-Roswell, GA; Houston-The Woodlands-Sugar Land, TX; Philadelphia-Camden-Wilmington PA-NJ-DE-MD; Cleveland-Elyria, OH; and San Jose-Sunnyvale-Santa Clara, CA.

and the highest found in Cleveland (74.5%).

We then examine how the constraints associated with discrimination vary with neighborhood attributes. First, we find that in nearly all cases, better amenities (e.g., better schools or lower air toxicity) are associated with higher levels of discrimination. [HOW DO WE WANT TO WORD THIS, GIVEN THE LEVEL OF STATISTICAL PRECISION – IS "ASSOCIATED" OKAY?] Considering neighborhood demographics, people of color face less discrimination in neighborhoods with greater shares of African American or Hispanic/LatinX households, while they face greater discrimination in higher income and higher percentage White neighborhoods. Second, discriminatory constraints are significantly greater among properties that have recently entered the market (listed for fewer than 3 days), which we interpret as evidence of greater constraints in neighborhoods with strong rental demand. Finally, discriminatory constraints facing minority identities become significantly greater after a property manager receives inquiries from other identities in our sample. While we cannot directly observe outside inquiries made to a given property, this result reinforces illustrates how the incidence and impact of discriminatory behavior can become stronger in the context of competition for rental housing.

Taken together, these results suggest that discriminatory constraints are not uniform in the housing market, and that they may interact with housing search to have important welfare consequences for renters of color. This is, however, a complicated problem. In particular, housing is a multi-dimensional good and discrimination may make housing search more difficult for renters of color in neighborhoods with different combinations of desirable and undesirable attributes. Combining these effects to yield an overall welfare cost requires a set of utility weights over these different attributes. A large literature in economics has been devoted to estimating these weights, both in hedonic and structural sorting model contexts. The models developed in those literatures have, however, ignored the crux of our problem – that, conditional upon income, individuals may not actually have access to all of the seemingly affordable choices, depending upon their race. Recovering utility weights from observed housing decisions therefore requires a model that explicitly accounts for the discriminatory constraints that different renters face. We construct such a model. It uses experimentally identified variation in discriminatory behavior on the part of landlords and leasing agents at the level of the census tract to differentially constrain the choice sets of renters based on their race. In combination with information about the location decisions of actual renters, observed in InfoUSA's Residential Historical Database,[2] our model recovers estimates of utility parameters that are statistically different in economically important ways from the estimates recovered from a naive model that ignores discriminatory constraints.

We use the estimated utility function to model the search process by income-constrained individuals of different races, which allows us to generate monetary measurements of the effects of discriminatory search constraints on the size of the resulting choice set. We measure the equivalent variation in income associated with these constraints for the average renter in our five cities to be 4.5% and 3.8% of the annual incomes for African American and Hispanic/LatinX renters, respectively. Moreover, we find that damages increase substantially at higher levels of income. Heterogeneity in income results from two interacting factors: (1) stronger discriminatory constraints in high amenity and high price neighborhoods (as shown in the reduced form results) and (2) higher marginal utility from those amenities at higher levels of income. The first factor is pronounced in the case of African American renters, who face damages greater than 10% of income at income levels above $100,000 per year. Placed in the context of growing evidence on the long-run impacts of exposure to high/low amenity neighborhoods, these results illustrate a channel through which housing discrimination can create an important potential barrier to intergenerational income mobility. Discrimination restricts access to the very neighborhoods that provide the greatest utility benefits to economically mobile minority households. Put another way, minority households are less able to use increased income to move to neighborhoods with better amenities (e.g., schools, environmental quality) that can have

[2]InfoUSA's Residential Historical Database tracks 120 million households, including renters, between 2006 and 2019. [QUESTION – DO WE WANT TO BRING UP THE PANEL ASPECT OF INFOUSA – WE DON'T USE IT, BUT WE DON'T WANT TO GET ASKED TO USE EXPAND THE ANALYSIS IN SOME WAY TO MAKE USE OF IT.] Data are compiled using 29 billion records from 100 sources including census statistics, billing statements, telephone directory listings, mail order purchases and magazine subscriptions. Data include information about gender, ethnicity, age, address, renter/owner status and estimated household income.

important effects on long-term economic and non-economic outcomes (Graham, 2018). However, we also find evidence that preferences for housing in same-race neighborhoods can mitigate the welfare effects associated with discriminatory constraints for African American renters particularly at higher income levels.

Discrimination drives a wedge between true amenity preferences and those revealed in a (constrained) search. A final section of the paper examines the effects of discrimination on bias in estimated willingness to pay for key neighborhood amenities. Allowing for racial heterogeneity in one component of preferences – marginal utility of income – we find that a naive model that ignores constraints imposed by discrimination significantly understates African American and Hispanic/LatinX amenity preferences relative to those of Whites by approximately 10% while also overstating African Americans' preferences to live in high percentage own-race neighborhoods.

This paper proceeds as follows. Section 2 summarizes a number of relevant literatures on housing discrimination and location choice. Section 3 describes the research design of our correspondence study. In Section 4, we develop a model of housing search to characterize the welfare effects of discrimination. Section 5 describes our data, Section 6 reports results, and Section 7 concludes.

2 The Impacts of Discriminatory Constraints

A large body of research has focused on measuring the incidence and persistence of discrimination in markets and describing the underlying behavioral mechanisms. Evidence from both audit and correspondence studies indicates that housing market discrimination continues to constrain the choices of people of color in the United States (Ewens et al., 2014, Carlsson and Eriksson, 2014, Hanson and Hawley, 2011, Ahmed and Hammarstedt, 2008) and steer them into disadvantaged neighborhoods (Christensen and Timmins, 2018).

By constraining an individual's choice during a search, housing discrimination distorts the sorting outcome away from that associated with true preferences and results in a *ceteris paribus* reduction in welfare. However, most experimental research on discrimination has focused entirely on the reduced-form effect of discriminatory behavior without explicit consideration of how it interacts with the *demand-side* factors that shape choices in a housing search. As a result, the experimental literature on discrimination has generally not provided estimates of the impacts of discriminatory constraints on the welfare of economic agents and on other market outcomes.[3]

The literature provides evidence that disparities in neighborhood effects observed between race groups result from the locational choices of households. For instance, Currie (2011) provides some evidence that the mothers who are most likely to live within the vicinity of a Superfund site after cleanup are more likely to be white and college educated. Similarly, white mothers are less likely to reside within the vicinity of a plant that emits toxic pollutants after emissions are disclosed. While these estimates suggest differential patterns of sorting in response to changes in the level or information about pollution exposures, it is not clear whether all households in these samples had access to the same choices.

Guryan and Charles (2013) review advances in understanding the behavioral mechanisms underlying discrimination but cite a gap in the study of its impact. The ability to disentangle the impact of discriminatory constraints from other factors affecting the sorting behavior of minority households such as income disparities, housing or neighborhood preferences, or other differences is critical for understanding persistent disparities between racial groups that have been revealed in recent research on neighborhood effects (Chetty et al., 2018).

Papers to add:

Sorting: (Ioannides, 2011) (Aliprantis et al., 2018) (Rahman and Foster, 2015) (Bayer and McMillan, 2008) (Bayer and McMillan, 2005) Segregation: (Akbar et al., 2019) Gentrification: (McKinnish et al., 2010)

[3]One exception is (Yinger, 1997), who built on the analysis of Courant (1978) to develop a model of housing search, where real estate agents' discrimination affects the surplus that homebuyers receive through five separate mechanisms: (1) the number of houses shown, (2) the amount of assistance and encouragement received, (3) assistance in the loan application process, (4) loan approval, and (5) physical moving costs. Calibrating the model, he finds that these mechanisms collectively result in a \$4,000 lower expected surplus for black homebuyers from the housing search process.

2.1 Models of Residential Sorting

A long line of research in economics has used the location decisions of renters and owners or the prices that they face to recover preferences for local public goods and neighborhood amenities. Going back to Tiebout (1964), researchers have realized that people "vote with their feet", revealing their willingness to trade-off other consumption for desirable amenities through higher rents, purchase prices, or property taxes. These tradeoffs have become the basis for most work on valuing non-marketed local attributes like environmental quality, public safety, and school quality. These values are used to do cost-benefit analysis of new regulations, and to determine how to best allocate public funds.

Initially, this work was done using the hedonic framework,[4] which has seen a resurgence in the last two decades. In addition, residential sorting models have sought to recover structural preference parameters directly from individual location decisions. Subject to some structural modeling assumptions, modeling those decisions directly allows one to introduce complications (e.g., forward-looking behavior, moving costs, Roy sorting, and random parameters). This literature was summarized by Kuminoff et al. (2013).

Sorting is important to consider in the present context of discrimination for two reasons. First, the literature to this point has mostly ignored discrimination and the constraints that it imposes on the choice set. This is because the data required to incorporate these constraints are not generally available for locations with information about transaction prices and rents, and even information about the families doing the buying and renting.[5] We will recover that information through an experimental sample design and show how it can be used in the the context of consideration sets, developed in the marketing literature and other contexts describing consumer choice sets.

Second, the sorting literature is important because it provides a useful modeling framework. With that framework, it becomes possible to derive utility-based welfare impacts

[4]See Champ et al. (2003) or Palmquist (2005) for a review.

[5]One exception to this statement is Li (2019). Li models the location decisions of households in the 1940's assuming that constraints on purchasing were binding in any census tract that doesn't contain at least one African American owner. This, of course, has the potential to overstate the size of these constraints. [WOULDN'T THIS UNDERSTATE THE SIZE OF THE CONSTRAINT, AS IT ASSUMES THERE IS NO CONSTRAINT IN ANY LOCATION WHERE AT LEAST ONE AFRICAN AMERICAN OWNER, EVEN THOUGH THERE PROBABLY WAS?]

(i.e., equivalent variations in income) of discrimination over multi-attribute residential units. In addition, with these models we are able to show how individual heterogeneity in preferences and income can interact with discrimination to either mask its welfare impacts or make them worse.

2.2 Consideration Sets

A substantial literature in marketing considers consumers who choose over large choice sets for retail goods. Noting that the costs of search increase with every new product that enters the choice set, but that the expected utility of the marginal expansion of the choice set is decreasing (Stigler, 1961), these papers argue that consumers will rationally constrain the set of options they consider before expending energy in a careful search (Pancras (2010), Draganska and Klapper (2011), Kim et al. (2010)). To identify the constraints on the choice set, most of the papers in this literature either use some sort of instrument that can be argued to affect consumers' attention to different products without affecting utility from consuming it (e.g., advertising),[6] or some auxiliary data source (e.g., marketing survey) that identifies the actual choice sets.[7] We draw upon this literature for the estimation techniques to deal with constrained choice sets, although in our setting these constraints do not arise because of limited information or a response to search costs.[8] Rather, they are the result of exogenously imposed constraints imposed by the lack of response from landlords in our experiment.

3 Experimental Design of the Correspondence Study

A large and growing literature utilizes field experiment techniques to detect discrimination. Bertrand and Duflo (2017) summarize this literature, focusing on the difference

[6]See Goeree (2008), Moraga-González et al. (2015), Koulayev (2009), and Gaynor et al. (2016)
[7]Abaluck and Adams (2016) consider an identification strategy based on asymmetric cross derivatives.
[8]In particular, we do not consider the constraints that individuals might impose upon themselves in response to costly search, assuming that search is relatively easy in the online environment that we focus on and that individuals can continue to send inquiries until they have found a suitable residence. To the extent that search costs matter in this environment, our results will present a lower bound on welfare effects.

between audit and correspondence studies. Audit studies typically utilize a matched-pair randomized design, where a pair of actors or "testers", differing only in the characteristic of interest (e.g., race), is sent into the field to carry out an economic activity. In a correspondence study, fictitious applicants correspond only by mail or via online platform. Correspondence studies have been used to study labor market discrimination related to race and ethnicity. One of the best known studies used fictitious resumes sent in reply to help-wanted ads in Boston and Chicago newspapers, differing by racialized name (Bertrand and Mullainathan, 2004). White names received 50% more callbacks, while better observable resume attributes reduced the negative callback effects of black names, suggesting statistical discrimination. Correspondence studies have subsequently been used to study discrimination in other aspects of the labor market, including race and ethnicity (McGinnity et al., 2009, Baert et al., 2015, Booth and Leigh, 2010, Maurer-Fazio, 2012, Galarza et al., 2014), 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 housing rental markets, correspondence studies have analyzed the role of race and ethnicity (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). Correspondence studies have also been used to study discrimination in ride-sharing services (Ge et al., 2016).

Our experiment utilizes a paired (tripled) experimental design that identifies differences in responses to inquiries for rental housing through correspondence on a major online platform. We isolate the effect of racial identity associated within a set of inquiries by varying first and last names that are associated with each of three racial groups. First, name labels for this study are constructed using the work of (Gaddis, 2017a, 2017b), 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).

The paired experimental design utilized in this study requires that inquiries for each listing are made from each of the three racial groups that we study. We have designed a bot that searches rental housing listings on a major online realty platform.[9] Immediately following compilation of the relevant listings in a given market,[10] an inquiry is sent by the bot to each using a randomly assigned name drawn from each of the three racial groups. Each rental apartment therefore receives three separate inquiries in the course of an experimental trial (one from each group). Our software is designed to ensure that inquiries for the same listing will never be sent from two race groups on the same day. Table 1 reports the results of balance tests for the correspondence study. Estimates indicate that the inquiries are balanced on sequence (first, second third), day of week, and the gender/maternal educational attainment of renter identity.

Responses from property managers are captured in email (i.e., Gmail addresses associated with each name), phone messages (i.e., individual "burner" phone numbers associated with each name), and text messages. Phone, text, and email responses from property managers are recorded by a team of human coders to assure the quality of the data. The time stamp, message length, and information about the sentiment of responses are coded for each response.

The full set of 3 bedroom, 2 bathroom rental listings are compiled for five major housing markets in the United States. As these apartments are more likely to be rented to families, this is a relevant market segment for consideration of the impact of discrimination on pollution exposures during critical periods of human development as well as for the impact of school quality and broader effects on intergenerational mobility.

The experimental component of our study is designed to first yield a set of tests of the reduced-from effects of racialized perceptions of first and last names on responses to inquiries made on an online realty platform from different renter-types and regarding different neighborhood amenities. Second, we use these data to structurally estimate the

[9] In particular, our study is implemented with a software stack and compute infrastructure designed by Christensen's team at the National Center for Supercomputing Applications.

[10] The rent, address, apartment characteristics, and information on neighborhood amenities (crime, school ratings, local amenities) are scraped and recoreded by the bot.

welfare effects of constraints placed on the choice sets of different groups. Specifically, after having collected information on responses to inquiries at each property in a given market and market segment for one member of each race group, we use a random utility choice model to analyze welfare implications of discrimination for the search process. That model is described in the following section.

4 Model

4.1 Experimental Estimates of Choice Constraints

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

$$P(response_{il}) = \beta RaceGroup_i + \theta X_i + \alpha_l + \epsilon_{il} \tag{1}$$

where $race$ indicates the race group associated with the identity from which an inquiry is sent. X_i is a vector of inquiry-specific control variables: gender, education level and the order in which the inquiry was sent.

4.2 Model of Housing Search

We next go on to model the housing search process for renters who vary in income and preferences for key neighborhood attributes. Welfare implications of discrimination are filtered by a search process. Buyers and renters optimally choose housing units based on preferences and income. Discriminatory behavior may differ by market segment. Using a large data set describing the location decisions of actual renters,[11] we estimate utility

[11]In particular, these data come from InfoUSA's residential historical dataset. InfoUSA Consumer database tracks 120 million households and 292 million individuals between 2006 â 2017, and is maintained using 29 billion records from 100 sources including census statistics, billing statements, telephone directory listings and mail order buyers/magazine subscriptions. Unique identifiers assigned to each individual and to each household allow one to follow them over time. Importantly, InfoUSA includes information about renters. Gender, ethnicity, age, address, renter/owner status and estimated household income and wealth.

function parameters for neighborhood attributes, allowing experimental variation in discriminatory behavior across properties to differentially constrain the choice sets of the renters (based on their race) that choose those exact properties. This welfare-theoretic approach also allows us to simultaneously account for impacts of discrimination on multiple neighborhood characteristics that may be traded-off for one another in the minds of property managers and renters. We are then able to generate monetary measurements of the effects of search constraints on the size of the resulting choice set, and to determine how those measurements vary across race groups and income. We begin by considering the utility of individual i choosing to live in tract j:

$$U_{i,j} = \alpha ln(I_i - R_j) + X_j'\gamma_i + \epsilon_{i,j} \tag{2}$$

where

I_i = monthly income of household i (in \$1000's)

R_j = monthly rent (in \$1000's) associated with housing units in tract j

X_j = attributes of census tract j

$\epsilon_{i,j}$ = idiosyncratic utility shock for household i associated with census tract j

Assuming that $\epsilon_{i,j} \sim$ $i.i.d.$ Type I Extreme Value, the probability that renter i will choose location j is given by:

$$P_{i,j} = \frac{exp\left[\alpha ln(I_i - R_j) + X_j'\gamma\right]}{\sum_k exp\left[\alpha ln(I_i - R_j) + X_k'\gamma\right]} \tag{3}$$

A substantial literature in marketing considers consumers who choose over large choice sets for retail goods. Noting that the costs of search increase with every new product that enters the choice set, but that the expected utility of the marginal expansion of the choice set is decreasing (Stigler 1961), these papers argue that consumers will rationally constrain the set of options they consider before expending energy in a careful search (Pancras, 2010, Draganska and Klapper, 2011, Kim et al., 2010). To identify the constraints on the choice set, most of the papers in this literature either use some sort of instrument that can be argued to affect consumers' attention to different products without affecting their utility from consuming them (e.g., advertising), or some auxiliary data source (e.g., marketing survey) that identifies the actual choice sets. We draw upon this literature for the estimation techniques to deal with constrained choice sets, but in our setting these constraints do not arise because of limited information or a response to search costs. Rather, they are the result of exogenously imposed constraints imposed by the lack of response from landlords in our experiment.[12]

Using these probabilities, we are able to write down the choice probability for any consideration set associated with renter i, Γ_i:

$$P_{i,j}|\Gamma_i = \frac{exp\left[\alpha ln(I_i - R_j) + X_j'\gamma\right]}{\sum_{k\in\Gamma_i} exp\left[\alpha ln(I_i - R_j) + X_k'\gamma_i\right]} \tag{4}$$

In this expression, i's choice, $j^*(i)$, must be an element of Γ_i. Our experiment identifies consideration sets probabilistically. We simulate N_s consideration sets and take the associated expected probability:

$$E[P_{i,j}] = \sum_{s=1}^{N_s}\left(\frac{exp\left[\alpha ln(I_i - R_j) + X_j'\gamma\right]}{\sum_{k\in\Gamma_{i,s}} exp\left[\alpha ln(I_i - R_k) + X_k'\gamma_i\right]}\right) W_{i,s} \tag{5}$$

where

$$W_{i,s} = \frac{P(\Gamma_{i,s})}{\sum_{m=1}^{N_s} P(\Gamma_{i,m})} \tag{6}$$

and

$$P(\Gamma_{i,s}) = \Pi_{j=1}^{J}\rho_{i,j}^{\chi_{i,j,s}}(1-\rho_{i,j})^{1-\chi_{i,j,s}} \tag{7}$$

$\chi_{i,j,s} = 1$ if j is included in i's simulated choice set s and $\rho_{i,j}$ is the race-specific response probability for an individual i in tract j.[13] $W_(i,s)$ is a weight reflecting the likelihood

[12] One could also model renters as facing additional constraints imposed by search costs unrelated to discrimination. We ignore these costs in the current analysis; to the extent that they do not vary by race, they would simply increase the overall magnitude of the welfare costs associated with discrimination, implying that our estimates are a lower bound.

[13] Owing to computational constraints imposed by the consideration set model described below, we model the renter's choice as over the census tract. In calculating the probability of receiving a response from a landlord at the census tract level, we adjust for the number of rental units available in that tract at the time at which our data were collected, assuming that the responses from each observed unit in the tract

that consideration set s, $\Gamma_{i,s}$, would be available. We then maximize the log-likelihood function based on these probabilities:

$$L = \sum_{i=1}^{N} lnE[P_{i,j^*(i)}] \tag{8}$$

where $j^*(i)$ refers to the observed census tract choice of individual i.

This structural approach to modeling utility serves two purposes. First, it provides a convenient tool for modeling housing as a multi-dimensional commodity. In particular, we are interested in the extent to which discrimination in the search process affects not only the quantity, but also the quality of the units that end up in the renter's post-search choice set. There may be tradeoffs between housing attributes – e.g., a unit may provide good public safety but poor schools. In order to add up these possibly offsetting effects, we require a set of utility weights. These are conveniently provided by the estimates from a residential sorting model. Second, our random utility choice framework allows us to simulate an actual search process. This is important, because the impacts of discrimination in the online search environment come in the form of an impact on a choice set. The random utility framework provides a convenient tool for modeling the welfare effects of alterations to the choice set. We are able to summarize the impacts in welfare-theoretic terms (i.e., compensating variation in income) and then use the model to ask how that welfare measure would change in counterfactual search environments. The difficulty with this exercise is in recovering preference parameters in the presence of discrimination. Normally, models of residential location choice (including property value hedonic models) assume that individuals have the entire range of options available to choose from. Our experimental evidence suggests that this is not the case, and we need to build this into our model directly.

are independent events. This means that the tract-level response probability in a tract with two units is *** while in a tract containing 10 units, that probability would be ***.

4.3 Measuring Welfare

An advantage of the structural modeling approach used in the previous section is that we can derive utility-theoretic measures of renter welfare associated with the constraints imposed by discrimination. In particular, the expected utility associated with the full (unconstrained) set of all census tracts is given by:

$$EU_i = log\left(\sum_{k=1}^{J} exp\left[\alpha ln(I_i - R_j) + X_j'\gamma\right]\right) \tag{9}$$

Alternatively, the expected utility associated with constrained choice sets is given by:

$$\tilde{EU_i} = log\left(\sum_{s=1}^{N_s} W_{i,s} \sum_{k\in\Gamma_{i,s}} exp\left[\alpha ln(I_i - R_j) + X_j'\gamma_i\right]\right) \tag{10}$$

We can therefore calculate the equivalent variation in income (EV_i) associated with choice set constraint using the following equality:

$$log\left(\sum_{k=1}^{J} exp\left[\alpha ln(I_i + EV_i - R_j) + X_j'\gamma\right]\right) = log\left(\sum_{s=1}^{N_s} W_{i,s} \sum_{k\in\Gamma_{i,s}} exp\left[\alpha ln(I_i - R_j) + X_j'\gamma_i\right]\right) \tag{11}$$

5 Data

5.1 Data from Responses

5.2 Census Data on Renters

In order to characterize population information about census tracts, we collect data from the 2013-17 five-year average ACS, a 1% sample of the total population (Ruggles et al., 2017). We limit the sample to data describing household heads who are renters from the five MSA's currently under consideration – Atlanta-Sandy Springs-Roswell, GA, Houston-The Woodlands-Sugar Land, TX, Philadelphia-Camden-Wilmington PA-NJ-DE, San Jose-Sunnyvale-Santa Clara CA, and Cleveland-Elyria OH.

[ADD TABLE TO SUMMARIZE INCOMES]

5.3 Rental Unit and Neighborhood Attributes

Rental unit and neighborhood characteristics are scraped from online realty platform at the time when inquiries are sent. Note that we only consider 3 bedroom - 2 bathroom rental units.

- House Type:
- Squre Footage
- Monthly Rent
- Public Safety: Assaults and Burglaries
- Average School Quality (Elementary, Middle and High School)
- Neighborhood Amenities: Cafes

Pollution (RSEI and PM2.5 concentrations) are collected from EPA websites and from satellite data.[14]

[ADD SOME FIGURES AND TABLES DESCRIBING RENTAL UNIT AND NEIGHBORHOOD ATTRIBUTES]

6 Results

Our initial results explore the effect of race on the likelihood of a response from the representative of a particular rental property, and how that likelihood differs with tester and neighborhood characteristics.

6.1 Reduced Form Estimates: Choice Constraints

In this section, we report reduced-form estimates of choice constraints in terms of relative response rates obtained from equation 1.[15] Table 2 reports estimates for each of

[14]https://www.epa.gov/rsei and http://fizz.phys.dal.ca/ atmos/martin/?page$_i d = 140$.

[15]Table 7 reports estimates with increasing controls for tester attributes (i.e. gender and education) in columns 1-4. Randomization of the inquiry process across the 18 identities in the sample ensures that the

the five housing markets (MSAs) included in the study and for the full sample. The top row reports estimates for minority identities, which combines both African American and Hispanic/LatinX identities. Estimates for the two minority race groups are broken out in the two rows below. At the bottom of the table, the average response rate for White identities (comparison group) are reported, along with the total observations (inquiries) and number of observations associated with properties that yielded an asymmetric response.

These estimates indicate evidence of discriminatory constraints facing both minority groups in each of the markets in the sample. We estimate that relative response rates for minority identities are 68.7%, indicating that a minority identities in our sample have a 31% lower likelihood of accessing a rental property that is listed in the 5 MSAs that we study at the time of our experiment. This is relative to a 43.4% response rate for inquiries from white identities. Estimates reported in columns 2-6 indicate substantial heterogeneity both in baseline response rates and in discriminatory constraints across MSAs, with the lowest relative response rates (52.7%) found in Philadelphia and the highest found in Cleveland (74.5%). We observe even greater heterogeneity in response rates by race group, with the lowest and highest relative response rates observed for inquiries from African American renters – 35.8% in Philadelphia and 88.8% in Houston. Three of the group-specific estimates are not statistically significant when broken out by minority group. In Houston and Atlanta, relative response rates are higher on average for African American than Hispanic/LatinX identities. In Philadelphia, Cleveland, San Jose, they are higher for Hispanic/LatinX identities.

6.2 Heterogeneity in Choice Constraints

The estimates above indicate that discriminatory constraints vary substantially across MSAs in the United States. In this section, we report the results of reduced form tests that

only difference between white and non-white testers is in the information conveyed by names. Attribute controls should have no effect. Estimates for minority identities indicate that estimates are robust across the sets of controls, including when broken out for African American or Hispanic testers. Attribute controls do increase the precision of estimates and are used throughout the analysis. A comparison of estimates on columns 4 and 5 indicates that within-listing estimates of relative response rates are slightly, but not significantly, different from response rates estimated from between-listing (using only first inquiries).

examine heterogeneity in constraints across neighborhoods within an MSA. In particular, estimates plotted in Figure 2 examine whether discriminatory constraints reduce the access of minority renters to property choices that confer greater amenity levels.[16] Each subfigure plots differences in relative response rates for properties that fall above or below the median level of a given attribute. While we lack the power that would be needed to detect statistical differences in response rates at high versus low amenity levels, the estimates above suggest that discriminatory constraints are generally stronger among properties that have higher rental prices, highly rated schools, fewer local point sources of chemical toxics (plants reporting emissions to the EPA Toxics Release Inventory), lower numbers of assaults, and higher average incomes in the neighborhood. On average, there is little evidence of differences in discriminatory constraints at high/low levels of PM2.5 concentrations. Properties that have greater access to nightlife have lower response rates.

One possible explanation is that discriminatory constraints are stronger in neighborhoods with strong demand. In markets with excess demand, models of animus-based, taste-based, and attention discrimination all predict that it could be more costly to respond uniformly to all applicants and the opportunity cost associated with losing a prospective applicant may be lower. Estimates reported in Table 4 dig deeper by comparing response rates for properties that have been on the market for 0-3 days, 3-7 days, and 7+ days. For both minority groups, we find evidence of stronger discriminatory constraints when sending inquiries to recently listed properties. Among properties that have been listed for less than 3 days, the relative response rate to an inquiry from a minority identity is 45.1%. It increases to 70% between 3-7 days and 77.5% after 7 days. Estimates and column 2 indicate that the patterns are similar across both of the minority race groups.

In Table 3, we go further by examining heterogeneity in response rates across trials where a minority identity sends the first, second, or third inquiry (these are each compared to the response rate to a white identity that sends a first inquiry). Column 1 shows that, in the average listing in the sample, the relative response rates to inquiries

[16] refer to Figures 12 and 13 for estimates broken our by race group.

sent from minority identities fall substantially – from 55.3% when first, to 36.0% when second, to 25.2% when third in the sequence. Columns 2 and 3 show that this pattern is consistent across neighborhoods with above-median shares of white and above-median shares of minority households, although discriminatory constraints are always stronger in neighborhoods with higher shares of white households. These patterns suggest that response rates for minority applicants diminish substantially in the presence of interest from other applicants.

6.3 Structural Model Estimates

Table ** reports results of our model of residential location choice, incorporating the choice set constraints imposed by discrimination. Estimates are statistically significant. For easier interpretation, they can be combined to yield measures of marginal willingness-to-pay for a one unit increase in the neighborhood attribute in question, measured as a percentage of income. We begin with our utility function for individual i living in census tract j:

$$U_{i,j} = c_i^{\alpha} e^{X_j' \gamma_i + \epsilon_{i,j}} \tag{12}$$

where γ is subscripted by i because individuals are only given a preference for their own-race share in location j (i.e., homophily preferences); preferences for other local attributes are common across race groups. Recognizing that $c_i = I_i - R_j$ given the individual's budget constraint, marginal willingness to pay (MWTP) for X_j is given by the following expression:

$$MWTP = \frac{\frac{\partial U}{\partial X}}{\frac{\partial U}{\partial C}} = \frac{\gamma}{\alpha}(I_i - R_j) \tag{13}$$

Dividing by I_i yields a convenient expression for MWTP as a share of income:

$$\frac{MWTP}{I_i} = \frac{\gamma}{\alpha}\frac{(I_i - R_j)}{I_i} = \frac{\gamma}{\alpha}(1 - s_H) \tag{14}$$

where s_H is the share of household income spent on rent. For instance, in the case of school quality, $\alpha = 0.637$ and $\gamma = 0.076$. For a household that consumes 20% of income on rent, this would imply a willingness to pay of 9.5% for a one-unit improvement in average school quality. For a household spending 70% of its income on rent, this would imply a willingness to pay of 3.6% of income. Figure ** describes how rent as a percentage of income varies with income (and race?).

We report WTP measures for all attributes below in a comparison of results with and without controls for consideration sets. At this point, we simply note that all utility function parameters have the anticipated signs and that magnitudes are reasonable.

6.3.1 Experimental Design

Two primary motivations for estimating a structural model of residential location choice with discrimination constraints are (i) the ability to combine the effects of discrimination on the consumption of a wide array of neighborhood amenities into a single measure of welfare, and (ii) the ability to explore the interaction between the sorting process and discriminatory constraints. In particular, we are interested in the extent to which heterogeneity in income and preferences alters the neighborhoods in which individuals search, and the extent to which this can accentuate or dilute the impacts of the discrimination.

We use our structural model to carry out an experimental exercise designed to isolate the effect of discrimination. In particular, we simulate the search behavior of a set of African American and Hispanic/LatinX renters using random draws from actual race- and city-specific income distributions. We then consider the welfare effects associated with search for these same renters, but confronting them with the response probabilities that we recovered for White renters. This exercise holds constant all other aspects of their search that are race specific – in particular, those associated with income and own-race (i.e., "homophily") preferences, allowing us to isolate the effects of discriminatory constraints.

We quantify these effects using the equivalent variation in income associated with the constraints imposed by discrimination, defined in equation (**). This measure incorporates the underlying search process. In particular, we calculate welfare measures for a simulated population of 5,000 residents of each race group in each city using either the

African American or Hispanic/LatinX income distribution for each city for all individuals. We begin by drawing their incomes from race-and-city specific income distributions. We perform this exercise first integrating over consideration sets to reflect the constraints imposed by discrimination. We next simulate welfare values if every individual had always had every census tract available regardless of race. We then ask what change in each individual's income in the second scenario would yield a change in utility equivalent to that imposed by the discriminatory constraints. Figure 4 reports the distributions of equivalent income variations associated with discriminatory constraints as a share of annual income. For African Americans, the median value is -3.6% compared to -2.6% for Hispanic/LatinX renters, although both distributions have long left tails with values over -20%. Figure 5 shows how EV varies with income for the two groups of renters of color. In both cases, welfare costs rise with income, although this is particularly true for African Americans. This result holds both in absolute terms and as a percentage of income, and reflects the fact that higher income renters of color, by virtue of the set of houses they are searching over, end up facing a greater welfare cost from discrimination. Figure 6 shows these effects as a percentage of income. Histograms show clearly that the mass of welfare effects moves to the left as income rises for African Americans, with a median value of approximately -3% for those with income in the 0-30K range, rising to -12% for those in the 120-150K range. For Hispanic/LatinX, we see that, while the distribution stretches out to the left, the effect on the median renter does not vary greatly with income, suggesting that discrimination as a barrier to upward mobility is primarily a concern for African Americans.

Figure 7 illustrates how welfare effects differ with hompohily preferences. Here, the idea is that, to the extent that African American or Hispanic/LatinX renters forcus their searches on neighborhoods with a similar racila composition, they may avoid discrimination's harmful welfare effects. Figure Â¶ reports EV with homophily preferences zeroed out as a percentage of baseline welfare effects. [REPLACE FIGURE 7 WITH BAR GRAPH SHOWING PERCENTAGE CHANGE IN EV WHEN HOMOPHILY EFFECTS ARE ELIMINATED AT EACH INCOME BIN] On average, eliminating the homophily preference increases EV by **% for African Americans and by **% for Hispanic/LatinX, suggesting that a preferences for similar neighbors steers renters (particularly high income African American renters) away from discriminatory behavior on the part of landlords.

6.4 Discrimination and the Bias in WTP Measurement

To this point, we have focused on the ways in which search can be used to better measure the costs of discrimination. In this section, we demonstrate that failing to account for discrimination can lead to biased estimates of the parameters underlying housing search behavior. This is important, as decisions in the housing market have been used for decades to measure the values placed on non-marketed local public goods and neighborhood amenities. These values are used to guide decisions about allocation of public resources and to measure benefits for cost-benefit analysis of regulatory policy. If biases in these estimated values are correlated with race, discrimination could have important distributional consequences.

The intuition for this bias is straightforward. Housing markets are used to place values on local public goods and amenities by looking at how much more households are willing to pay to live in a neighborhood with a marginally better attribute (e.g., lower crime rates) compared to an otherwise similar neighborhood with higher crime rates. Bias would arise if people of color are systematically excluded from neighborhoods with nicer amenities. The naive model would assume that they simply have low willingness-to-pay for those amenities.

With our experimental data and consideration set model, we are able to estimate WTP measures that incorporate choice set constraints. We can then compare these to results of a naive model that ignores these constraints. In order to demonstrate the particularly important role that these biases might play, we re-estimate using a specification that allows for limited heterogeneity in MWTP for all amenities based on race. In particular, we allow the coefficient on c_i in the utility function to be different for White, African American and Hispanic/LatinX renters. This coefficient plays a key role in that all marginal willingness to pay measures incorporate it in the denominator of the calculation described in equation (**). Formally, we estimate the following utility function:

$$U_{i,j} = c_i^{\alpha_k} e^{X_j' \gamma_i + \epsilon_{i,j}} \tag{15}$$

where $k = [W, A, H]$. The formula for willingness to pay as a percentage of after-housing income is then given by:

$$\frac{MWTP}{I_i} = \frac{\gamma}{\alpha_k}(1 - s_H) \tag{16}$$

Results of the estimation are reported in Table **, and are consistent with those reported above in our main specification with similar signs, magnitudes, and significance levels. Focusing on the α_k parameters, we see that ignoring consideration sets increases the disparity between White renters and renters of color (particularly for Hispanic/LatinX renters). This will have the effect, *ceteris paribus* of increasing reducing measures of MWTP for renters of color relative to their White counterparts. In order to demonstrate this, we consider the following. Take the raio of MWTP without and with consideration sets for each race group for each common amenity – e.g., school quality, cafes, crime, and air pollution (we come to homophily preferences below).

$$\mu_k^{NCS} = \frac{\gamma^{NCS}}{\alpha_k^{NCS}}(1 - s_H) \quad \mu_k^{CS} = \frac{\gamma^{CS}}{\alpha_k^{CS}}(1 - s_H) \tag{17}$$

$$\rho_k = \frac{\mu_k^{NCS}}{\mu_k^{CS}} = \frac{\gamma^{NCS}}{\gamma^{CS}} \frac{\alpha_k^{CS}}{\alpha_k^{NCS}} \tag{18}$$

ρ_k describes the percentage over/under-statement of MWTP for group k from failing to account for the effect of discrimination on the choice set. Taking the ratios of ρ_k between renters of color and White renters, we see the effects of ignoring discrimination on the relative estimates of MWTP:

$$\frac{\rho_A}{\rho_W} = 0.924 \qquad \frac{\rho_H}{\rho_W} = 0.901 \tag{19}$$

Ignoring the constraints imposed by discrimination leads to a 7.6% understatement of MWTP for African Americans and a 9.9% understatement of MWTP for Hispanic/LatinX renters, relative to White renters. [NOTE – WE HAVE NOT REPORTED THE VALUES OF μ OR ρ HERE, BUT WE COULD. THE THING THAT MIGHT BE COMPLICATING IS THAT THE MWTP GENERALLY GOES UP FOR ALL GROUPS WHEN WE IGNORE CONSIDERATION SETS – IT JUST GOES UP BY MORE FOR WHITE RENTERS THAN IT DOES FOR RENTERS OF COLOR. IGNORING THIS MIGHT BE MORE COMPLICATING THOUGH.]

Finally, we consider the effect of ignoring consideration sets on estimates of homophily preferences. Here, the direction of bias that one would expect is in the direction of overstating preference for one's own racial group when one is steered into that group by discriminatory constraints on one's choice set. Describing this bias is more complicated than doing so was in the case of the common amenities, as preferences for the share of each race group are race specific and (owing to non-linearity of the way in which race shares enter preferences) they vary with the level of the race share. Figure ** therefore describes the MWTP for an incremental increase in the share of own-race for each race group, both with and without consideration sets, along with 95% confidence intervals. In each case, MWTP declines with increasing own-race share and is greater at every level of own-race share when consideration sets are ignored. This is consistent with our priors. However, only in the case of African American renters is this different statistically signficant. Own-race shares are commonly treated as an amenity in models of residential location decisions, and these results suggest that, particularly in the case of African Americans, these preferences may be significantly overstated.

7 Conclusions

The literature on discrimination has largely ignored two things: (1) the fact that housing is a multi-dimensional good, and (2) the role of search. A unit of housing is made up of many attributes including the structure itself along with many features of the surrounding neighborhood. In order to measure the welfare effects of discrimination, we need a way to combine the impacts of choice set constraint on many different attributes (i.e., utility weights). Typically, this has been hard to do because constraints are not explicitly observed. We overcome this problem by running an experiment. [ADD SUMMARY OF REDUCED FORM RESULTS]

Unlike previous studies that have run experiments on the housing search process, we combine these data with a utility-based structural model of housing search, drawing upon estimation techniques developed in the marketing literature to describe limited choice sets. [ADD MORE ABOUT METHODOLOGY]

Our structural estimation approach allows us to derive utility-theoretic measures of welfare cost associated with the choice set restrictions imposed by discrimination. [ADD SOME SUMMARY OF SIMPLE WELFARE EFFECTS]

In terms of search, income and preferences guide the neighborhoods where households target their search. In the logit framework, this means that they put higher probability on choosing those locations, and weight them more heavily in calculating expected utility. In order to measure the impact of search, we need a structural representation of utility and how it enters the residential choice process. With this, we can "turn off" various components of preferences, or give individuals counterfactual draws from a common income distribution. Doing so, we find that strong preferences for low crime, good schools, college educated neighbors and a vibrant nightlife all increase the costs of discrimination for people of color. Having a high income has a similar effect.

Finally, we see that homophily preferences are also responsible for masking the welfare consequences of discrimination. Preferences that induce households to seek out neighbors of their own race group, reduce the welfare impacts on black households, as these preferences move them towards neighborhoods that they are being steered towards by discrimination.

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Table 1. Balance Statistics

(Panel A) Inquiry Order

	Dependent Variable: Inquiry Sent		
	First	Second	Third
Hispanic	0.0152	−0.0432	0.0280
	(0.0450)	(0.0453)	(0.0455)
Black	−0.0280	−0.0152	0.0432
	(0.0455)	(0.0450)	(0.0453)
Observations	8,775	8,775	8,775
Note:			*p<0.1; **p<0.05; ***p<0.01

(Panel B) Evidence of Differential Choices by Weekday

	Dependent Variable: Inquiry Sent				
	Mon	Tues	Wed	Thurs	Fri
Hispanic	0.0931	−0.0830	0.0277	−0.0143	−0.0086
	(0.0966)	(0.1019)	(0.0607)	(0.0564)	(0.0587)
Black	0.0476	0.0439	−0.0094	−0.0402	0.0017
	(0.0976)	(0.0988)	(0.0612)	(0.0567)	(0.0585)
Observations	8,775	8,775	8,775	8,775	8,775
Note:					*p<0.1; **p<0.05; ***p<0.01

(Panel C) Gender and Mother's Education Level

	Dependent Variable: Inquiry Sent				
	Male	Female	Low Education	Medium Education	High Education
Hispanic	−0.0057	0.0057	−0.0394	0.0609	−0.0213
	(0.0534)	(0.0534)	(0.0550)	(0.0552)	(0.0551)
Black	−0.0128	0.0128	−0.0333	0.0458	−0.0121
	(0.0534)	(0.0534)	(0.0550)	(0.0553)	(0.0551)
Observations	8,775	8,775	8,775	8,775	8,775
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 2. Evidence of Discrimination on Housing Choice by City

Race Group	(1) All Cities	(2) Atlanta	(3) Houston	(4) Philadelphia	(5) Cleveland	(6) San Jose
Minority	0.6865***	0.6519***	0.7940***	0.5274***	0.7450***	0.6088***
	(0.6250 - 0.7541)	(0.5370 - 0.7912)	(0.7045 - 0.8949)	(0.4043 - 0.6880)	(0.6311 - 0.8796)	(0.5155 - 0.7190)
Hispanic	0.7437***	0.6262***	0.7114***	0.7828	0.7896	0.7326***
	(0.6648 - 0.8318)	(0.4853 - 0.8081)	(0.6396 - 0.7913)	(0.5794 - 1.0576)	(0.6079 - 1.0257)	(0.6049 - 0.8873)
African American	0.6342***	0.6806***	0.8876	0.3582***	0.7028***	0.5162***
	(0.5629 - 0.7145)	(0.5526 - 0.8383)	(0.7680 - 1.0258)	(0.2581 - 0.4972)	(0.6192 - 0.7975)	(0.4320 - 0.6168)
Mean Choice (White)	0.434	0.347	0.173	0.528	0.459	0.692
Observations	5,451	1,128	792	402	1,506	1,623
Total obs	18045	3093	4710	972	4254	5016

Robust cieform in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3. Discriminatory Constraint by Inquiry Sequence

Group	(1) Full Sample	(2) White Neighborhoods	(3) Minority Neighborhoods
Minority-1st	0.5532***	0.3149***	0.5959***
	(0.4418 - 0.6926)	(0.1898 - 0.5224)	(0.4505 - 0.7883)
Minority-2nd	0.3596***	0.2004***	0.4352***
	(0.2654 - 0.4873)	(0.1164 - 0.3451)	(0.2860 - 0.6624)
Minority-3rd	0.2519***	0.1598***	0.2851***
	(0.1840 - 0.3449)	(0.0984 - 0.2596)	(0.1868 - 0.4353)
White-2nd	0.4030***	0.2821***	0.3727***
	(0.3058 - 0.5311)	(0.1560 - 0.5104)	(0.2520 - 0.5513)
White-3rd	0.3334***	0.1899***	0.3417***
	(0.2356 - 0.4719)	(0.1000 - 0.3604)	(0.2117 - 0.5516)
Observations	3,828	903	978
Total obs	13029	3243	3276
Mean Choice (White)	0.334	0.334	0.334

Robust cieform in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Columns 1-3 report estimates of relative response rates to inquiries that were the first, second or third in the sequence, relative to response rates to a first inquiry that is sent from a White identity (the omitted category). Estimates in Columns 2-3 split the sample into listings in census block groups where the share of White households is above or below the median within the MSA. Standard errors are clustered at the MSA level. 90% confidence intervals are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4. Discriminatory Constraint by Days on Market

Race Group	(1) odds ratio	(2) odds ratio
Hispanic: 0-3 Days		0.4213*
		(0.2001 - 0.8870)
Hispanic: 3-7 Days		0.6842**
		(0.5333 - 0.8778)
Hispanic: 7+ Days		0.8157**
		(0.7092 - 0.9382)
Black: 0-3 Days		0.4813
		(0.2262 - 1.0243)
Black: 3-7 Days		0.7137
		(0.4323 - 1.1783)
Black: 7+ Days		0.7362***
		(0.6109 - 0.8873)
Minority: 0-3 Days	0.4511*	
	(0.2249 - 0.9050)	
Minority: 3-7 Days	0.6988**	
	(0.5194 - 0.9402)	
Minority: 7+ Days	0.7752***	
	(0.6802 - 0.8834)	
Observations	3,828	3,828
Total obs	13029	13029
Mean Choice (White)	0.334	0.334

Robust cieform in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Columns 1-2 report estimates of relative response rates for properties that, as of the beginning of a trial, were on the market for 0-3, 3-7, or greater than 7 days. Estimates in Column 1 pool all minority identities, while estimates in Column 2 report group-specific effects. split the sample into listings in census block groups where the share of White households is above or below the median within the MSA. Standard errors are clustered at the MSA level. 90% confidence intervals are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

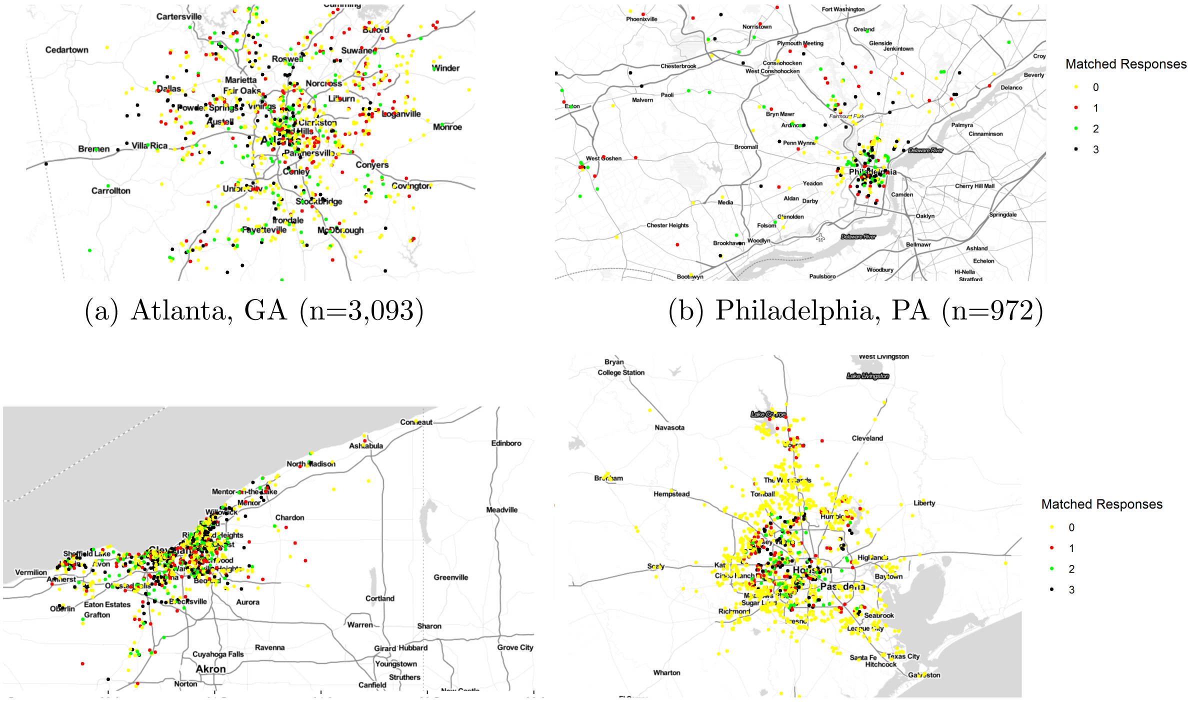
Table 5. Parameter Estimates

Parameter	Coef	Std. Error	T-Stat
ln(I-R)	0.637	0.0210	30.771
$(HHI/10000)^2$	−0.017	0.0001	−162.449
School Quality	0.076	0.0044	17.183
Cafes	0.010	0.0003	38.234
High Burglary	-0.428	0.0282	−15.181
High Assaults	-0.365	0.0290	-12.577
Toxics Concentrations (RSEI)	−0.080	0.0310	−2.587
PM2.5	−0.053	0.0000	−8272.381
White $*$% White	0.063	0.0013	50.045
White $*$% White^2	-0.00046	0.00000	-40.623
Black $*$% African American	0.062	0.0000	13283.744
Black $*$% African American^2	-0.0000	0.00002	-60.111
Hisp $*$% Hispanic	0.041	0.0000	10272.263
Hisp $*$% Hispanic^2	-0.0005	0.0000	-−43.063
Inc(I)*(HHI/10000)	0.0035	0.0000	314.455

Table 6. Parameter Estimates

Parameter	Consideration Sets	No Consideration Sets
African American: ln(I-R)	0.6218	0.5542
	(0.0441)	(0.0314)
Hispanic: ln(I-R)	0.6896	0.6305
	(0.0565)	(0.0438)
White: ln(I-R)	0.6176	0.5087
	(0.0357)	(0.0273)
$(HHI/10000)^2$	-0.0159	-0.0158
	(0.0002)	(0.0002)
Inc(I)*(HHI/10000)	0.0035	0.0035
	(0.0000)	(0.0000)
School Quality	0.0715	0.0717
	(0.0046)	(0.0044)
Cafes	0.0088	0.0131
	(0.0003)	(0.0002)
High Burglary	-0.4154	-0.5443
	(0.0284)	(0.0282)
High Assaults	-0.3154	-0.2711
	(0.0275)	(0.0267)
ln(Toxics Concentrations) (RSEI)	-0.2155	-0.1847
	(0.0025)	(0.0017)
PM2.5	-0.0427	-0.0504
	(0.0000)	(0.0000)
White $*$% White	0.0618	0.0603
	(0.001)	(0.0009)
White $*$% White^2	-0.00047	-0.00047
	(0.0000)	(0.0000)
Black $*$% African American	0.0578	0.0717
	(0.0017)	(0.0015)
Black $*$% African American^2	-0.00003	-0.00005
	(0.0000)	(0.0000)
Hispanic $*$% Hispanic	0.0448	0.0350
	(0.0023)	(0.002)
Hispanic $*$% Hispanic^2	-0.00053	0.00038
	(0.0000)	(0.0000)

Figure 1. Response Sets



(a) Atlanta, GA (n=3,093)

(b) Philadelphia, PA (n=972)

(c) Cleveland, OH (n=4,254)

(d) Houston, TX (n=4,710)

Notes: Figures show the matched response sets for the three cities. Matched responses refer to the number of responses returned from a single property over the course of the 3-day trial.

Figure 2. Response Rates by Housing Attribute

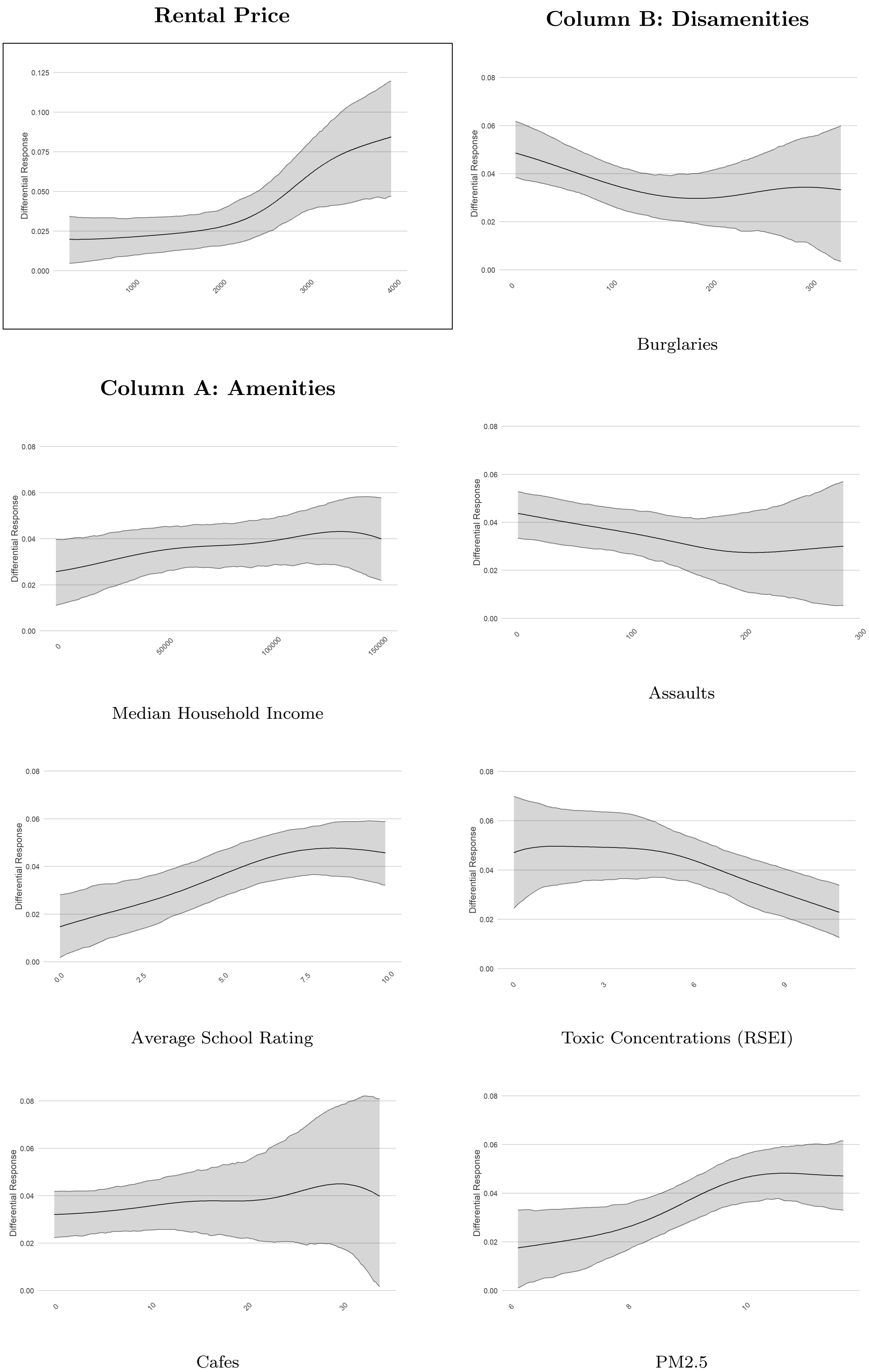
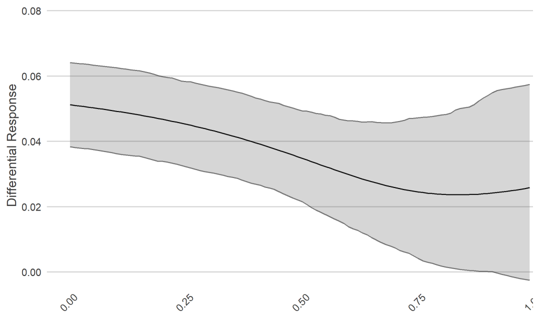
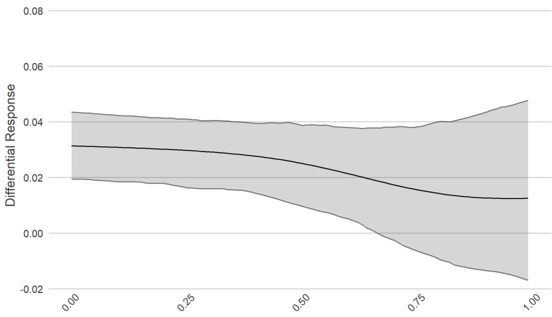


Figure 3. Response Rates by Neighborhood Demographic Shares

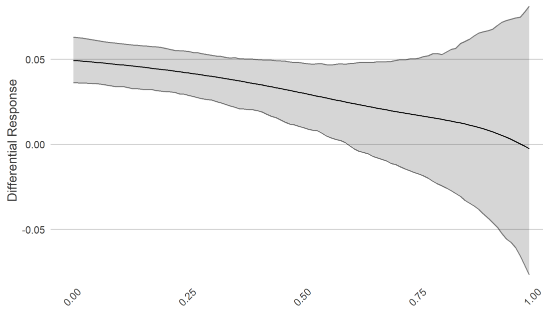
African American | **Hispanic/LatinX**



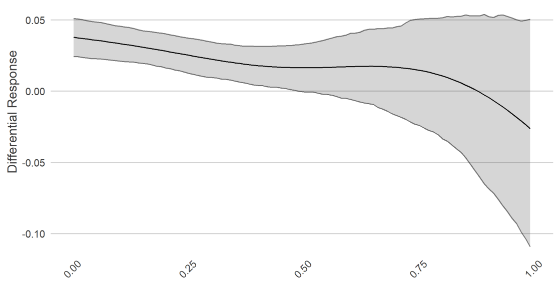
(a) Share African American



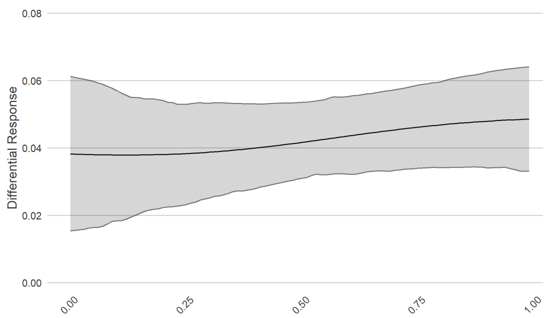
(b) Share African American



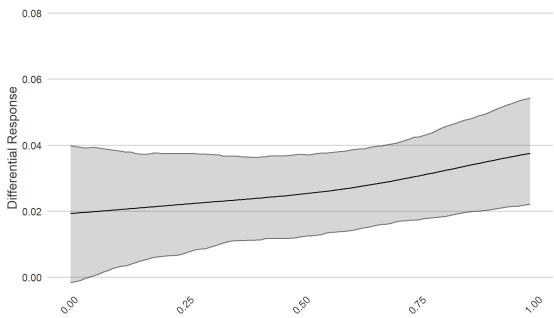
(c) Share Hispanic/LatinX



(d) Share Hispanic/LatinX

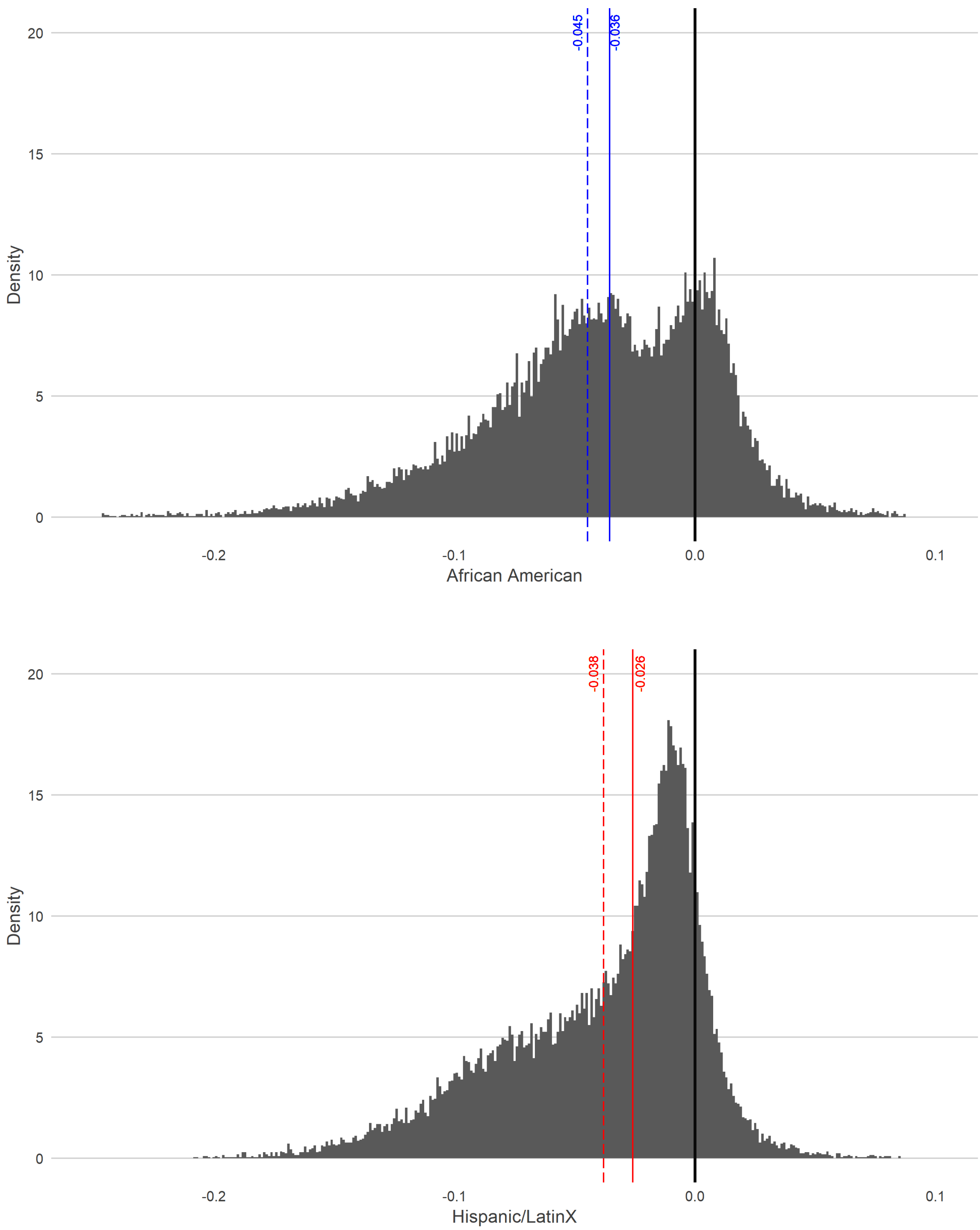


(e) Share White



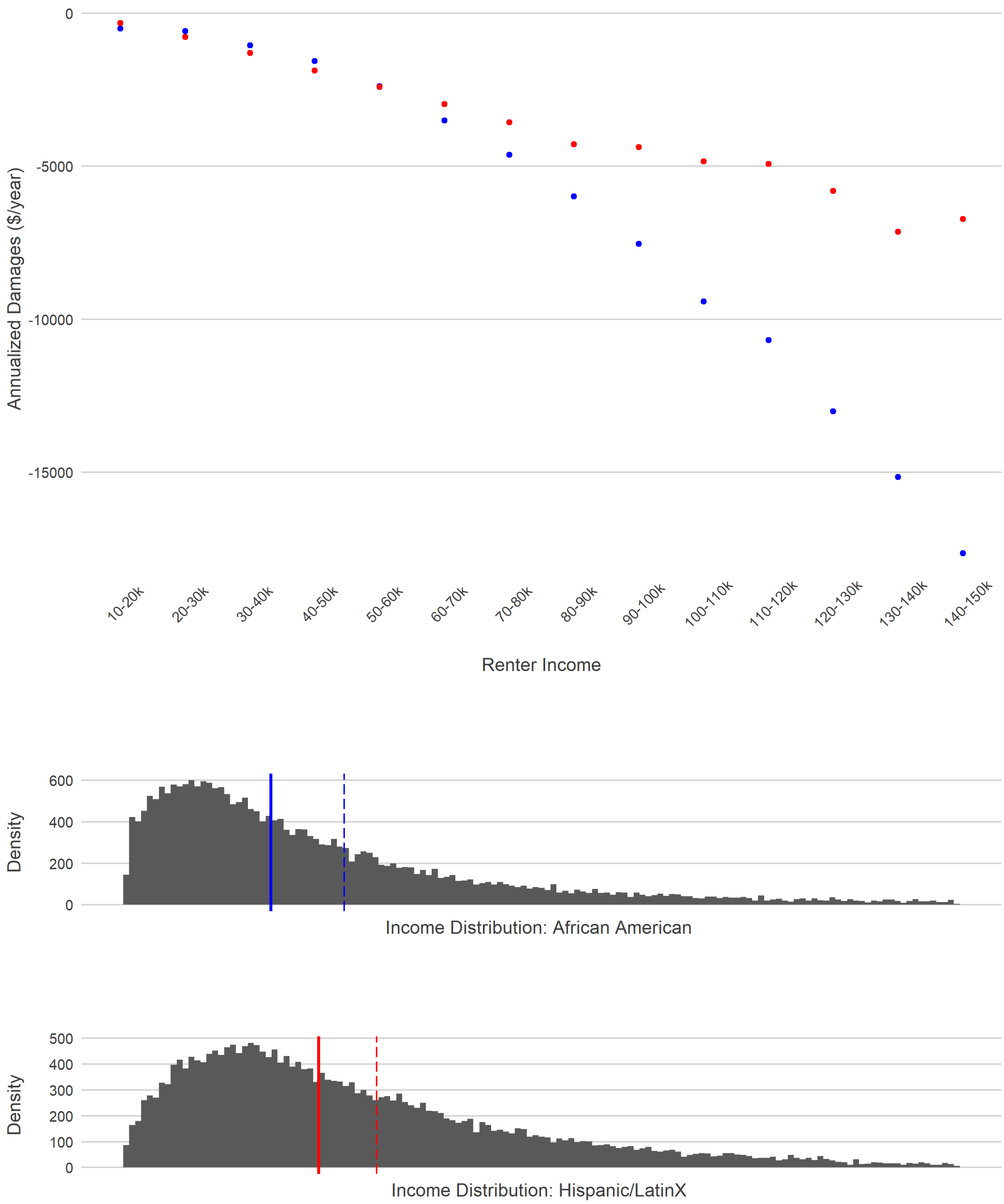
(f) Share White

Figure 4. Annualized Damages as a Share of Annual Income (Equivalent Variation)



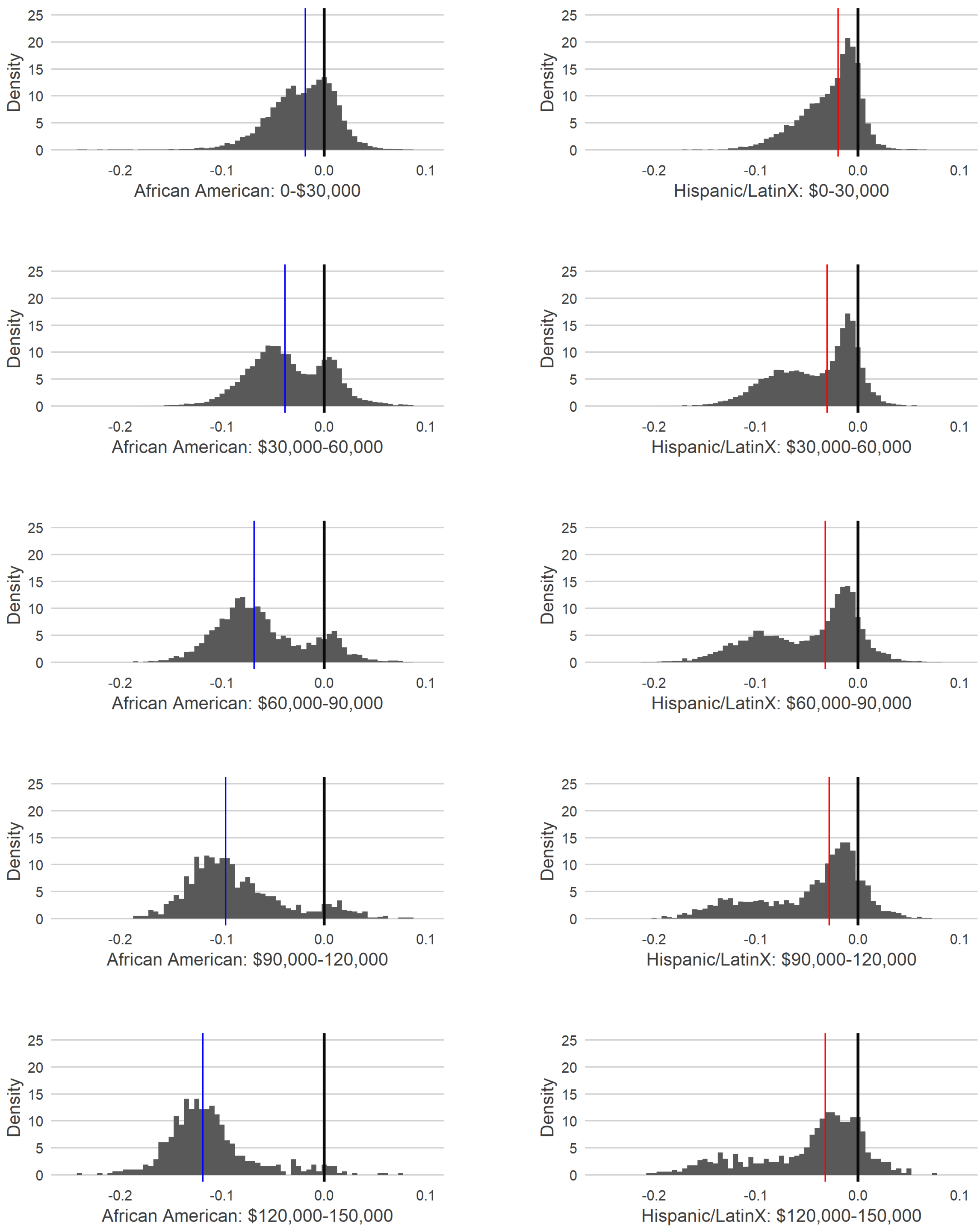
Note: The figure above graphs effects of discriminatory constraints in terms of compensating variation (top) and choice set constraints (bottom) by income. Effects estimated using the baseline model with all preferences. Blue points show effects for African American renters and red points plot effects for Hispanic/LatinX renters.

Figure 5. Annualized Damages by Income (Equivalent Variation)



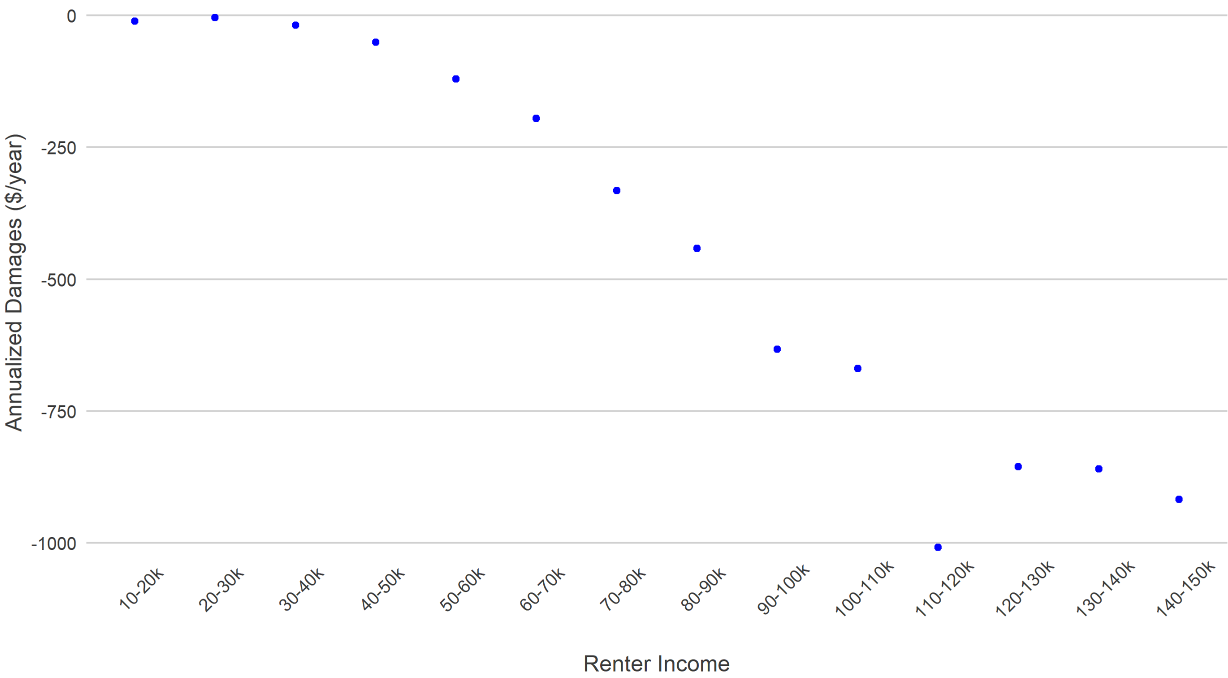
Note: The figure above graphs effects of discriminatory constraints in terms of compensating variation (top) and choice set constraints (bottom) by income. Effects estimated using the baseline model with all preferences. Blue points show effects for African American renters and red points plot effects for Hispanic/LatinX renters.

Figure 6. Annualized Damages as a Share of Annual Income (Equivalent Variation)



Note: The figure above graphs effects of discriminatory constraints in terms of compensating variation (top) and choice set constraints (bottom) by income. Effects estimated using the baseline model with all preferences. Blue points show effects for African American renters and red points plot effects for Hispanic/LatinX renters.

Figure 7. Annualized Damages: Heterogeneity by Homophily Preferences



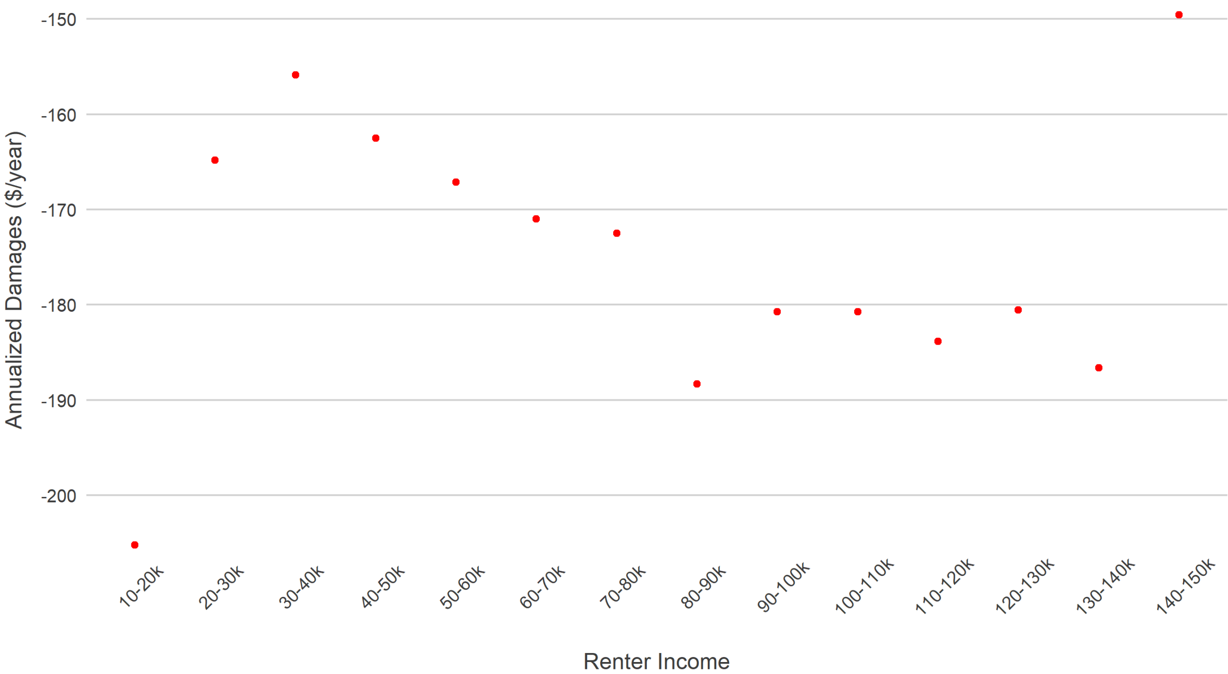
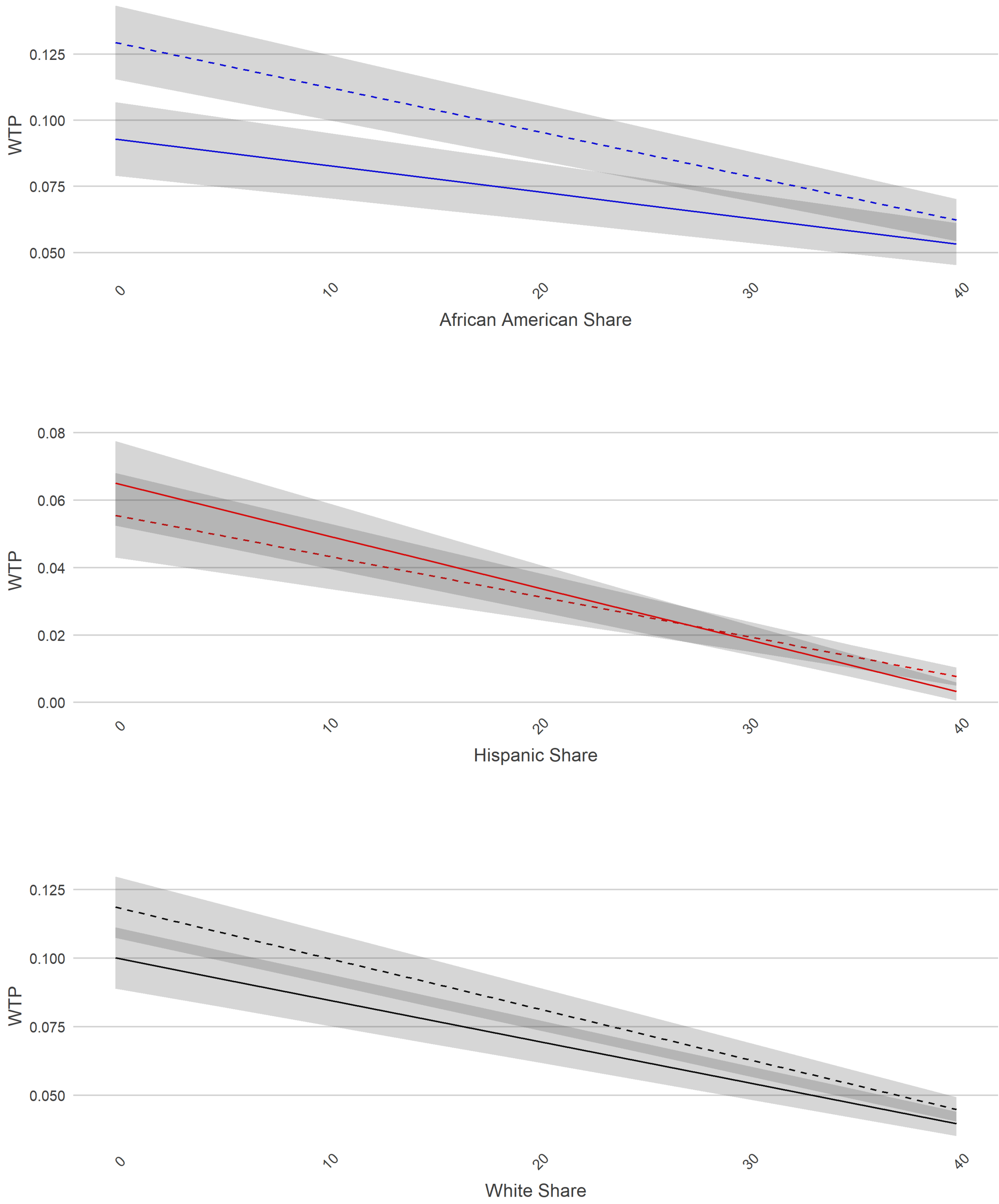


Figure 8. Revealed Willingness to Pay: Homophily Preferences



8 Online Appendix

Table 7. Evidence of Discrimination on Housing Choice by Race Group

Race Group	(1)	(2)	(3)	(4)	1st Inquiry
Minority	0.6955***	0.6943***	0.6977***	0.6865***	0.7245***
	(0.6296 - 0.7684)	(0.6299 - 0.7652)	(0.6323 - 0.7698)	(0.6250 - 0.7541)	(0.6470 - 0.8114)
Hispanic	0.7502***	0.7470***	0.7481***	0.7437***	0.7673***
	(0.6691 - 0.8411)	(0.6670 - 0.8367)	(0.6661 - 0.8400)	(0.6648 - 0.8318)	(0.6735 - 0.8742)
African American	0.6448***	0.6453***	0.6509***	0.6342***	0.6843***
	(0.5669 - 0.7335)	(0.5699 - 0.7306)	(0.5763 - 0.7352)	(0.5629 - 0.7145)	(0.6038 - 0.7757)
Mean Choice (White)	0.434	0.434	0.434	0.434	0.434
Observations	5,451	5,451	5,451	5,451	5,049
Total obs	18045	18045	18045	18045	6015
Gender	No	Yes	Yes	Yes	Yes
Education	No	No	Yes	Yes	Yes
Inquiry Order	No	No	No	Yes	Yes

Robust cieform in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8. Heterogeneity in Discrimination by Neighborhood Type:
City-Specific Estimates

		Dependent Variable: Housing Choice							
		All		Atlanta		Houston		Philadelphia	
		High	Low	High	Low	High	Low	High	Low
Rent	*Hispanic*	0.6622	0.7655	0.5603	0.6672	0.7177	0.8501	0.7439	0.8787
		(0.52-0.84)	(0.59-0.99)	(0.42-0.75)	(0.47-0.94)	(0.50-1.04)	(0.59-1.21)	(0.45-1.23)	(0.49-1.58)
	Black	0.6573	0.7984	0.6364	0.8630	0.8964	0.9917	0.3738	0.4156
		(0.52-0.84)	(0.62-1.03)	(0.48-0.85)	(0.62-1.20)	(0.62-1.29)	(0.69-1.42)	(0.22-0.62)	(0.23-0.75)
	Observations	4,290	4,485	1,539	1,461	2,268	2,250	483	483
Elementary [4]	*Hispanic*	0.6133	0.8705	0.5330	0.8334	0.6332	0.9750	0.8342	0.7083
		0.48-0.78	0.67-1.13	(0.41-0.70)	(0.52-1.34)	(0.47-0.86)	(0.60-1.59)	(0.50-1.38)	(0.33-1.54)
	Black	0.8145	0.6334	0.7468	0.7201	1.0106	0.6708	0.3979	0.3370
		0.65-1.03	0.49-0.82	(0.57-0.97)	(0.45-1.15)	(0.75-1.37)	(0.41-1.10)	(0.23-0.68)	(0.16-0.71)
	Observations	4,974	3,801	1,410	1,014	2,706	1,773	459	342
Arrests	*Hispanic*	0.7666	0.6815	0.7195	0.5997	0.7195	0.7850	0.6654	0.8118
		0.58-1.01	0.54-0.86	(0.55-1.00)	(0.42-0.86)	(0.49-1.07)	(0.53-1.17)	(0.36-1.22)	(0.48-1.37)
	Black	0.6454	0.8009	0.7197	0.7027	1.0203	0.7621	0.4449	0.3096
		0.5330	0.64-1.01	(0.53-0.98)	(0.49-1.01)	(1.02-0.70)	(0.51-1.12)	(0.24-0.81)	(0.18-0.53)
	Observations	4,854	3,921	1,320	1,305	2,256	2,259	459	510
TRI Plants	*Hispanic*	0.7822	0.6581	0.7419	0.5622	0.7105	0.7787	0.7876	0.7839
		0.61-1.01	0.52-0.84	(0.49-1.12)	(0.41-0.78)	(0.46-1.09)	(0.51-1.19)	(0.46-1.34)	(0.33-1.85)
	Black	0.7855	0.6784	0.8044	0.6979	1.0826	0.7357	0.4102	0.3444
		0.61-1.01	0.53-0.86	(0.53-1.21)	(0.51-0.96)	(0.71-1.66)	(0.48-1.13)	(0.24-0.70)	(0.14-0.83)
	Observations	4,011	4,764	1,134	1,959	2,142	2,568	735	237
College	*Hispanic*	0.6634	0.7687	0.5604	0.7027	0.7424	0.7489	0.6934	1.087
		0.52-0.85	0.60-.98	(0.42-0.76)	(0.52-0.96)	(0.50-1.11)	(0.54-1.04)	(0.39-1.06)	(0.60-1.97)
	Black	0.7605	0.6929	0.7752	0.6874	1.0498	0.7937	0.3653	0.4588
		0.59-0.97	0.54-0.89	(0.58-1.04)	(0.51-0.93)	(0.71-1.55)	(0.57-1.11)	(0.22-0.60)	(0.25-0.83)
	Observations	4,395	4,380	1,620	1,410	2,847	1,830	483	483
Nightlife	*Hispanic*	0.6967	0.7519	0.5787	0.7420	0.7726	0.6539	0.6847	0.9161
		0.55-0.88	0.58-0.98	(0.43-0.77)	(0.53-1.03)	(0.56-1.06)	(0.41-1.03)	(0.38-1.24)	(0.55-1.53)
	Black	0.7192	0.7481	0.6738	0.8843	0.9233	0.7836	0.3449	0.4236
		0.57-0.91	0.57-0.98	(0.51-0.90)	(0.64-1.22)	(0.68-1.26)	(0.50-1.23)	(0.19-0.62)	(0.25-0.71)
	Observations	4,854	3,921	1,698	1,332	2,670	2,007	486	480

Table 9. Heterogeneity in Discrimination by Neighborhood Racial Composition

		Dependent Variable: Housing Choice							
		All		Atlanta		Houston		Philadelphia	
		low	high	low	high	low	high	low	high
White Share	*Hispanic*	0.7968	0.6391	0.7021	0.5706	0.8213	0.6691	1.0871	0.6381
		(0.63-1.02)	(0.50-0.82)	(0.52-0.96)	(0.42-0.77)	(0.59-1.14)	(0.45-0.99)	(0.60-1.96)	(0.38-1.06)
	Black	0.8334	0.6321	0.7633	0.7125	1.0484	0.7280	0.5257	0.3362
		(0.65-1.07)	(0.50-0.81)	(0.56-1.04)	(0.53-0.96)	(0.75-1.46)	(0.49-1.08)	(0.29-0.94)	(0.20-0.56)
	Observations	4,386	4,389	1,548	1,545	2,352	2,358	486	486
Hispanic Share	*Hispanic*	0.6132	0.8185	0.5006	0.7554	0.6539	0.7936	0.6911	0.9489
		(0.47-0.79)	(0.64-1.04)	(0.37-0.69)	(0.56-1.02)	(0.43-0.99)	(0.57-1.10)	(0.41-1.17)	(0.54-1.66)
	Black	0.6887	0.7883	0.6730	0.7859	0.8981	0.8842	0.3984	0.4032
		(0.53-0.89)	(0.60-0.96)	(0.50-0.91)	(0.58-1.06)	(0.60-1.34)	(0.64-1.23)	(0.23-0.68)	(0.23-0.69)
	Observations	4,377	4,398	1,545	1,548	2,349	2,361	483	489
African American Share	*Hispanic*	0.6056	0.8450	0.5558	0.7247	0.7147	0.7790	0.4356	1.8861
		(0.47-0.78)	(0.66-1.08)	(0.41-0.75)	(0.53-0.99)	(0.49-1.05)	(0.56-1.09)	(0.26-0.74)	(1.02-3.48)
	Black	0.6096	0.8763	0.7028	0.7769	0.7905	0.9960	0.2725	0.7074
		(0.48-0.78)	(0.68-1.12)	(0.53-0.94)	(0.57-1.06)	(0.54-1.16)	(0.71-1.40)	(0.16-0.46)	(0.39-1.27)
	Observations	4,329	4,446	1,548	1,545	2,349	2,361	486	486

Figure 9. Matched Responses

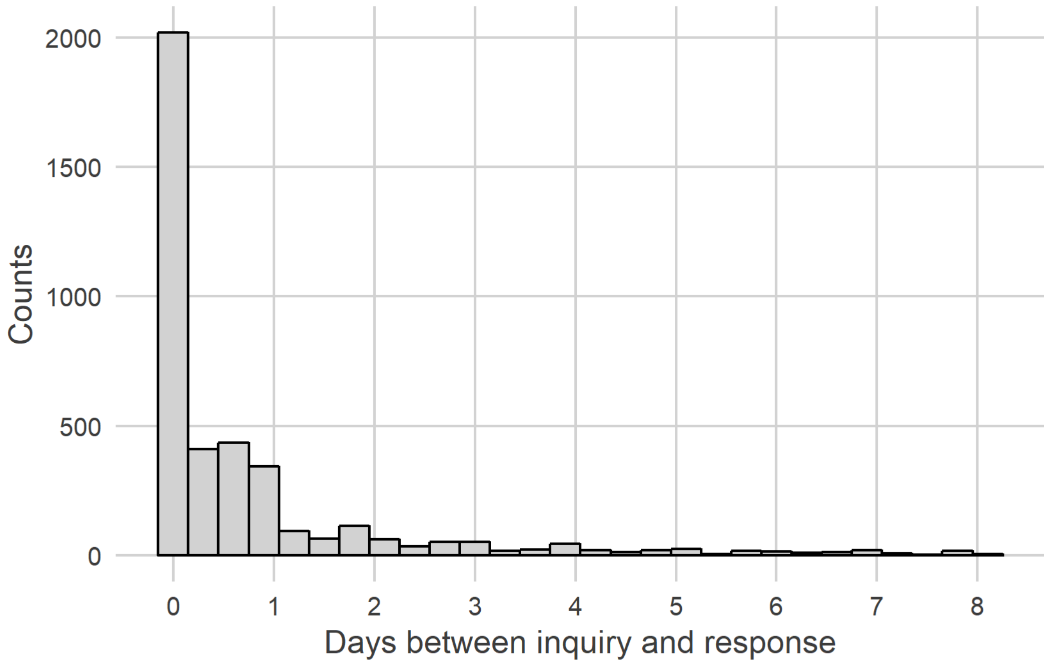
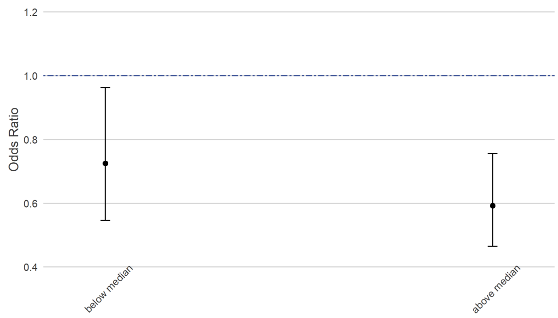
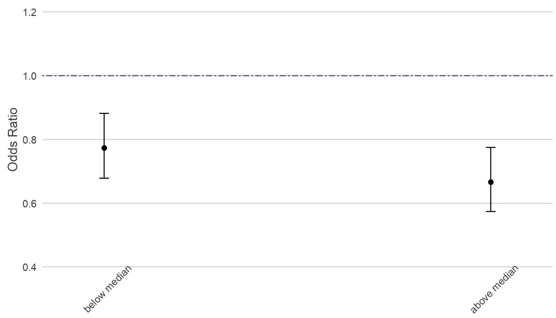


Figure 10. Response Rates by Housing Attribute

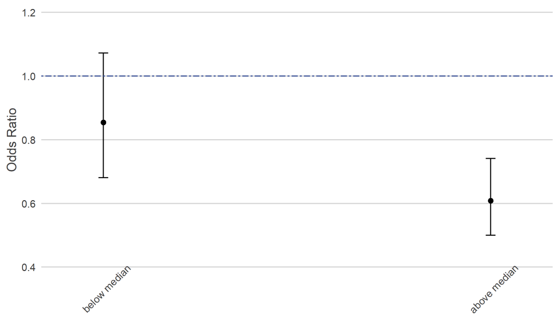
African American **Hispanic/LatinX**



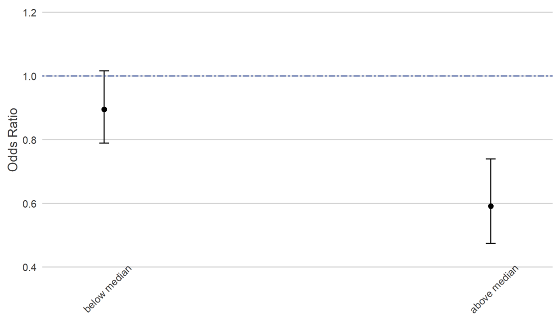
(a) Rental Price



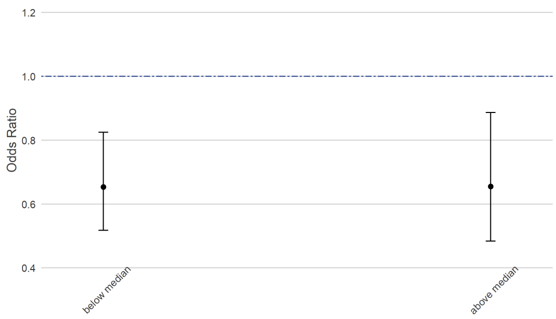
(b) Rental Price



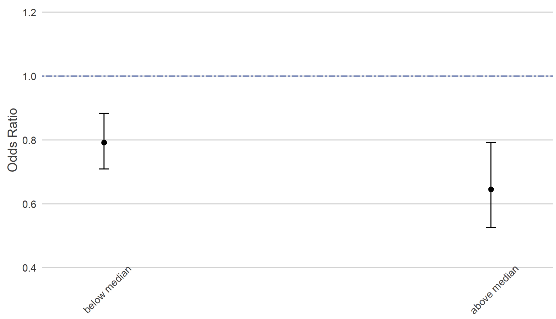
(c) Average School Rating



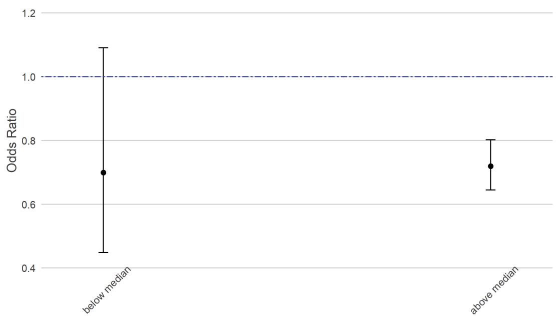
(d) Average School Rating



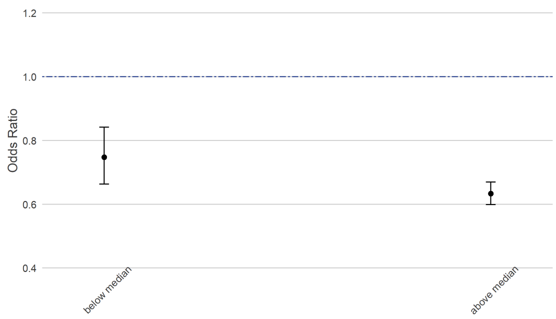
(e) Median Household Income



(f) Median Household Income



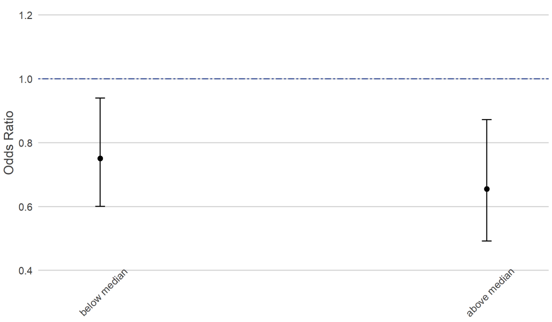
(g) Cafes



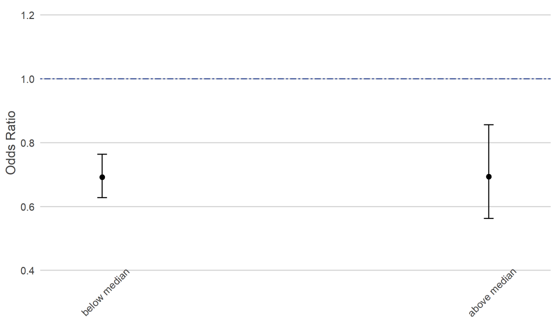
(h) Cafes

Figure 11. Response Rates by Housing Attribute

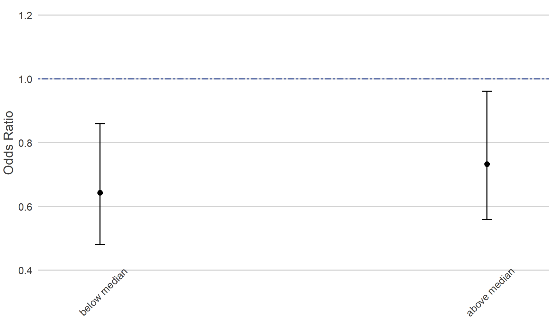
African American | **Hispanic/LatinX**



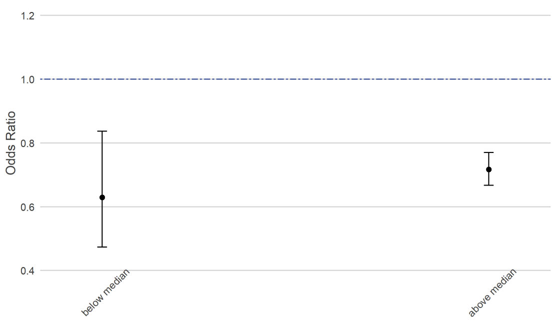
(a) PM2.5



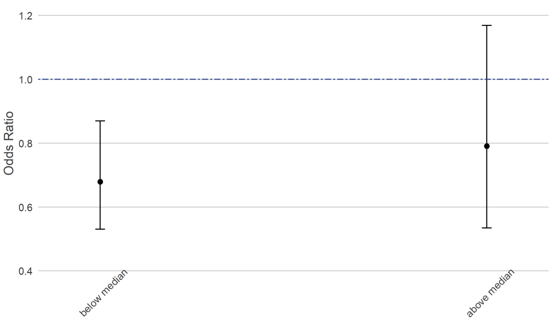
(b) PM2.5



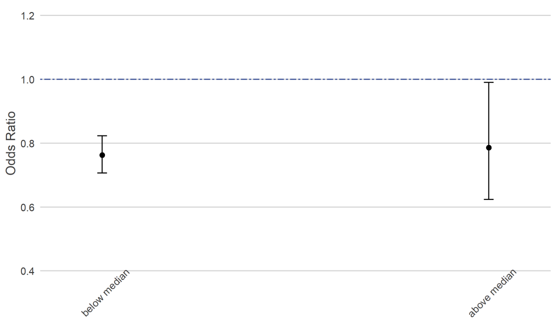
(c) Toxic Concentration



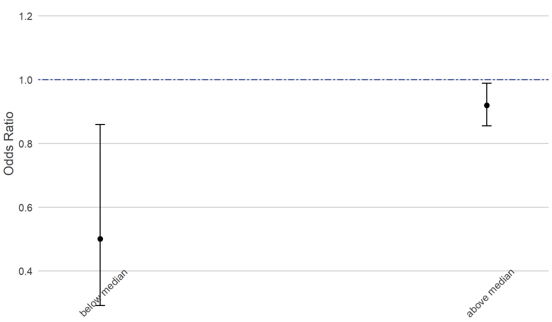
(d) Toxic Concentration



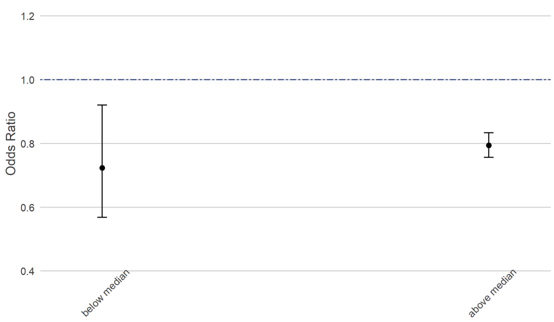
(e) Assaults



(f) Assaults



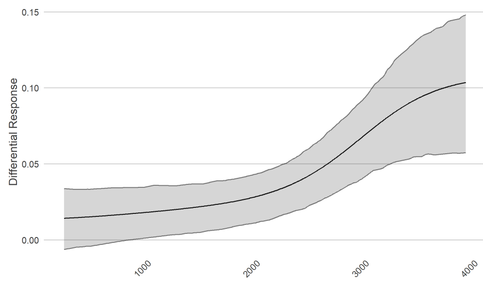
(g) Burglaries



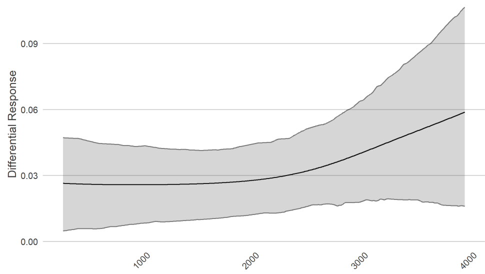
(h) Burglaries

Figure 12. Response Rates by Housing Attribute

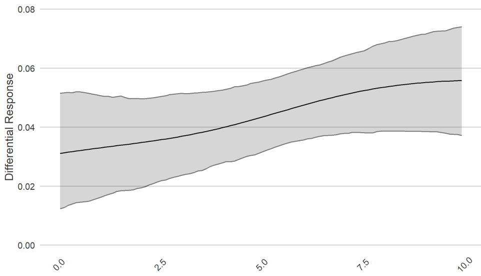
African American | **Hispanic/LatinX**



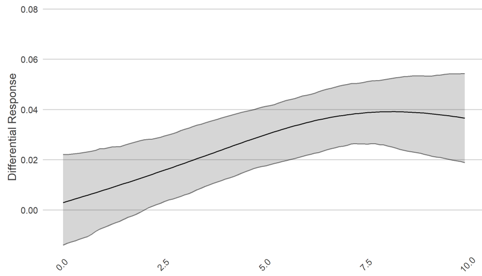
(a) Rental Price



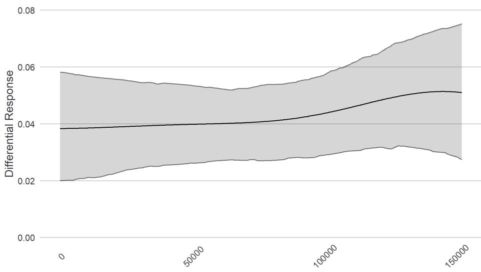
(b) Rental Price



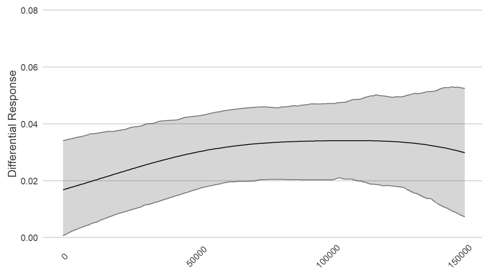
(c) Average School Rating



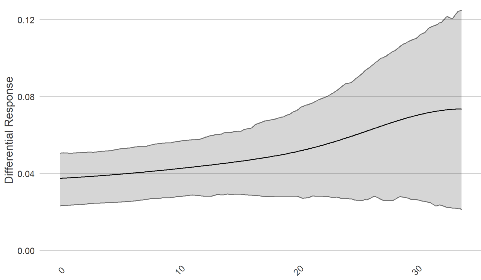
(d) Average School Rating



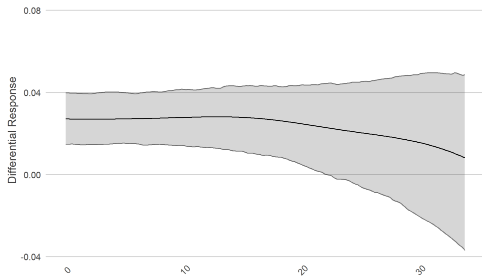
(e) Median Household Income



(f) Median Household Income



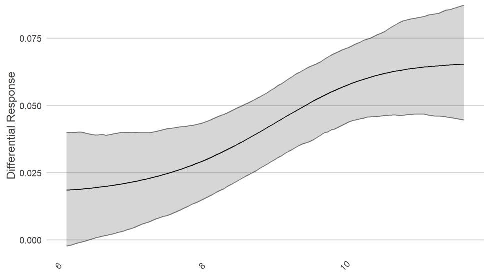
(g) Cafes



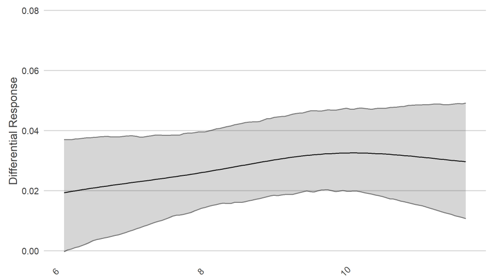
(h) Cafes

Figure 13. Response Rates by Housing Attribute

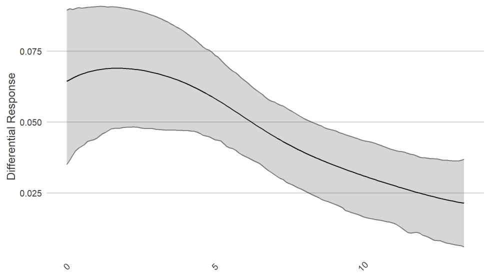
African American | **Hispanic/LatinX**



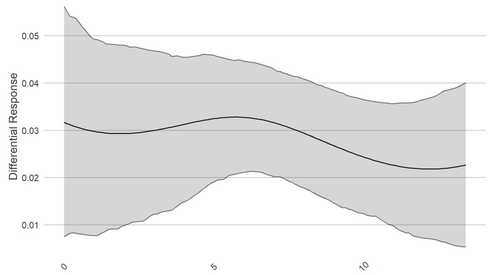
(a) PM2.5



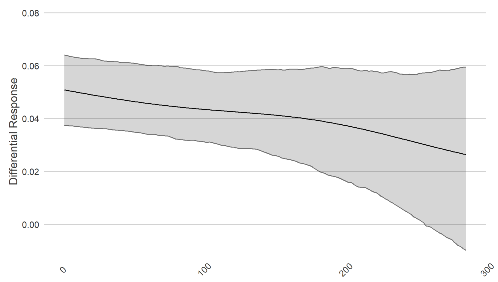
(b) PM2.5



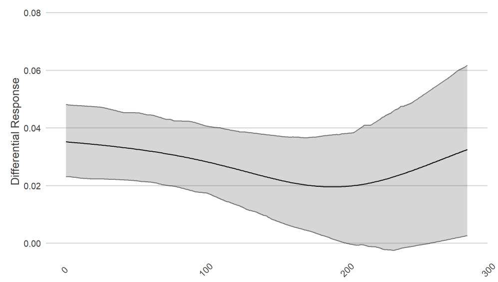
(c) Toxic Concentration



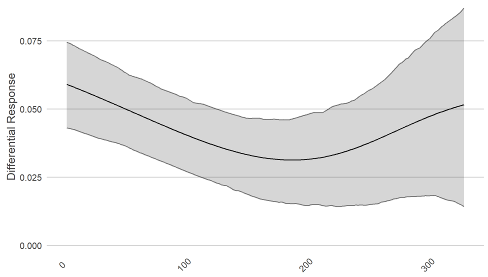
(d) Toxic Concentration



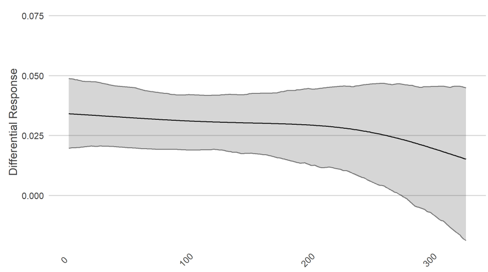
(e) Assaults



(f) Assaults



(g) Burglaries



(h) Burglaries