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 buyer welfare. This study combines a large-scale field experiment with a residential sorting model to derive utility-theoretic measures of renter welfare loss associated with the constraints imposed by discrimination in the rental housing market. In the five 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 discriminatory constraints during the first phase of a search in these cities to be equivalent to 4.6% and 4.7% of the annual incomes for the average African American and Hispanic/LatinX households, respectively. For African American renters, these costs increase substantially at higher levels of income due to systematic exclusion from high amenity neighborhoods. African American renters face damages greater than 7% of income at income levels above $100,000 per year. We then 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 estimated without accounting for discriminatory constraints. A naive model that ignores those constraints understates the marginal willingness to pay of renters of color for a variety of neighborhood amenities by 2.2% to 5.2% relative to White renters.

Key words: Housing Discrimination, Experimental Design, Correspondence Study, Consideration Sets, Neighborhood Effects, Environmental Justice
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1 Introduction

By constraining an individual's choice during a search process, discrimination can distort decisions away from true preferences and result in a *ceteris paribus* reduction in the welfare of those that face it. Discriminatory behavior has been shown to introduce group-specific search frictions in a wide variety of settings, including labor (Lang and Lehmann, 2012), housing and mortgage (Christensen et al., 2020, Hanson et al., 2016), and consumer markets (Edelman et al., 2017, List, 2004). Growing reliance on digital search tools raises concern about algorithmic discrimination, which could exacerbate differential constraints in online markets (Kleinberg et al., 2018). Experimental research on discrimination to date has largely focused on detecting discriminatory behavior without considering interactions with search, limiting our understanding of the ultimate impacts of discriminatory constraints on economic outcomes (Neumark, 2018, Bertrand and Duflo, 2017, Guryan and Charles, 2013).

The present study combines a large-scale field experiment with structural methods to examine the effects of discrimination in the housing market. 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 and steer them into neighborhoods that confer disadvantage (Christensen and Timmins, 2018, Ewens et al., 2014, Carlsson and Eriksson, 2014, Hanson and Hawley, 2011, Ahmed and Hammarstedt, 2008). A key innovation involves the integration of a correspondence experiment in a welfare-theoretic framework, which we use to estimate damages to African American and Hispanic/LatinX renters. The approach is motivated by the basic insight that the damages from discriminatory constraints depend on the value that an individual places on the set of choices that are made inaccessible as a consequence of discriminatory behavior. Since housing is a multi-dimensional good and discrimination may differentially constrain access to choices in certain neighborhoods, an estimate of the welfare cost to a renter or buyer requires a set of utility weights over different attributes of each housing choice.

We develop a correspondence research design to measure within-property variation in housing choices that are made available (or not) by property managers in response to renter inquiries. The structural sorting model then recovers utility weights from observed housing decisions in the context of discriminatory constraints that different renters face in the set of markets. Our experimental sample is obtained through interactions on a major online search platform and includes the entire set of listings for three-bedroom, two-bathroom rental units in each of five different major U.S. metropolitan housing markets: Atlanta, GA; Houston, TX; Philadelphia, PA; Cleveland, OH; and San Jose, CA.[1] Reduced-form tests reveal 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%) and the highest found in Cleveland (74.5%).

Our reduced-form estimates also indicate that higher neighborhood amenity levels are systematically correlated with higher levels of discrimination facing African American renters in particular. These results are consistent with findings on discriminatory steering by real estate agents in the buyer market (Christensen and Timmins, 2018), suggesting that African American households face strong frictions when searching for housing in high-amenity neighborhoods. In the rental markets that we study, these relationships are particularly strong for school quality and toxic air concentrations, but the pattern holds for neighborhood-level murder rates and access to cafes, which proxy for a range of retail amenities (Glaeser et al., 2018, Papachristos et al., 2011). However, choice constraints in the online rental market are mediated by direct interactions with property managers and cannot be circumvented by shifting to a different agent. Consistent with prior correspondence literature, we find that people of color also 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. Discriminatory constraints are significantly higher among properties that have recently

[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.

entered the market (listed for fewer than 3 days), which indicates that constraints are stronger in neighborhoods with strong rental demand. Discriminatory constraints facing minority identities become significantly stronger when a property manager receives inquiries from other identities in our sample, suggesting that discriminatory behavior may be exacerbated in highly competitive markets.

The reduced-form results suggest that discriminatory constraints are not uniform in the housing market, such that they will interact with heterogeneous preferences and incomes among renters. Welfare impacts on the renter population depend on these interactions. Building on estimation techniques developed in the consideration sets literature, we introduce a structural sorting model that uses experimentally identified variation in discriminatory behavior at the level of the census tract in combination with information about the location decisions of households observed in rental housing in our 5 MSAs between 2016-2018 using InfoUSA's Residential Historical Database.[2] This method provides an approach for integrating the results from audit/correspondence research to search models in a variety of settings. The sorting 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 generate welfare estimates of the impact of discriminatory search constraints on the choice sets of minority renters. For the average renter in our five cities, the magnitude of the damages from discriminatory constraints – i.e., the constraints faced by a renter of color over and above those faced by a White renter with the same income – are equivalent to 4.6% and 4.7% of the annual incomes for African American and Hispanic/LatinX renters, respectively. These damages increase substantially at higher levels of income – African American renters face damages greater than 7% of income at income levels above $100,000 per year. Heterogeneity in income results from two interacting factors: (1) stronger discriminatory constraints in high amenity and high

[2]InfoUSA's Residential Historical Database tracks 120 million households, including renters, between 2006 and 2019. 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.

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 results in pronounced impacts on African American renters.

These results illustrate an important channel through which housing discrimination can create a potential barrier to intergenerational income mobility – by restricting access to the very neighborhoods that provide the greatest utility to economically mobile minority households. This is a key result given growing evidence on the long-run impacts of exposure to high/low amenity neighborhoods (Chetty and Hendren, 2018a,b, Graham, 2018). Our findings contribute to a growing literature on the effects of search constraints that can impede the ability of minority households to use increased income or subsidy programs to move to high-opportunity neighborhoods (Bergman et al., 2019, Aliprantis et al., 2018, Ioannides, 2011).

A final section of the paper contributes to a long-standing literature on the relationship between preferences revealed by sorting in the housing market and the efficient allocation of local public goods (Epple et al., 1984, Tiebout, 1956). By constraining an individual's choice set, discrimination can drive a wedge between true amenity preferences and those revealed in a (constrained) search. We examine the effects of market distortions introduced by discrimination in the markets that we study. Allowing for racial heterogeneity in preferences, we find that a naive model that ignores constraints imposed by discrimination significantly understates African American and Hispanic/LatinX willingness-to-pay for average school quality and to avoid toxic air pollution. This suggests that the discriminatory constraints can distort revealed preferences in ways that have important effects on the interpretation of revealed preference estimates and on the local provision of public goods (Kuminoff et al., 2013, Bayer et al., 2007).

The 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

Disentangling 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 (Christensen and Timmins, 2018, Chetty et al., 2018, Graham, 2018, Aliprantis et al., 2018, Ioannides, 2011, Bayer and McMillan, 2008). Recent experimental evidence indicates that barriers in the search process, rather than differences in neighborhood preferences, may be the primary driver of segregation processes (Bergman et al., 2019). This is troubling, particularly given mounting evidence from both audit and correspondence studies indicates that racial discrimination continues to constrain the choice sets of people of color during search in the rental or owner-occupied housing markets in the United States (Christensen et al., 2020, Ewens et al., 2014, Carlsson and Eriksson, 2014, Hanson and Hawley, 2011, Ahmed and Hammarstedt, 2008, Christensen and Timmins, 2018). To the extent that discriminatory constraints reduce the access of certain groups to beneficial neighborhood effects and induce segregation, they could directly impact the long-run accumulation of human capital (Chetty and Hendren, 2018a,b) and wealth (Akbar et al., 2019). Discriminatory constraints may reduce the efficacy of housing voucher and other programs that are designed to reduce barriers to accessing high-opportunity neighborhoods (Aliprantis et al., 2019).

By constraining an individual's set of choices during a search, housing discrimination distorts the sorting outcome away from that associated with true preferences and results in a *ceteris paribus* reduction in the welfare of a buyer/renter. However, experimental research on discrimination has focused almost 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 not yielded much evidence on the welfare impacts of discriminatory constraints, on location-based sorting processes, or to equilibrium outcomes such as housing purchase prices (Bayer et al., 2017, Ihlanfeldt and Mayock, 2009, Myers, 2004), neighborhood segregation (Shertzer and Walsh, 2019, Bayer et al., 2014), and wealth accumulation (Akbar et al., 2019).[3]

2.1 Residential Sorting with Discriminatory Constraints

Beginning with the seminal work of Tiebout (1956), who showed that households express their demand for local public goods by "voting with their feet," revealed preference models have focused on capturing a households' willingness to trade-off outside 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 (Epple and Sieg, 1999). A now 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 (Kuminoff et al., 2013). Methodological advances in empirical modeling of the residential sorting process have increased their use by researchers and policymakers in determining the *value* of local public goods and amenities (Bayer et al., 2007, Palmquist, 2005). Together with findings from reduced form hedonic methods (Chay and Greenstone, 2005, Gibbons, 2004, Champ et al., 2003, Black, 1999), these revealed preferences estimates play an important role in determining the budgets for these key public services in cities throughout the United States and other countries.

The key assumption underlying the "vote-with-your-feet" model is freedom of choice with respect to location. In order to express their demand for local public goods and influence the level of service provision by local governments, households must be free to choose from all of the available housing options in a local housing market.[4] By im-

[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.

[4]This includes the option to move to another local market, which creates an equilibrium in which multiple local governments compete to attract residents by adjusting the provision of local spending according to the demand that is signaled by the population (Epple et al., 1984). Prior empirical evidence indicates that segregation can directly result in lower levels of public goods provision (Trounstine, 2016, Alesina et al., 1999).

posing constraints on the choice set, discriminatory behavior creates a key challenge for revealed preference studies of housing, labor and other markets. While there has been some recognition of this issue, empirical researchers have not incorporated data on discriminatory constraints with information about buyer or renter outcomes (Christensen and Timmins, 2018, Graham, 2018). An exception is Li (2019), who develops a model of location decisions of households in the 1940's using the assumption that constraints on purchasing were binding in any census tract that did not contain at least one African American owner.

The current study examines the process by which discriminatory constraints can drive a wedge between the preferences of minority households and the location outcomes that result from their search. In contrast to the approach developed by Li (2019), the current paper uses experimentally identified estimates of discriminatory constraints to model choice constraints in a residential choice model. We introduce a novel structural framework that explicitly accounts for the effects of discriminatory constraints in housing search, allowing us to: (1) recover utility parameters that may be affected by choice constraints and examine how they differ from a model that is naive to discrimination; (2) derive utility-based welfare impacts of discrimination over multi-attribute residential units, which are expressed in terms of equivalent variation in income; and (3) study interactions between individual heterogeneity in preferences and income that can interact to either mitigate its welfare impacts or make them worse.

2.2 Consideration Sets

Over the past three decades, a large literature has emerged to model the constraints on consumers when choosing among large sets of goods or services. This work is motivated by the seminal finding from Stigler (1961), which demonstrates that the costs of search increase while the expected utility of the choice set decreases with every new product that enters a consumer's choice set. The consideration sets literature argues 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). The consideration sets model has provided an approach for applying bounded rationality and rational inattention models in revealed preference settings (Caplin et al., 2019, Manzini and Mariotti, 2014, Masatlioglu et al., 2012, Eliaz and Spiegler, 2011). To identify the effects of constraints on a consumer's choice set, empirical studies typically introduce an instrument that plausibly affects consumers' attention to different products without affecting the utility generated from consuming it,[5] or some auxiliary data source that identifies the actual choice sets, such as marketing surveys.[6]

We draw upon the techniques developed in this literature, which provide a tractable approach for empirical estimation of the effects of choice set constraints. However, as opposed to standard applications where constraints arise as a result of cognitive limits among buyers, we use this approach to examine discriminatory constraints that are exogenous to buyer attention or processing, arising instead from discriminatory behavior on the part of property managers. In particular, in the current setting, discriminatory behavior among property managers imposes an ex ante restriction on the housing choices in sets considered by renters.[7] The closest existing application of the consideration sets model may be Gaynor et al. (2016), who examined changes in the elasticity of demand with respect to quality of health care in the wake of a reform that exogenously expanded patient choice sets.

The consideration sets estimator in the present study identifies preference parameters in the context of experimentally-identified differences in the probability that choices will be made available to renters in different race groups from a correspondence study. This method provides an approach for integrating the results from audit/correspondence research to search and discrete choice models in a variety of settings.

[5]See Goeree (2008), Moraga-González et al. (2015), Koulayev (2009), and Gaynor et al. (2016).
[6]Abaluck and Adams (2016) consider an identification strategy based on asymmetric cross derivatives.
[7]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.

3 Correspondence Experiment

3.1 Sampling Frame and Data Collection

Our study was executed using a bot designed to collect comprehensive, real-time data on rental housing listings on a major online realty platform and while sending inquiries from racially distinct renter identities.[8] The bot compiled information for all 3 bedroom, 2 bathroom rental listings that appeared in five major Metropolitan Statistical Areas: 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. The sampling design ensures that estimates reflect differences across the full set of housing options advertised to prospective renters at the time of an experimental trial, simulating the set of options available to a prospective renter that is searching on the platform at that time.

We focus on this market segment as one that corresponds to the choices of renter families who are considering key neighborhood amenities such as pollution exposures (Currie et al., 2015) and school quality (Bayer et al., 2007). In addition to housing features such as monthly rent, square footage, house type, bedrooms, bathrooms, the bot collected neighborhood characteristics that are visible to renters on the search platform: average school quality (elementary, middle and high school), the number of local cafes, and an index of the number of recent murders.[9]

The bot also collected data on the ambient concentrations of chemical toxic pollution at the location of each listing as reported by the EPA's Risk-Screening Environmental Indicators (RSEI) model. The RSEI model accounts for differential releases, meteorological conditions such as wind speed and direction, decay rates, and other key characteristics

[8]The design was implemented with a software stack and compute infrastructure designed by Christensen's team at the National Center for Supercomputing Applications.

[9]We construct a single aggregate index of school quality using the geometric average of the elementary, middle and high school scores presented for each listing. This aggregate measure to addresses collinearity between the three school quality measures. Similarly we use a single measure of crime (murders) rather than multiple measures (e.g., murders, burglaries, etc.) and a single measure of retail (cafes) rather than additional measures (e.g., groceries, nightlife) to avoid problems of collinearity. Murder rates have been shown in other work to capture the dominant and most salient form of crime in revealed preference studies of damages in the housing market Albouy et al. (2020).

of emissions that can affect exposures (EPA, 2018).[10] Recent work provides evidence that minority renters face discriminatory constraints in neighborhoods with lower levels of concentration (Christensen et al., 2020).

The top panel of Table 1 reports summary statistics for key characteristics for each rental listing. We find substantial variation in rent and neighborhood characteristics both between and across the five cities in the sample. The average monthly rent in San Jose, CA ($2,137 per month) is more than double the size of rents in Cleveland, OH ($995 per month). But even within San Jose, the standard deviation of rents ($513 per month) is substantial. There is similar heterogeneity across MSA's in air quality, with a mean RSEI concentration over 37,000 in Houston, while that in San Jose is only 114. As was the case with rents, there is substantial within-MSA heterogeneity in RSEI. Average school quality can range from 0 to 10. The mean value in San Jose (6.81) contrasts with that in Philadelphia (3.43). We see similar heterogeneity in the murders index, with a high of 298.89 (Philadelphia) and a low of 44.98 (San Jose), and cafes, with a high of 47.05 (Philadelphia) and a low of 5.63 (Houston).

In order to characterize the racial composition of each census tract in the study, 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 cities. White households constitute the largest average group across tracts in each city, ranging from a high of 70% in Cleveland to 33% in Houston. Different races constitute the second largest group in each city – LatinX at 35% and 22% in Houston and San Jose, respectively, and African Americans at 41%, 30% and 19% in Atlanta, Philadelphia and Cleveland. In the following section, we provide descriptive evidence of how the likelihood of receiving a response varies for memebers of different race groups with respect to neighborhood attributes, including these racial compositions.

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

3.2 Correspondence Design and Randomization

In a correspondence study, fictitious applicants correspond by mail or via online platform Bertrand and Duflo (2017). 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) in rental housing markets.

Two recent experiments study the racial perceptions of names used in correspondence research by quantifying the congruence between the occurrence of distinctly African American, Hispanic/LatinX, and White names and the rate of identification (cognitive association with each group) among survey respondents in the United States (Gaddis, 2017a,b).[11] Using the results from Gaddis (2017a,b), we constructed 18 pairs of first and last names that have the highest probability of identification as belonging to each race group. The resulting set of fictitious renter identities consisted of 6 distinct first-last name pairs for each of the three groups. A question that has emerged in prior correspondence studies using racialized names is the possibility that any given name may signal race as well as other unobserved characteristics such as income (Guryan and Charles, 2013, Fryer Jr and Levitt, 2004). To test this empirically, we stratify the sample of first names using statistical distribution of maternal educational attainment (low, medium, and high) and gender (male and female) reported in Gaddis (2017a,b). The resulting name groups consists of three male and three female names, one drawn from each of three levels of maternal educational attainment (high/medium/low).

Each rental apartment received a sequence of three separate inquiries directly through the online platform in the course of an experimental trial. Names were drawn randomly from the full set of six for each race group. Inquiries for the same listing were never sent from the same identity or from two different identities on the same day.[12] Randomization of the timing, sequence, and gender/maternal education associated with each inquiry

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

[12]Balance tests are reported in Table **??**.

should guarantee that these characteristics are balanced across the inquiries for each group. Differences in name pairs or timing could occur, for example, if a listing is taken offline in the midst a trial. Appendix Table C1 reports balance statistics for the matched response dataset. We do not find any evidence of differences in the sequence of inquiries, the day the week that an inquiry is sent, or the frequency of inquiries made from a given race-gender or race-education pair.

As it executed each experimental trial, the bot collected data on the exact location, sequence, and timing of responses. Responses to inquiries were coded using two criteria that determine whether or not a housing choice is made available: (1) a response was received within 7 days of the associated inquiry and (2) the response indicated that the property is available for rent.[13] Figure 1 maps raw response data for the listings in each of the five cities, illustrating the locations where a trial yielded responses to 0, 1, 2, or all 3 of the matched sets of inquiries for a given listing. Figure A.1 graphs the average response times for the different inquiries. We find that when property managers operating on this search platform respond, they generally do so within a day of receiving an inquiry. We received 82% of responses within the first 24 hours, 94% within the first three days, and 97% within the first 5 days of an inquiry.

3.3 Estimating Choice Constraints

The experimental component of our study was designed to yield tests for discriminatory constraints, which are expressed in terms of within-property *relative response rates*. We use the term 'relative response rates' interchangeably with 'odds ratios' in this paper, since an odds ratio measures the within-property difference in the odds of a response to a minority identity relative to a White identity (the comparison group) for a given listing. We then use these data to structurally estimate the welfare effects of constraints placed on the choice sets of different groups using the random utility choice model that is described in the following section.

As described in the previous section, each rental apartment receives an inquiry from

[13]The 7-day cutoff was used to restrict responses that may be received weeks or months after an inquiry and are not counted as choices in the study.

each of the racial groups in three separate days. For example, on day one, the manager of the unit could receive an inquiry from the White identity, then from an African American identity on day two, and from a Hispanic/LatinX identity on day three. Based on this design, we observe a sequence of binomial decisions, where the landlord-listing i decides whether to respond ($y_{ij} = 1$, $j = 1, 2, 3$) or not if her underlying utility is positive[14]:

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

where u_{ij}^* is the utility of the landlord i from inquiry j and ϵ_{ij} follows a logistic distribution.[15] Therefore:

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

F is the logistic cumulative distribution function. $Minority_j$ is an indicator that takes the value one if the race group associated with the identity is either African American or Hispanic/LatinX; and is zero if it is the White identity. X_j is a vector of renter-specific control variables: gender, education level and the order in which the inquiry was sent. Assuming that names are drawn randomly and balanced across gender, education level, and inquiry order, estimates of β_{kj} should be robust to the inclusion/omission of X_j. In Appendix Table C2, we further show that experimental estimates are not sensitive to the inclusion of these controls.[16]

[14]See Appendix B for more details.

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

[16]Table C2 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 only difference between white and non-white testers is in the information conveyed by names. Attribute

3.4 Experimental Findings: Choice Constraints

Experimental Findings: Choice Constraints

Table 2 reports estimates for each of 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 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.

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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).

Heterogeneity in Choice Constraints: Neighborhood Characteristics

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 examine heterogeneity in constraints across neighborhoods within an MSA. In particular, estimates plotted in Figure 3 examine whether discriminatory constraints reduce the access of minority renters to property choices that confer greater levels of different amenities.[17] Each subfigure plots a smoothed function describing the average difference between the response to a White renter minus that to a renter of color (stacking the data to consider both differences between White and African American renters and between White and LatinX renters) using the model:

$$g(x_0) = \frac{1}{2N} \sum_{i=1}^{N} \left[(W_i - AA_i) + (W_i - HL_i) \right] f\left(\frac{x_i - x_0}{h\sigma_x} \right) \tag{3}$$

where W_i, AA_i and L_i take the value 1 or 0 depending upon whether the White, African American, or Hispanic/LatinX renter inquiring at property i received a positive response or not. A function value at x_0 equal to 1 would indicate that, at that level of the amenity, White renters always received responses while renters of color never did. A value of -1 would indicate the opposite. Averages of this discrimination index are smoothed using a Gaussian kernal, $f(.)$ with a smoothing parameter h equal to five-times Silverman's rule of thumb (Silverman, 1986). Bootstrapped 95% confidence intervals are displayed around each function.

While the study was not designed to provide the statistical power that would be needed to obtain precise estimates of statistical differences in response rates at high versus low amenity levels across cities in the sample, the estimates above suggest that discriminatory constraints are 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), and lower murder rates in the neighborhood. On average, there is little evidence of differences in discriminatory constraints with high/low numbers

[17]Refer to figure D.1 for estimates of heterogeneous effects by neighborhood amenity levels for each race group.

of cafes, though the standard errors are very high in high cafe neighborhoods, suggesting that this may be driven by variation across the MSAs.

Heterogeneity in Choice Constraints: Listing Age

One possible explanation for the findings above 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.

Heterogeneity in Choice Constraints: Inquiry Order

In Table 3, we extend the analysis 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 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.

4 Neighborhood Sorting with Choice Constraints

In this section, we integrate the experimentally identified estimates of discriminatory constraints with a structural sorting model where housing is a multi-dimensional commodity, allowing us to study the extent to which discriminatory constraints imposed during the search process affect both the quantity and also the quality of options that end up in the renter's post-search choice set. There may be trade-offs between housing attributes that renters are considering in the context of discriminatory constraints. For example, a unit may provide a high level of public safety but poor schools. In order to study the cumulative impact of constraints on neighborhood choices, we require a set of utility weights. These are provided by the estimates from the residential sorting model.

4.1 Housing Search Model

We model the housing search process for renters who vary in income and preferences for key neighborhood attributes. Renters optimally choose a housing unit within a census tract based on individual incomes and preferences for neighborhood attributes that vary across tracts. This approach accounts for impacts of discrimination on multiple neighborhood characteristics that may be traded-off for one another in the minds of renters.

We estimate utility function parameters for neighborhood attributes using InfoUSA's residential historical dataset, which provides a large panel of the incomes and (ultimate) location decisions of households who moved into rental properties during 2018. InfoUSA's consumer database tracked 120 million households and 292 million individuals between 2006-2019, and is maintained using 29 billion records from 100 sources including census statistics, billing statements, telephone directory listings and mail order buyers/magazine subscriptions. Household-level identifiers provide information on the gender, race/ethnicity, age, address, renter/owner status and estimated household income of renters that made a move in 2018.

The bottom panel of Table 1 summarizes these data by MSA. In each city, White renters have the highest mean income, although the difference between White renters and renters of color differs greatly across cities. In addition, the ordering of mean income across groups differs by MSA, with African Americans having the second highest income in Atlanta, Houston and Philadelphia. Hispanic/LatinX renters have the second highest income on average in San Jose, and the two groups of color have roughly the same mean income in Cleveland. Compared to the Census ACS population shares, the InfoUSA sample of renters is over-representative of White households, but generally follows the demographic patterns that we see across MSA's. Figure 2 maps the response rates in each of the five MSAs across the set of census tracts for renter moves were observed during 2018 in InfoUSA.

While models of residential location choice (including property-value hedonic models) typically assume that individuals have the entire range of options available to choose from in a given market, the experimental evidence reported in Section 3.2 indicates that this assumption is violated in all five of the MSAs that we study. We build constraints into our structural model directly, allowing experimental variation in choice constraints across census tracts to differentially constrain the choice sets of the renters observed in the panel. We begin by considering the utility of renter i choosing to live in tract j:

$$U_{i,j} = \alpha ln(I_i - R_j) + X_j'\gamma_i + \beta_{1,g}\sigma_{g(i),j} + \beta_{2,g}\sigma^2_{g(i),j} + \epsilon_{i,j} \quad (4)$$

where I_i is the monthly income of renter i (in \$1000's), R_j is the monthly rent (in \$1000's) associated with housing units in tract j, X_j captures other attributes of tract j, $\sigma_{g(i),j}$ measures the share of tract j population in group g corresponding to race of renter i, and $\epsilon_{i,j}$ is an idiosyncratic utility shock for renter i associated with census tract j. The $\sigma_{g(i),j}$ parameter captures the effect of race-specific preferences for local public goods and amenities that might determine differential sorting patterns. Importantly, the $\sigma_{g(i),j}$ parameter will capture any differences in unobserved neighborhood characteristics such as retail establishments, churches, and schools that may have an association with the sorting patterns of a particular racial/ethnic group in the sample. In the absence of preferences for unobserved neighborhood characteristics that are specific to a given racial group, $\sigma_{g(i),j}$ captures homophily preferences – a preference to live near others who are of the same race. We include a quadratic polynomial in $\sigma_{g(i),j}$ to allow for a bliss-point in own-race.

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:

$$P_{i,j} = \frac{exp\left[\alpha ln(I_i - R_j) + X_j'\gamma + \beta_{1,g}\sigma_{g(i),j} + \beta_{2,g}\sigma^2_{g(i),j}\right]}{\sum_k exp\left[\alpha ln(I_i - R_j) + X_k'\gamma + \beta_{1,g}\sigma_{g(i),k} + \beta_{2,g}\sigma^2_{g(i),k}\right]} \tag{5}$$

The choice probability of any consideration set for renter i is given by Γ_i:

$$P_{i,j}|\Gamma_i = \frac{exp\left[\alpha ln(I_i - R_j) + X_j'\gamma + \beta_{1,g}\sigma_{g(i),j} + \beta_{2,g}\sigma^2_{g(i),j}\right]}{\sum_{k\in\Gamma_i} exp\left[\alpha ln(I_i - R_j) + X_k'\gamma_i + \beta_{1,g}\sigma_{g(i),k} + \beta_{2,g}\sigma^2_{g(i),k}\right]} \tag{6}$$

The choice of $j^*(i)$ renter i must be an element of Γ_i. We simulate N_s consideration sets and take the associated expected probability:

$$E[P_{i,j}] = \sum_{s=1}^{N_s}\left(\frac{exp\left[\alpha ln(I_i - R_j) + X_j'\gamma + \beta_{1,g}\sigma_{g(i),j} + \beta_{2,g}\sigma^2_{g(i),j}\right]}{\sum_{k\in\Gamma_{i,s}} exp\left[\alpha ln(I_i - R_k) + X_k'\gamma_i + \beta_{1,g}\sigma_{g(i),k} + \beta_{2,g}\sigma^2_{g(i),k}\right]}\right) W_{i,s} \tag{7}$$

where

$$W_{i,s} = \frac{P(\Gamma_{i,s})}{\sum_{m=1}^{N_s} P(\Gamma_{i,m})} \tag{8}$$

and

$$P(\Gamma_{i,s}) = \Pi_{j=1}^{J} \rho_{i,j}^{\chi_{i,j,s}}(1 - \rho_{i,j})^{1-\chi_{i,j,s}} \tag{9}$$

If j is included in the simulated choice set s for renter i, then $\chi_{i,j,s} = 1$. The parameter $\rho_{i,j}$ measures the probability that a renter i in each race/ethnic group can access a choice in tract j. The weight parameter $W_{i,s}$ reflects the likelihood that consideration set s with choice probability $\Gamma_{i,s}$ is available to renter i. We then maximize the log-likelihood function based on these probabilities:

$$L = \sum_{i=1}^{N} lnE[P_{i,j^*(i)}] \tag{10}$$

where $j^*(i)$ refers to the observed census tract choice of individual i. Our analysis pools data from the five different metropolitan areas in order to increase the external validity and to provide greater variation in the neighborhood attributes that individuals are choosing over. Importantly, while we estimate a common set of preference parameters across markets, we restrict the choice set available to an individual to only include the tracts in their associated MSA.

4.2 Structural Model Estimates

Table 5 reports the results of our model of residential location choice, incorporating the choice set constraints imposed by discrimination. Column 1 reports parameter estimates, all of which are statistically significant. For each of the primary neighborhood attributes, Column 2 reports measures of marginal willingness-to-pay for a one unit increase in the attribute, measured as a percentage of income. We begin with our utility function for individual i living in census tract j:

$$U_{i,j} = c_i^{\alpha} e^{X_j'\gamma + \beta_{1,g}\sigma_{g(i),j} + \beta_{2,g}\sigma^2_{g(i),j} + \epsilon_{i,j}} \tag{11}$$

Recognizing that $c_i = I_i - R_j$ given the budget constraint for each renter i, the marginal willingness to pay (MWTP) for X_j is given by the following expression:

$$MWTP = \frac{\frac{\partial U}{\partial X}}{\frac{\partial U}{\partial C}} = \frac{\gamma}{\alpha}(I_i - R_j) \tag{12}$$

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

$$\frac{MWTP}{I_i} = \frac{\gamma}{\alpha}\frac{(I_i - R_j)}{I_i} = \frac{\gamma}{\alpha}(1 - s_H) \tag{13}$$

where s_H is the share of household income spent on rent. This implies that marginal willingness to pay as a share of non-housing expenditures is given by:

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

In the case of average school quality, $\alpha = 1.3060$ and $\gamma = 0.0537$ and the average standard deviation across our five MSAs is 1.684. This implies a willingness to pay of 6.9% of non-housing expenditures for a one standard deviation improvement in school quality. For a household that consumes 20% of income on rent, this would imply a willingness to pay of about 5.52% of total income for that one standard deviation improvement.[18]

4.3 Measuring the Effects of Discrimination on Renter Welfare

Discrimination in the online search environment directly affects a renter's choice set. The random utility choice framework simulates an actual search process and is well-suited for analyzing impacts of alterations to an individual's choice set. We describe impacts in terms of equivalent variation in income by first measuring the expected utility associated with the full (unconstrained) set of all census tracts versus the constrained set.

$$EU_i = log\left(\sum_{k=1}^{J} exp\left[\alpha ln(I_i - R_k) + X_k'\gamma + \beta_{1,g}\sigma_{g(i),k} + \beta_{2,g}\sigma^2_{g(i),k}\right]\right) \tag{15}$$

Alternatively, the expected utility associated with the constrained set of choices is given by:

$$\tilde{EU}_i = log\left(\sum_{s=1}^{N_s} W_{i,s} \sum_{k\in\Gamma_{i,s}} exp\left[\alpha ln(I_i - R_k) + X_k'\gamma + \beta_{1,g}\sigma_{g(i),k} + \beta_{2,g}\sigma^2_{g(i),k}\right]\right) \tag{16}$$

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

$$log\left(\sum_{k=1}^{J} exp\left[\alpha ln(I_i + EV_i - R_k) + X_k'\gamma + \beta_{1,g}\sigma_{g(i),k} + \beta_{2,g}\sigma^2_{g(i),k}\right]\right) =$$

[18] Figure D plots rent-to-income by income and race.

$$\log\left(\sum_{s=1}^{N_s} W_{i,s} \sum_{k\in\Gamma_{i,s}} exp\left[\alpha ln(I_i - R_k) + X_k'\gamma + \beta_{1,g}\sigma_{g(i),k} + \beta_{2,g}\sigma^2_{g(i),k}\right]\right) \quad (17)$$

We use Eq. 17 to simulate changes in the EV_i that an individual renter receives in counterfactual search environments. In particular, we simulate the search behavior of a set of 5,000 African American and 5,000 Hispanic/LatinX renters using random draws from actual race-specific income distributions in each city. For each renter, we compute the welfare effects associated with search when confronted with choice set constraints given by the response probabilities for their group. We then confront the same renter with the choice set constraints given by the response probabilities recovered for White identities. This simulation holds constant all aspects of search that are race-specific – in particular, those associated with income and homophily preferences. This allows us to: (i) isolate the effects of discriminatory constraints that affect the consumption of an array of neighborhood amenities and (ii) estimate their combined effects with a single welfare measure.

Figure 5 reports the distributions of equivalent income variation associated with discriminatory constraints as a share of annual income. For African Americans, the median value is -3.6% compared to -3.3% for Hispanic/LatinX renters. The mean effects for both groups is higher (4.6-4.7%) as a result of left tails with damages of over -15%. These findings indicate that the discrimination incurred during the first stage of a search process can translate result in lost choices that both groups would be willing-to-pay significant sums to avoid. Furthermore, they suggest important differences across different renters in each group. The distribution of damages for Hispanic/LatinX is bimodal, with a large mass of damages centered around 8-10% of annual income. Figure 6 investigates this further by illustrating shifts in the distribution of damages across different renter income groups. These histograms demonstrate that the mass of welfare effects increases (moves to the left) as income rises for African Americans, with a median value of approximately -3% for those with annual incomes in the $0-30,000/year range. This rises to -8% for those in the $120,000-150,000/year range. By contrast, damages for Hispanic/LatinX renters become smaller and the distribution more compressed at higher incomes.

Figure 7 provides a clear illustration of the way in which monetized damages from discriminatory constraints vary with the incomes of African American and Hispanic/LatinX renters. Damages rise steadily with income for African Americans, exceeding $10,000/year for households that earn more than $140,000/year and reaching nearly $15,000/year at the upper end of the income distribution in our sample. This contrasts with damages facing Hispanic/LatinX renters, which grow far less slowly among households that earn more than $60,000/year and begin to stabilize at around $4,000-5,000/year. This reflects the stronger constraints facing African American renters that search for housing in high amenity tracts, which are consistent with stronger reduced form effects in high amenity neighborhoods reported in Appendix C. This difference sheds light on the implications of housing discrimination on the economic mobility of African American households, which is shown to differ systematically from that of Hispanic/LatinX households (Chetty and Hendren, 2018b). Discriminatory constraints impose a higher cost of search on economically mobile African American households that would optimally invest an increasing fraction of income in high amenity neighborhoods, which are shown to be important for human capital accumulation.

4.4 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 damages from discrimination. In this section, we examine the distortionary effects of discriminatory behavior on bias in estimates of revealed preference parameters underlying housing search behavior. This is important, as decisions in the housing market send powerful implicit signals about demand for local public goods and have been used for decades to measure the value of key non-market goods and neighborhood amenities. These values are used to guide decisions about allocation of public resources and to conduct cost-benefit analysis of regulatory policy. If biases in these estimated values are correlated with race, discrimination could have important distributional consequences.

The intuition underlying the bias hypothesis is straightforward. Housing markets provide valid revealed preference estimates of demand for local public goods assuming that households have access to all available choices. Under that condition households reveal their willingness-to-pay to live in a neighborhood with a marginally better attribute (e.g., lower crime rates) compared to an otherwise similar neighborhood with the marginally worse attribute (e.g., higher crime rates). Systematic exclusion from housing choices in neighborhoods with higher amenity levels would bias the preferences estimated for the excluded group. A naive model would assume that this group has low willingness-to-pay for those amenities. We construct a test for bias using the experimental data and consideration set model to estimate MWTP as a share of non-housing expenditures that incorporates choice set constraints. We then compare these to estimates from 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 coefficients on the log of income after paying rent and on all non-race tract amenities to be different for White renters versus Renters of Color (ROC).[19]

The top panel of Table 6 reports estimates from models with and without (naive model) consideration sets, based on our main specification. While the parameters in Table 6 include race-specific heterogeneity in preferences parameters, estimates from the considerations sets model are consistent in signs, magnitudes, and significance level with those reported in Table 5. In the lower panel, we report the difference in MWTP as a share of non-housing expenditures without and with consideration sets for White renters and Renters of Color. Ignoring consideration sets raises this number for White renters by 0.81%, whereas doing so only raises it by 0.27% for Renters of Color. Ignoring consideration sets could, therefore, bias the allocation of school funding based on these benefit numbers away from a neighborhood that is composed primarily of Renters of Color and towards a neighborhood composed primarily of White renters. We find a similar result with respect to cafes, though the difference is smaller. In the case of murders, ignoring consideration sets tends to understate MWTP as a share of non-housing expenditures for both White renters and Renters of Color, but it does so to a greater extent for the latter

[19]Renters of Color combines the African American and Hispanic/LatinX groups.

group. The impact of ignoring consideration sets is most stark in the case of RSEI, where the effects go in opposite directions – increasing the willingness to pay to avoid air toxics for White renters, while reducing it for Renters of Color.

5 Conclusions

The experimental literature on the effects of discrimination has focused largely on reduced form differences in discriminatory behavior. This paper combines a correspondence study with a utility-based structural model of housing search, drawing upon estimation techniques developed in the consideration sets literature to estimate the structural parameters in the context of discriminatory constraints that restrict renter choice sets in five major metropolitan housing markets in the United States.

The structural estimation approach recovers utility-theoretic measures of welfare cost associated with the choice set restrictions imposed by discrimination. We find that the damages from discriminatory constraints in the first stage of a search process, measured as equivalent variations in income, are equivalent to 4.5% and 4.6% of income for the average African American and Hispanic/LatinX renters in our sample, respectively. Considering African American renters, these damages as a share of income grow considerably with the level of income, which is consistent with stronger discrimination rates found in high-amenity/high-rent neighborhoods and the higher marginal marginal value of neighborhood amenities at higher incomes.

In a final section, we explore the effect of discriminatory constraints on estimates of the revealed willingness-to-pay for the amenities that we study. Findings from this analysis indicate that by driving a wedge between true amenity preferences and those revealed by a housing search, discrimination can distort estimates of willingness-to-pay derived using standard methods. The same distortion affects signals that the housing market sends to policymakers about the value of key local public goods.

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Table 1. Summary Statistics: Neighborhood Characteristics

	Atlanta, GA		Houston, TX		Philadelphia, PA		Cleveland, OH		San Jose, CA	
Parameter	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Rental Listings (Search Platform)										
Monthly Rent	1167.19	290.17	1120.00	355.13	1157.94	336.31	994.55	379.42	2137.11	513.53
Ave School Quality	5.07	1.46	4.57	1.82	3.43	1.24	4.93	2.17	6.81	1.73
Cafes	15.90	14.09	5.63	7.19	47.05	37.29	3.20	3.38	11.75	7.98
Murder Index	273.87	281.89	175.00	155.50	298.89	311.38	98.75	149.39	44.98	62.31
Toxics Concentration (RSEI)	638.30	466.76	37006.13	45389.93	4312.55	3266.31	9605.46	9523.51	114.36	133.18
American Community Survey										
African American Share	0.41	0.34	0.21	0.22	0.30	0.31	0.19	0.25	0.02	0.02
LatinX Share	0.07	0.09	0.35	0.21	0.08	0.07	0.05	0.07	0.22	0.18
White Share	0.43	0.30	0.33	0.25	0.51	0.29	0.70	0.26	0.38	0.20
InfoUSA Renter Dataset										
Renter Income										
African American	36, 390	16, 460	36, 970	20, 660	36, 730	24, 380	28, 470	14, 540	79, 480	47, 440
Hipanic/LatinX	44, 790	20, 130	39, 730	22, 450	47, 830	30, 630	28, 950	13, 930	74, 730	43, 780
White	49, 010	21, 290	50, 800	27, 150	62, 810	31, 320	36, 090	17, 820	90, 800	50, 820
Housing Expenditure Share										
African American	0.40	0.16	0.40	0.17	0.42	0.18	0.42	0.16	0.40	0.19
Hipanic/LatinX	0.39	0.16	0.39	0.17	0.39	0.18	0.38	0.13	0.40	0.19
White	0.37	0.16	0.36	0.18	0.34	0.17	0.35	0.15	0.36	0.19
Rent-to-Income Ratio	0.37	0.16	0.38	0.17	0.36	0.18	0.37	0.15	0.37	0.19
Population Share										
African American	0.25		0.23		0.21		0.25		0.02	
Hipanic/LatinX	0.06		0.22		0.06		0.05		0.22	
White	0.68		0.55		0.72		0.71		0.77	
Census Tracts	n = 129		n = 322		n = 138		n = 92		n = 184	

Notes: Table reports descriptive statistics (mean and std. dev. at the census tract level) for neighborhood characteristics obtained from rental listings on the search platform used in the experiment (toxics concentrations come from the EPA RSEI model), from the 2013-2017 American Community Survey, and from InfoUSA renter data.

Table 2. Evidence of Discrimination on Housing Choice by City

Race Group	All Cities	Atlanta, GA	Houston, TX	Philadelphia, PA	Cleveland, OH	San Jose, CA
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
Matched Listings	5,451	1,128	792	402	1,506	1,623
Total Observations	18045	3093	4710	972	4254	5016

Notes: Columns 1 reports estimates of relative response rates for the full sample of listings across all cities, with standard errors clustered at the MSA level. Estimates in Columns 2-5 report estimates of relative response rates by city. Response rates are estimated relative to responses to inquiries sent from a White identity (the omitted category). The average response rate for inquiries sent from White identities are reported for each sample. 90% confidence intervals are reported in parentheses. Sample sizes are reported for matched inquiry sets (a set includes inquiries sent from all three identities) and total observations (where a fully matched set was not obtained). *** p<0.01, ** p<0.05, * p<0.1

Table 3. Discriminatory Constraint by Inquiry Sequence

Group	Full Sample	White Neighborhoods	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)
Mean Choice (White)	0.334	0.334	0.334
Matched Listings	3,828	903	978
Total Observations	13029	3243	3276

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.Sample sizes are reported for matched inquiry sets (a set includes inquiries sent from all three identities) and total observations (where a fully matched set was not obtained) *** p<0.01, ** p<0.05, * p<0.1

Table 4. Discriminatory Constraint by Days on Market

Race Group	Combined	Group Specific
LatinX: 0-3 Days		0.4213*
		(0.2001 - 0.8870)
LatinX: 3-7 Days		0.6842**
		(0.5333 - 0.8778)
LatinX: 7+ Days		0.8157**
		(0.7092 - 0.9382)
African American: 0-3 Days		0.4813
		(0.2262 - 1.0243)
African American: 3-7 Days		0.7137
		(0.4323 - 1.1783)
African American: 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)	
Mean Choice (White)	0.334	0.334
Matched Listings	3,828	3,828
Total Observations	13029	13029

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. Sample sizes are reported for matched inquiry sets (a set includes inquiries sent from all three identities) and total observations (where a fully matched set was not obtained). *** p<0.01, ** p<0.05, * p<0.1

Table 5. Parameter Estimates

Parameter	Consideration Sets	WTP/Non-Housing Exp
ln(I-R)	1.3060***	
	(0.0293)	
Avg School Quality	0.0537***	0.0411
	(0.0038)	$[0.0394, 0.0429]$
Cafes	0.0076***	0.0059
	(0.0002)	$[0.0056, 0.0061]$
Murders	-0.0017***	-0.0013
	(4.02×10^{-5})	$[-0.0013, -0.0012]$
ln(RSEI)	-0.0625***	-0.0479
	(0.0064)	$[-0.0500, -0.0459]$
White $*$% White	0.0900***	
	(0.0014)	
White $*$% White^2	-7.32×10^{-4}***	
	(1.22×10^{-5})	
African American $*$% African American	0.0985***	
	(0.0019)	
African American $*$% African American^2	-6.06×10^{-4}***	
	(1.67×10^{-5})	
LatinX $*$% LatinX	0.0812***	
	(0.0023)	
LatinX $*$% LatinX^2	-8.97×10^{-4}***	
	(2.70×10^{-5})	

Notes: Table reports parameter estimates from baseline model specification with consideration sets. Column 1 reports coefficient estimates. Column 2 reports estimates of willingness-to-pay as a share of non-housing expenditures with 95% confidence intervals derived by sampling the willingness to pay ratio from the variance-covariance matrix of the estimated parameters. *** p<0.01, ** p<0.05, * p<0.1.

Table 6. Bias in Willingness to Pay

Variable	Consideration Sets	No Consideration Sets
ln(I-R)	1.2996***	1.2369***
	(0.0363)	(0.0360)
Avg School Quality	0.0618***	0.0687***
	(0.0043)	(0.0043)
Cafes	0.0083***	0.0130***
	(0.0002)	(0.0002)
Murders	−0.0013***	−0.0012***
	(0.0001)	(0.0001)
ln(RSEI)	−0.0255***	−0.0285***
	(0.0078)	(0.0077)
ln(I-R) x ROC	0.0929	0.0502
	(0.0620)	(0.0611)
Avg School Quality x ROC	−0.0321***	−0.0378***
	(0.0088)	(0.0043)
Cafes x ROC	−0.0042***	−0.0045***
	(0.0006)	(0.0006)
Murders x ROC	−0.0007***	−0.0006***
	(0.0001)	(0.0001)
ln(RSEI) x ROC	−0.1327***	−0.0326**
	(0.0136)	(0.0135)
White ∗% White	0.0908***	0.0875***
	(0.0014)	(0.0013)
White ∗% White^2	-7.32×10^{-4}***	-7.06×10^{-4}***
	(1.23×10^{-5})	(1.22×10^{-5})
African American ∗% African American	0.0985***	0.1031***
	(0.0019)	(0.0019)
African American ∗% African American^2	-5.98×10^{-4}***	-6.63×10^{-4}***
	(1.68×10^{-5})	(1.64×10^{-5})
LatinX ∗% LatinX	0.0753***	0.0681***
	(0.0024)	(0.0024)
LatinX ∗% LatinX^2	-8.51×10^{-4}***	-6.83×10^{-4}***
	(2.73×10^{-5})	(2.70×10^{-5})

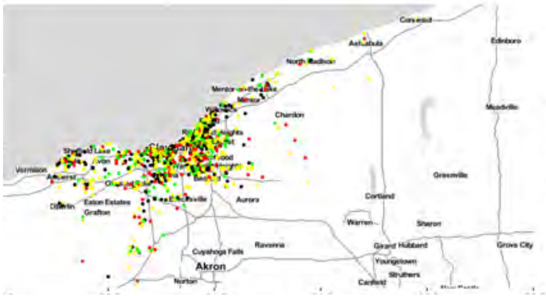
	[WTP(NCS) - WTP(CS)]/Non-Housing Exp	
Variable	White	People of Color
Avg School Quality	0.0081	0.0027
	[0.0039 , 0.0122]	[0.0010 , 0.0045]
Cafes	0.0041	0.0037
	[0.0034 , 0.0048]	[0.0033 , 0.0041]
Murders	2.00×10^{-5}	7.00×10^{-5}
	[-5.00×10^{-5} , 1.10×10^{-4}]	[-4.00×10^{-5} , 1.80×10^{-4}]
ln(RSEI)	−0.0034	0.0662
	[−0.0052 , −0.0017]	[0.0603 , 0.0729]

Notes: Table reports differences in parameter estimates from model specifications that include/omit consideration sets using experimentally identified discriminatory constraints. Upper panel reports differences in parameter estimates with 95% confidence intervals derived by sampling the willingness to pay ratio from the variance-covariance matrix of the estimated parameters. Lower panel reports differences in willingness to pay as a share of non-housing expenditure without and with consideration sets, for white renters and renters of color for four different amenities. 95% confidence intervals are derived by sampling willingness to pay ratios from the variance-covariance matrices of the estimated parameters. *** p<0.01, ** p<0.05, * p<0.1.

Figure 1. Within-Listing Response Differential by MSA

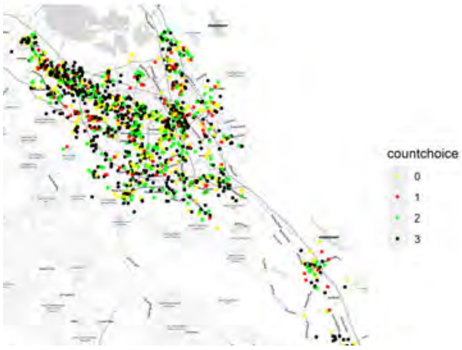
(a) Atlanta, GA (n=3,093)

(b) Philadelphia, PA (n=972)



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

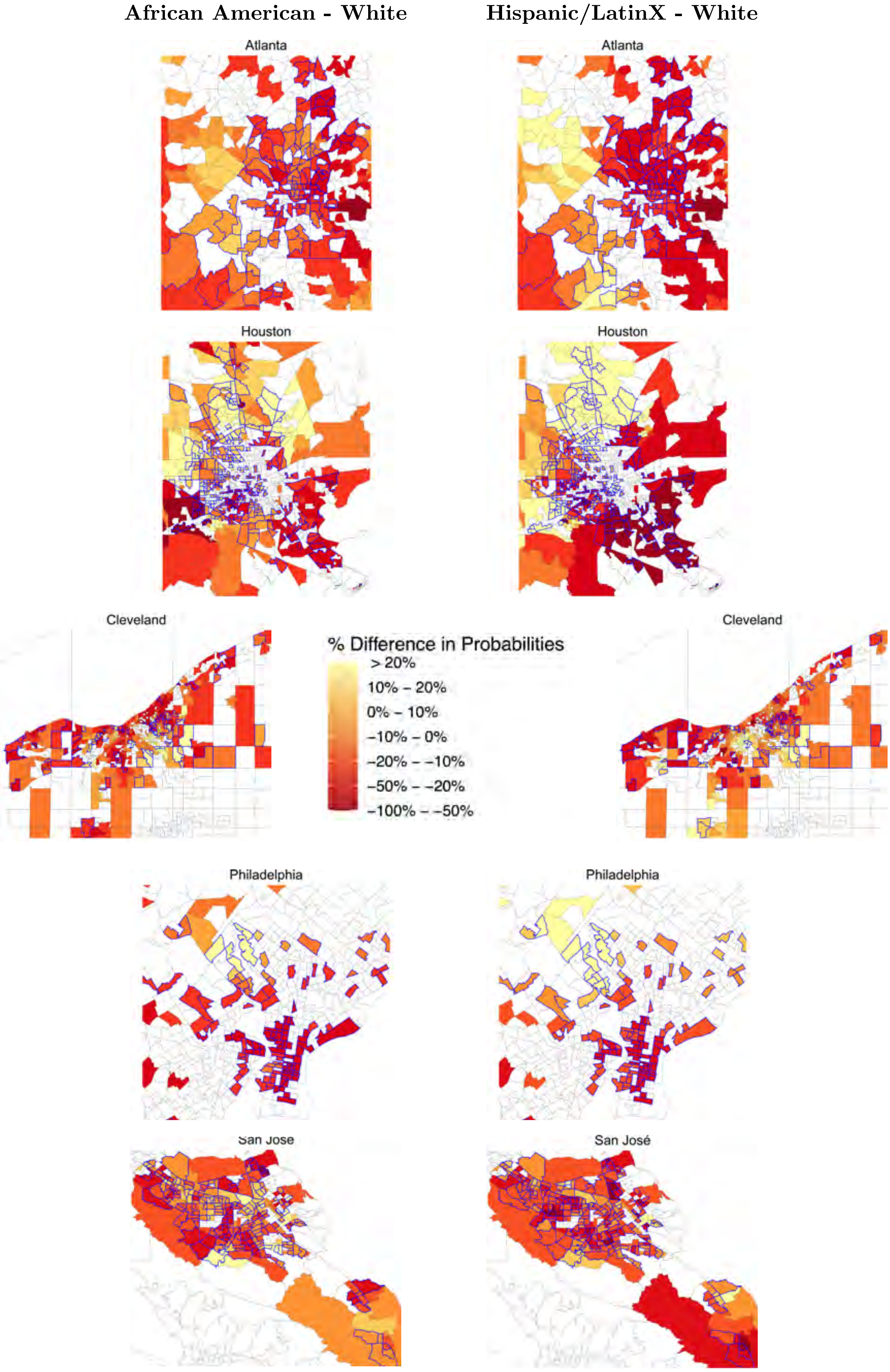
(d) Houston, TX (n=4,710)



(e) San Jose, CA (n=5,016)

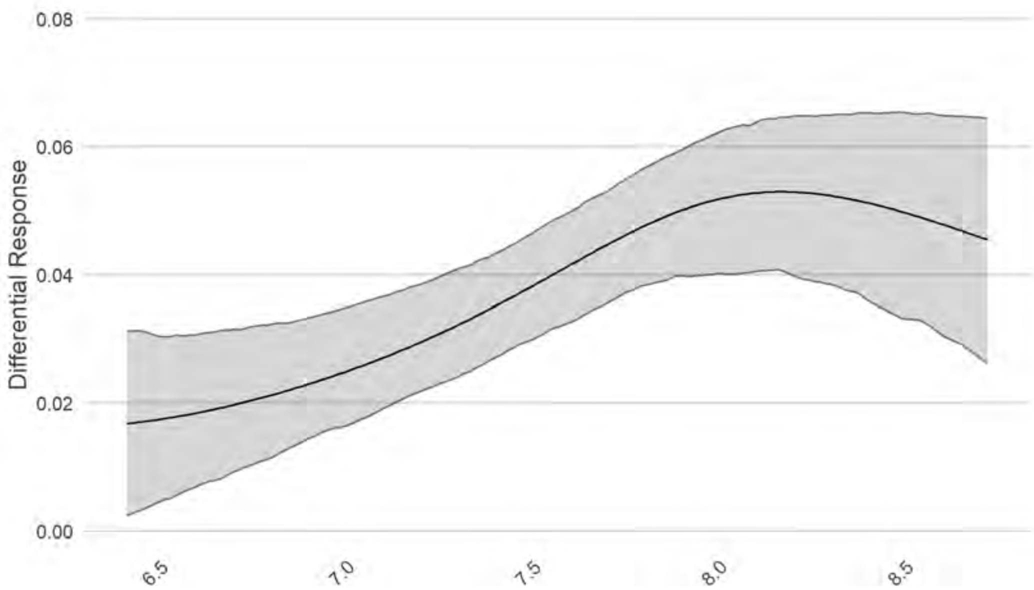
Notes: Figures map the raw data from matched response sets for the five Metropolitan Statistical Areas in the experiment. Matched responses refer to the number of responses returned from a single property over the course of the 3-day trial.

Figure 2. Differential Responses by Tract

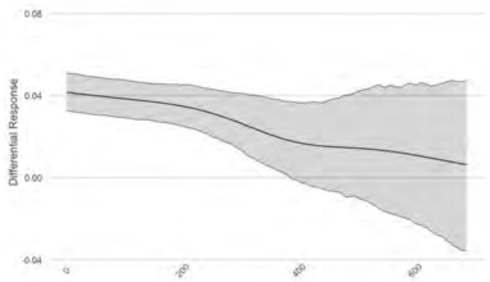


Notes: Figures map the average difference in response rates to African American and Hispanic/LatinX identities (relative to White) in each census tract for the five Metropolitan Statistical Areas in the experiment. Census tracts where renters are observed to move in 2018 are included in the sample and colored. Census tracts that contain information from the experimental trials are shown with blue borders. All other tracts do not contain data on renter moves/response rates and are omitted from the structural model.

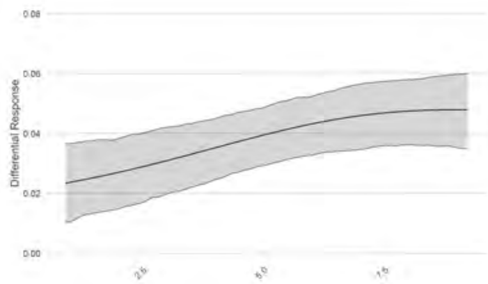
Figure 3. Discriminatory Constraints by Attribute (White - Renter of Color)



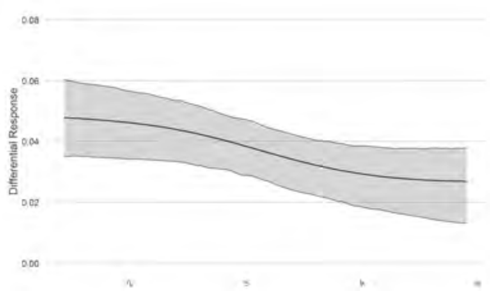
A: Rental Price



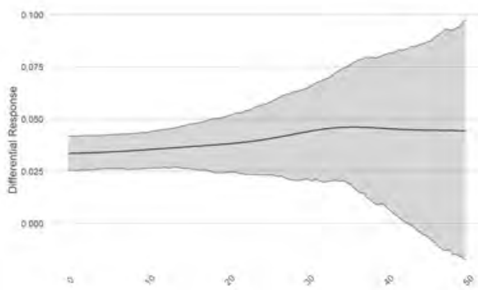
B: Murder Index



C: Average School Rating



D: Toxic Concentrations (RSEI)

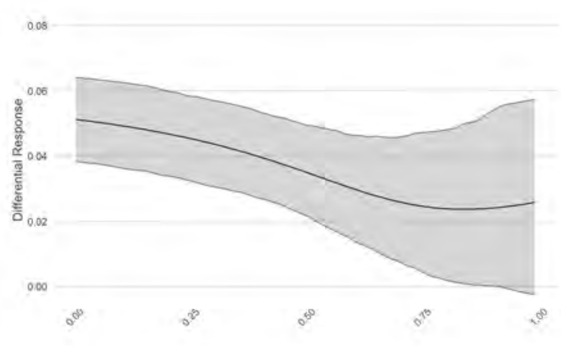


E: Cafes

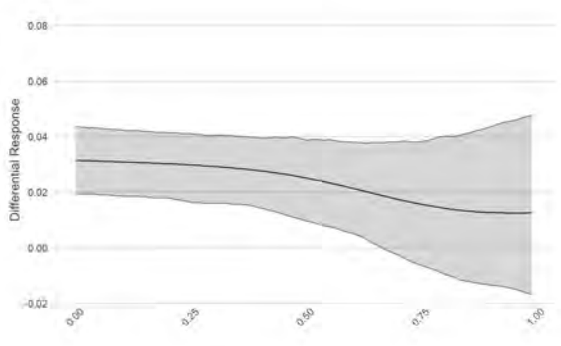
Notes: Figures plot differential constraints for renters of color (African American and Hispanic/LatinX) relative to White by attributes observed in rental listings collected in the experiment using estimates from Eq. 3. Increases in differential response correspond to increases in discriminatory constraints.

Figure 4. Response Rates by Neighborhood Demographic Shares

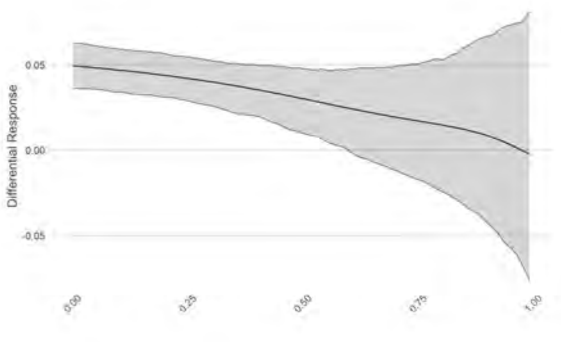
African American **Hispanic/LatinX**



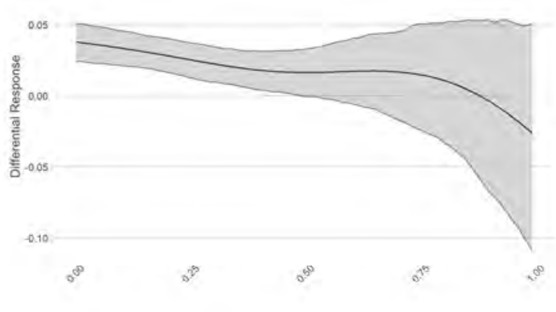
(a) African American Share



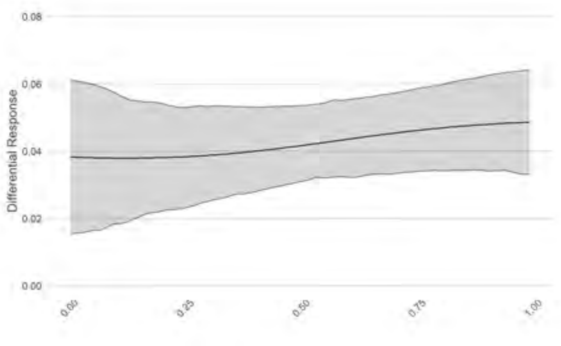
(b) African American Share



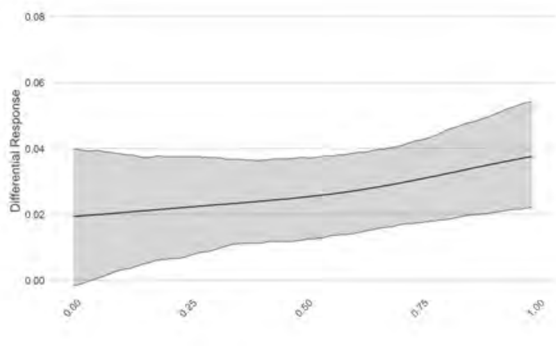
(c) Hispanic/LatinX Share



(d) Hispanic/LatinX Share



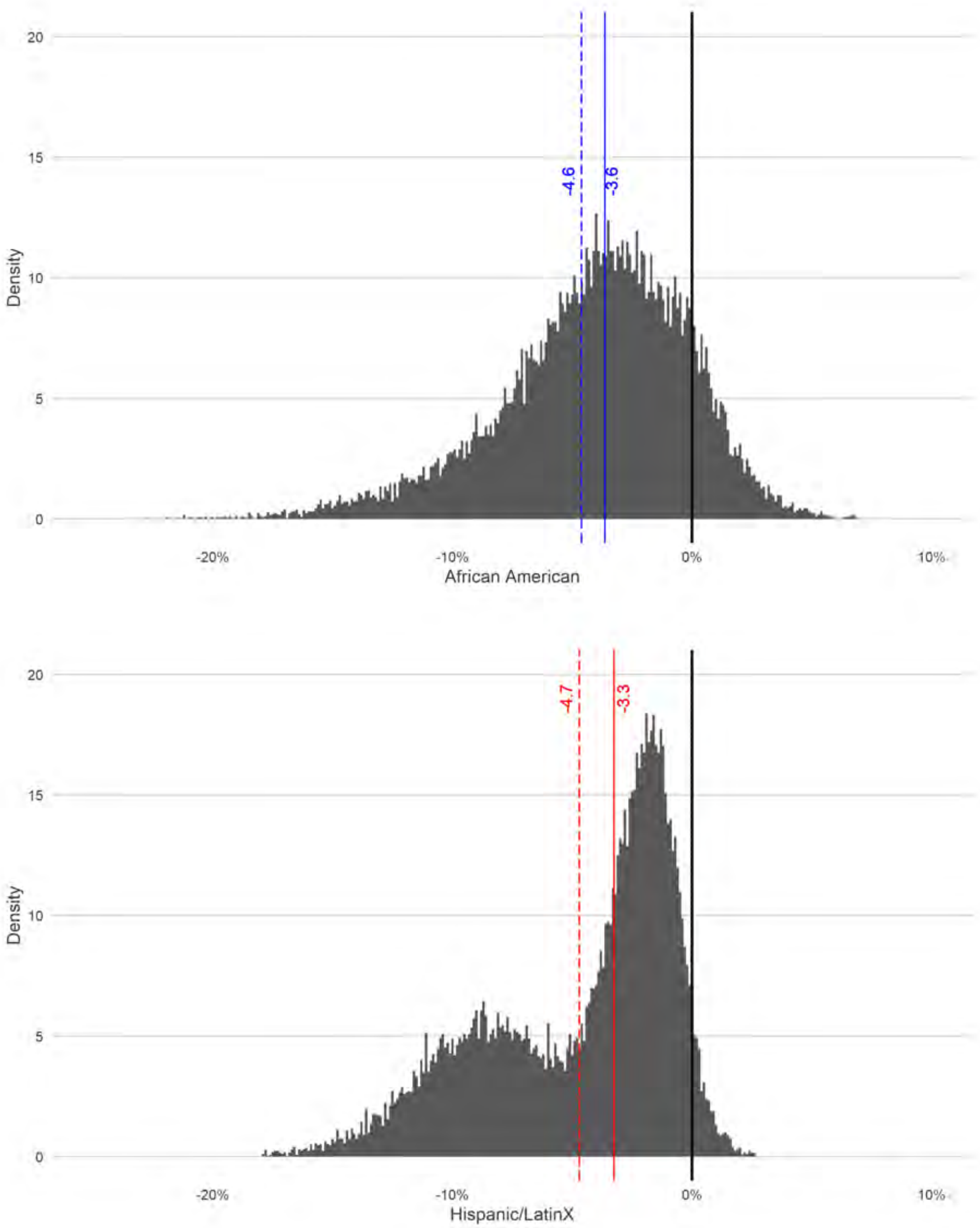
(e) White Share



(f) White Share

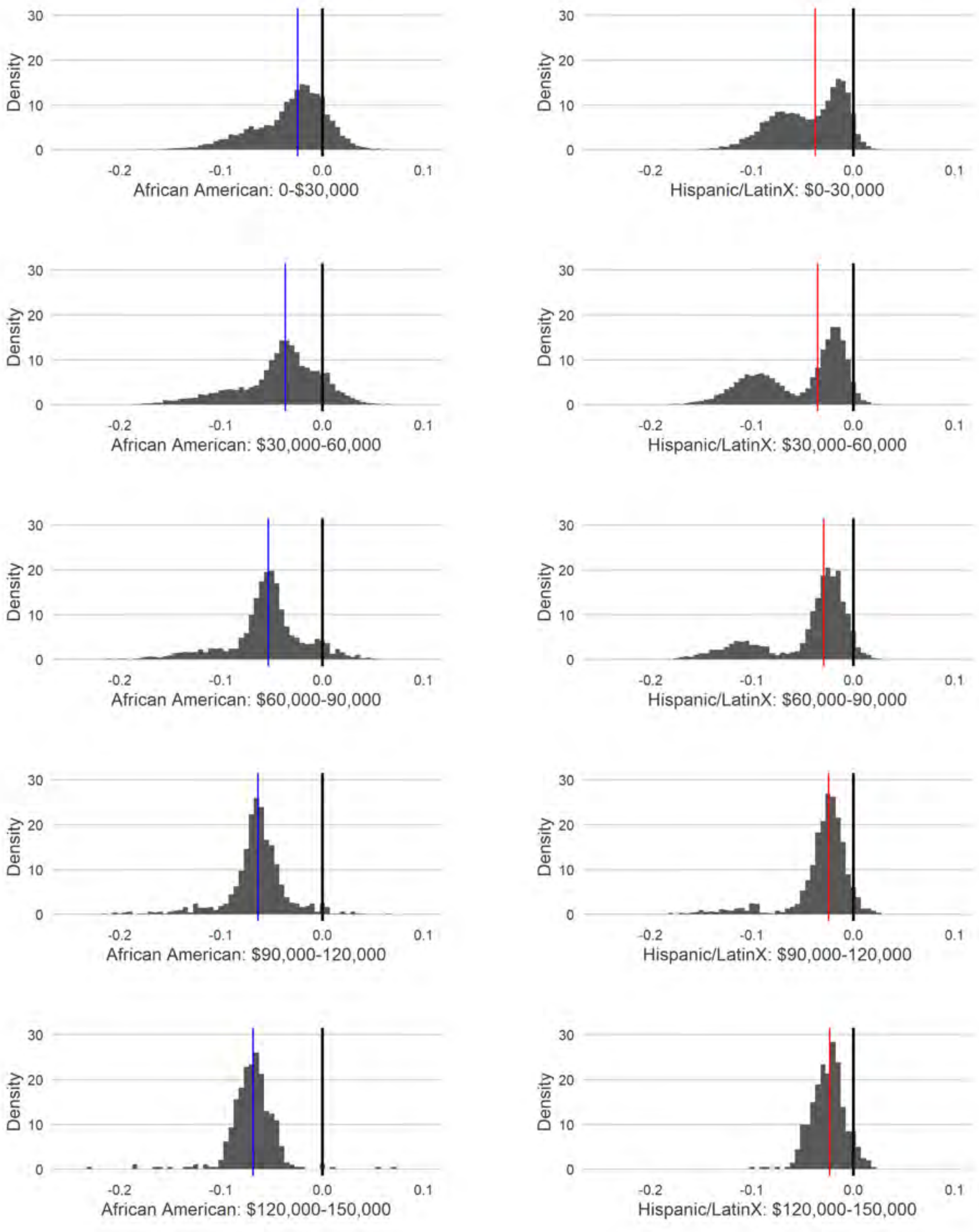
Notes: Figures plot differential constraints for renters of color (African American and Hispanic/LatinX) relative to white renters by ethnic/racial composition using estimates from Eq. 3. Increases in differential response correspond to increases in discriminatory constraints. Racial composition is observed at the block group level using the 2013-2017 American Community Survey.

Figure 5. Annualized Damages as a Share of Annual Income (Equivalent Variation)



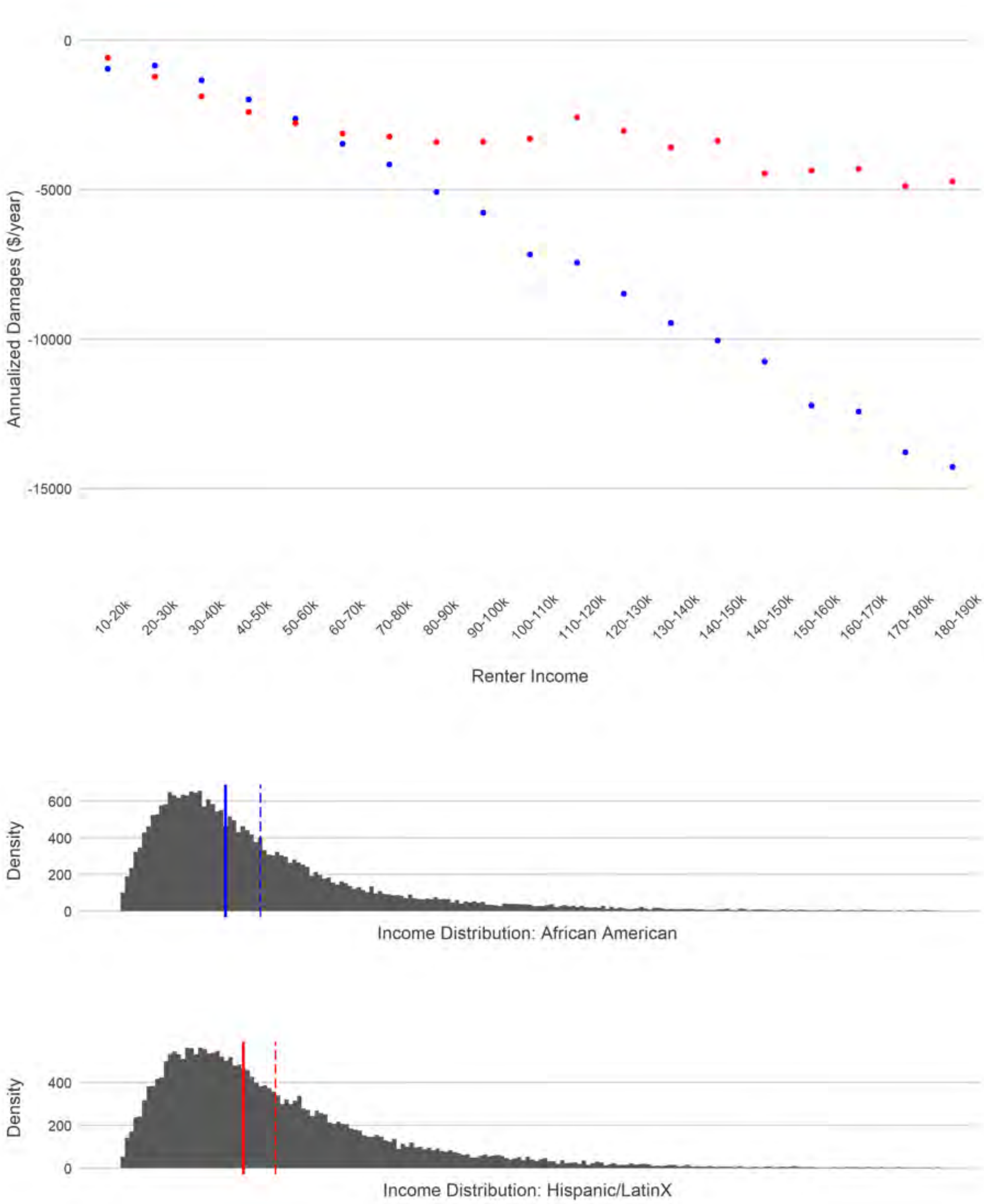
Note: The figure graphs the distribution of renter welfare effects (compensating variation as a share of renter income) resulting from discriminatory constraints as measured by the correspondence experiment. Plots illustrate damages to African American renters (top) and Hispanic/LatinX renters (bottom), with solid vertical lines denoting the mean and dashed vertical lines denoting the median estimates.

Figure 6. Annualized Damages by Income Group (Equivalent Variation)



Note: Graphs plot the distributions of renter welfare effects (compensating variation as a share of renter income) at different levels of renter income. Each plot illustrates a distribution of effects for the following renter income groups: \$0-30,000, \$30,000-60,000, \$60,000-90,000, \$90,000-120,000, \$120,000-150,000. Blue and red vertical lines denote median effects for African American renters and Hispanic/LatinX renters, respectively.

Figure 7. Annualized Damages by Income (Equivalent Variation)



Note: Top panel graphs the distribution of renter welfare effects (compensating variation in dollars per year) resulting from discriminatory constraints as measured by the correspondence experiment. Blue points show effects for African American renters and red points plot effects for Hispanic/LatinX renters. Bottom panels graph the distribution of renter incomes from the InfoUSA renter sample.

Appendix

A Experimental Design

Correspondence Research Design

In a correspondence experiment, a researcher elicits racialized perceptions in a trial by constructing fictitious identities and experimentally varying a single trait (Bertrand and Duflo, 2017). The majority of correspondence research has focused on the use of racially distinct names as the trait used to elicit discriminatory behavior. While there are limitations associated with the use of a particular trait, the consistent use of this design has enabled researchers to learn about racial perceptions of names across studies as well as in the general population. Correspondence studies select names that are likely to elicit behavior, such that the resulting actions can be clearly attributed to racialized perceptions. These names are not necessarily representative of names in the population at large. Multiple randomized experiments have focused exclusively on the alignment between perceived associations with an ethnic/racial group and self-identified racial identity (Crabtree and Chykina, 2018, Gaddis, 2017a,b).

A concern that arises in both audit and correspondence studies is the potential for those being audited to check the online profile of the tester or fictitious applicant. Nearly all correspondence studies rely on the assumption that online search tools will not affect the interpretation of results. The extent to which this assumption holds may vary across different settings. We highlight the following features of the present setting in this regard:

1. Our correspondence design focuses on the first contact in a housing search, where the returns to learning about a respondent are low. We might expect online research to occur in later stages of contact.

2. Our study utilizes names that are sampled from the highest percentiles of the distribution of each of three racial groups. By construction, these very common names will be linked to many possible online identities. For example, if a property manager were to conduct a google search of one of our fictitious identities, they would retrieve results like: this example. It is likely that a large fraction of the renter population also has a weak online presence. We assume that the likelihood that property managers will be affected by (the absence of) identifiable online information is low.

Name Selection

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

> "I selected names for this study using New York state birth record data for all births from 1994 to 2012 obtained from the New York State Department of Health to examine population-level race and SES characteristics. These data separately list the total number of births by (1) name and mother's race and (2) name and mother's education. This data structure allowed me, for example, to choose two

> names similar in terms of mother's race but different in terms of mother's education-in other words, a black lower-SES name and a black middle- to upper-SES name. Two examples used in this study are DaQuan and Jabari; 91.8 percent of children named DaQuan and 92.1 percent of children named Jabari are born to black mothers. These names are equal in blackness but vary by mother's education; only 12.8 percent of mothers who name their child DaQuan have some college or more education, whereas 56.8 percent of mothers who name their child Jabari have some college or more education. Additionally, when possible, I selected names that were used in previous or ongoing audit studies from different disciplines (e.g., Bertrand and Mullainathan 2004; Gaddis 2015; Milkman et al. 2012)."

Gaddis finds congruence rates of 75%, 75.5%, and 87.3%, respectively, for African American, Hispanic, and White first names. When last names are included, Gaddis finds that congruence rates increase to 82.5%, 97.3%, and 92.4% for African American, Hispanic, and White first-last name pairs, respectively. Gaddis also shows that congruence rates for all groups decline when first names are (mis)matched with last names from a different group. Based on this evidence, we select first-last name pairs that are shown to have a high probability of eliciting racially congruent perceptions. Panel A of Table A1 reports the identification rates from Gaddis (2017a,b) for the specific subset of first names that we use in the present study. In the study, we use the following first-last name pairs: Nia Harris, Jalen Jackson, Ebony James, Lamar Williams, Shanice Thomas, DaQuan Robinson, Isabella Lopez, Jorge Rodriguez, Mariana Morales, Pedro Sanchez, Jimena Ramirez, Luis Torres, Aubrey Murphy, Caleb Peterson, Erica Cox, Charlie Myers, Leslie Wood, Ronnie Miller. In every case, congruence rates increase with the inclusion of a correctly matched last name.

Table A1. Identification Rates for First Names and Last Name Frequencies

Panel A. Identification Rates from Gaddis (2017a,b) (%)				
Race	First Name	No Last Name	Last Name Included	Quartile mother's education
African American	Nia	41	65	High
African American	Jalen	63	71	High
African American	Ebony	91	95	Med
African American	Lamar	88	94	Med
African American	Shanice	93	92	Low
African American	DaQuan	91	96	Low
Hispanic/LatinX	Isabella	48	98	High
Hispanic/LatinX	Jorge	86	98	High
Hispanic/LatinX	Mariana	78	99	Med
Hispanic/LatinX	Pedro	98	99	Med
Hispanic/LatinX	Jimena	49	97	Low
Hispanic/LatinX	Luis	83	99	Low
White	Aubrey	90	93	High
White	Caleb	77	84	High
White	Erica	82	93	Med
White	Charlie	86	91	Med
White	Leslie	72	93	Low
White	Ronnie	71	89	Low
Panel B. Last Names Frequency of Occurrence in 2010 Census (%)				
Race	Last Name	African American	Hispanic/LatinX	White
African American	Harris	42.4	2.3	51.4
African American	Jackson	53.0	2.5	39.9
African American	James	38.9	3.1	51.6
African American	Williams	47.7	2.5	45.8
African American	Thomas	38.8	2.5	52.6
African American	Robinson	44.9	2.6	48.7
Hispanic/LatinX	Lopez	0.6	92.9	4.9
Hispanic/LatinX	Rodriguez	0.5	93.8	4.8
Hispanic/LatinX	Morales	0.6	93.2	4.6
Hispanic/LatinX	Sanchez	0.5	93.0	5.0
Hispanic/LatinX	Ramirez	0.3	94.5	3.9
Hispanic/LatinX	Torres	0.6	92.2	5.4
White	Murphy	11.5	2.3	83.1
White	Peterson	10.1	2.4	84.4
White	Cox	12.1	2.3	82.6
White	Myers	10.5	2.1	84.5
White	Wood	5.6	2.4	88.7
White	Miller	10.8	2.2	84.1

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

Panel B reports the set of last names used in our study and examined in Gaddis (2017a,b), which were generated using the distribution from the 2010 Census. We note that imperfect ($< 100\%$) name-race congruence shown by Gaddis has implications for the interpretation of our results since names with lower levels of congruence will be less likely to induce discriminatory behavior. The fact that African American names are associated with lower congruence than LatinX names suggests that our results may understate discriminatory constraints facing the African American group relative to the LatinX group. We also note that heterogeneity in congruence by maternal education (lower congruence for the low maternal education group) may mean that our estimates understate constraints for renters with low maternal education.

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

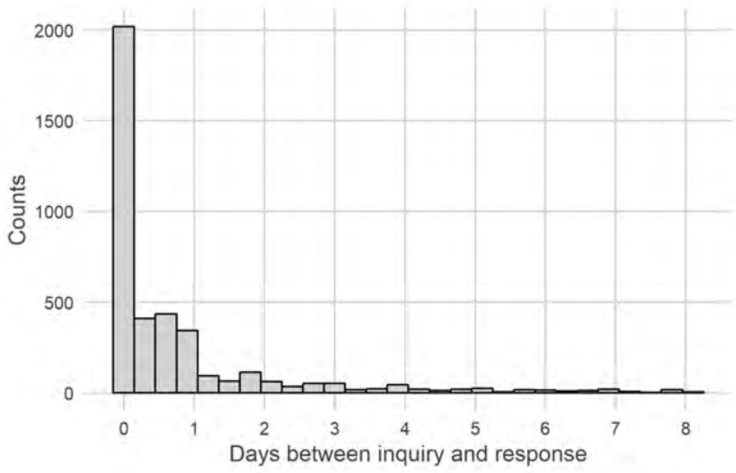
Randomization Protocol and Response Coding

The research design simulates a housing search using all available listings in a ZIP code at a given time and is therefore reflective of the true set of options available in the given online market. By generating within-property estimates of response for each racial group, we can more directly examine the effect of discriminatory constraints on each choice set in the sample.

Immediately following the compilation of the relevant listings in a given market, a name is randomly drawn and assigned from each of three racial groups. Each rental apartment, therefore, receives a sequence of three separate inquiries in the course of an experimental trial (one from each group). The sequence of inquiries from the different race groups is randomized, and inquiries for the same listing are never sent from two race groups on the same day. Responses from property managers are transmitted via email (gmail address associated with each name), phone messages (individual phone numbers associated with each name), and text messages. The content of phone, text, and email responses from property managers are recorded by a team of human coders to ensure the quality of the data. They are coded using two criteria that determine whether or not a response indicates that a housing choice is made available to a prospective renter: (1) a response is received within 7 days of the associated inquiry and (2) the response indicates that the property is available for rent.

Figure A.1 plots the distribution of inquiry response time in the sample: 52% of responses are received within the first 8 hours of an inquiry, 74% are received within 24 hours and 98% are received within 5 days. The 7-day cutoff is used to restrict responses that may be received weeks or months after an inquiry and are not counted as choices in the study. Discriminatory constraints are expressed in terms of relative response rates, which measure the within-property difference in access to a housing choice. Relative response rates are estimated relative to an inquiry made to the same property from a White identity.

Figure A.1. Response Time



Note: Figure plots times elapsed between inquiries and responses in the sample using the timestamp given at the moment that an inquiry is sent and the timestamp given on the phone, email, or text response.

B Estimating Equation

Estimating the Magnitude of Housing Discrimination

Given the experimental setup described in Section 3.2 and Section 3.3, we model the response of a landlord listing property i as choosing to respond to a renter j as:

$$u^*_{ij} = \beta Minority_j + \theta X_j + \delta_i + \epsilon_{ij} \quad j = 1, 2, 3 \tag{18}$$

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

$$P(y_{ij} = 1|X, \delta) = F(\beta Minority_j) + \theta X_j + \delta_i) \tag{19}$$

$F(.) = \frac{exp(.)}{1+exp(.)}$ is the logistic cumulative distribution function. $Minority_j$ indicates whether the fictitious identity belongs to one of our minority groups: African American or Hispanic/LatinX, the White identity is the base group. X_j is a vector of renter-specific control variables: gender, education level and the order in which the inquiry was sent. δ_i is landlord-property specific fixed effect that controls for time invariant unobservable characteristics. As shown by Hsiao (1986), the presence of an incidental parameter (δ_i) can lead to biased and inconsistent estimates. To avoid this problem we estimate a Chamberlain's (1980) conditional logit function, where $\sum_{j=1}^{J} y_{ij}$ is a minimal sufficient statistic. Then the conditional likelihood function is

$$L_c = \sum_i \frac{exp(\sum_j y_{ij}(Minority_j \beta + \theta X_j))}{\sum_{s \in S_i} exp(\sum_j s_j(\beta Minority_j + \theta X_j))} \tag{20}$$

with $S_i = \{(s_1, \ldots, s_J)|s_j \in 0, 1 and \sum_j s_j = \sum_j y_{ij}\}$. The likelihood is free of any unobserved fixed heterogeneity and invariant listing level characteristics. Note that in cases where a property manager does not respond to any identity or responds to all of them, i.e. $\sum_{j=1}^{J} y_{ij}$ is 0 or 3, drop out from the likelihood because $lnL_c = 0$. Then $exp(\beta)$ is the odds ratio and measures the odds that a minority identity receives a response relative to a White identity from a landlord-listing i:

$$\frac{P(y_{ij} = 1|Minority_j = 1, x, \delta)}{P(y_{ij} = 0|Minority_j = 1, x, \delta)} \frac{P(y_{ij} = 1|Minority_j = 0, x, \delta)}{P(y_{ij} = 0|Minority_j = 0, x, \delta)} = exp(\beta) \tag{21}$$

Standard errors are clustered at the MSA level. Robust standard errors require consideration of the *randomization design* and the *sampling design* (Abadie et al., 2017). In this study, randomization occurs at the level of a listing and sampling occurs at the level of an MSA (we sample from the set of MSAs and send inquiries to all available listings).

C Balance Tests and Robustness

Balance Tests

Table C1 reports balance statistics for our experimental dataset. We note that some differences in name pairs or timing can occur if a listing is taken offline during a trial. We do not find any evidence of differences in the sequence of inquiries or the day of the week, or the frequency of names associated with a given race-gender pair. We detect a small difference in the frequency of inquiries associated with different levels of maternal education. African American names associated with higher maternal education are slightly more common in our trials, and Hispanic/LatinX names with high levels of maternal education are slightly less common in our trials. These variables are used as controls in our tests.

Table C1. Balance Statistics

	Dependent variable: Response				
	(1)	(2)	(3)	(4)	(5)
Panel A: Inquiry Order					
	First	Second	Third		
Hispanic/LatinX	0.0152	-0.0432	0.0280		
	(0.0450)	(0.0453)	(0.0455)		
African American	-0.0280	-0.0152	0.0432		
	(0.0455)	(0.0450)	(0.0453)		
Panel B: Evidence of Differential Choices by Weekday					
	Mon	Tue	Wed	Thurs	Fri
Hispanic/LatinX	0.0931	-0.0830	0.0277	-0.0143	-0.0086
	(0.0966)	(0.1019)	(0.0607)	(0.0564)	(0.0587)
African American	0.0476	0.0439	-0.0094	-0.0402	0.0017
	(0.0976)	(0.0988)	(0.0612)	(0.0567)	(0.0585)
Panel C: Gender and Mother's Education Level					
	Gender		Mother's Education		
	Male	Female	Low	Medium	High
Hispanic/LatinX	-0.0057	0.0057	-0.0394	0.0609	-0.0213
	(0.0534)	(0.0534)	(0.0550)	(0.0552)	(0.0551)
African American	-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

Notes: Table reports balance statistics for the experimental data set. It shows the coefficients of logistic regression on different outcomes. In Panel A, the dependent variable takes 1 or 0 depending the order in which the inquiry was sent out, i.e. in Column (1) takes 1 if the inquiry was sent first and 0 otherwise. In Panel B, takes 1 or 0 depending the weekday the inquiry was sent. Panel C, does the same for male and females, and levels of maternal education. Standard errors are clustered by MSA. *$P < 10\%$ level, **$P < 5\%$ level, ***$P < 1\%$ level.

Robustness to Controls

Columns 1-4 of Table C2 report results with successive sets of controls and indicate that there is no difference in estimates that include or omit the maternal education or other controls. Phillips (2016) shows that matched-inquiry experimental designs can affect estimates of discriminatory response in competitive markets. Column 5 reports estimates from a model that considers differences in first inquiries only, which reflect random assignment of identities to listings but do not control for within-listing characteristics. The point estimates from the preferred model in columns 1-4 are slightly smaller than those in column 5, when we include data from all three inquiry rounds, which follows from evidence reported in Table 3 that indicates lower relative response rates when minority identities are assigned to later inquiries. We do not find that these estimates are statistically different, however, indicating that estimates from both models are consistent.

Table C2. Evidence of Discrimination on Housing Choice by Race Group

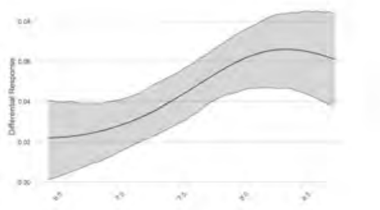
Race Group	(1)	(2)	(3)	(4)	1st Inquiry
Minority	0.6955***	0.6943***	0.6977***	0.6865***	0.7245***
	(0.6296 - 0.7684)	(0.6299 - 0.7652)	(0.6323 - 0.7698)	(0.6250 - 0.7541)	(0.6470 - 0.8114)
Hispanic	0.7502***	0.7470***	0.7481***	0.7437***	0.7673***
	(0.6691 - 0.8411)	(0.6670 - 0.8367)	(0.6661 - 0.8400)	(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
Matched Listings	5,451	5,451	5,451	5,451	5,049
Total Observations	18045	18045	18045	18045	6015
Gender	No	Yes	Yes	Yes	Yes
Education	No	No	Yes	Yes	Yes
Inquiry Order	No	No	No	Yes	Yes

Notes: Columns 1-4 report estimates of relative response rates for the full sample of listings across all cities, with standard errors clustered at the MSA level. Estimates in Column 5 report estimates of relative response rates from a model that tests for differences in first inquiries. Response rates are estimated relative to responses to inquiries sent from a White identity (the omitted category). The average response rate for inquiries sent from White identities are reported for each sample. 90% confidence intervals are reported in parentheses. Sample sizes are reported for matched inquiry sets (a set includes inquiries sent from all three identities) and total observations (where a fully matched set was not obtained).

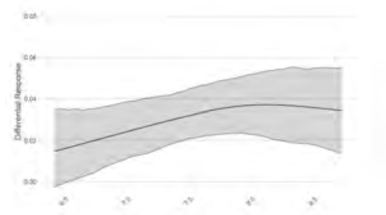
D Heterogeneity by Housing/Neighborhood Attributes

Figure D.1. Response Rates by Housing/Neighborhood Attribute

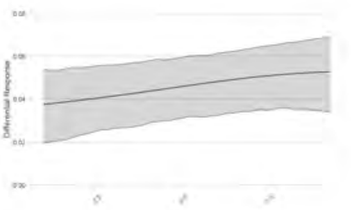
African American | **Hispanic/LatinX**



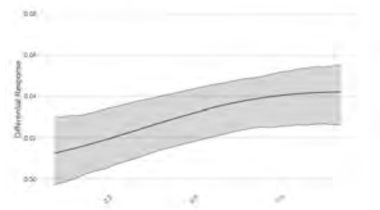
(a) Rental Price



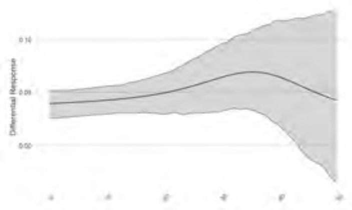
(b) Rental Price



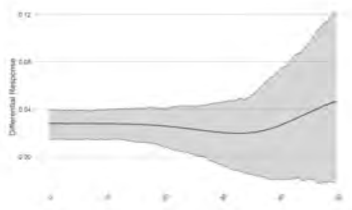
(c) School Rating



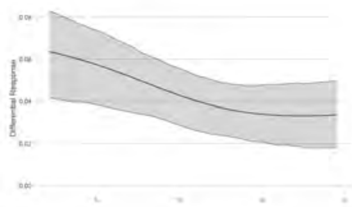
(d) School Rating



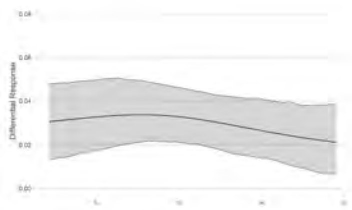
(e) Cafes



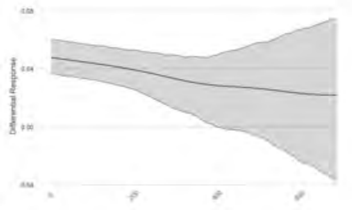
(f) Cafes



(g) Toxic Concentration



(h) Toxic Concentration



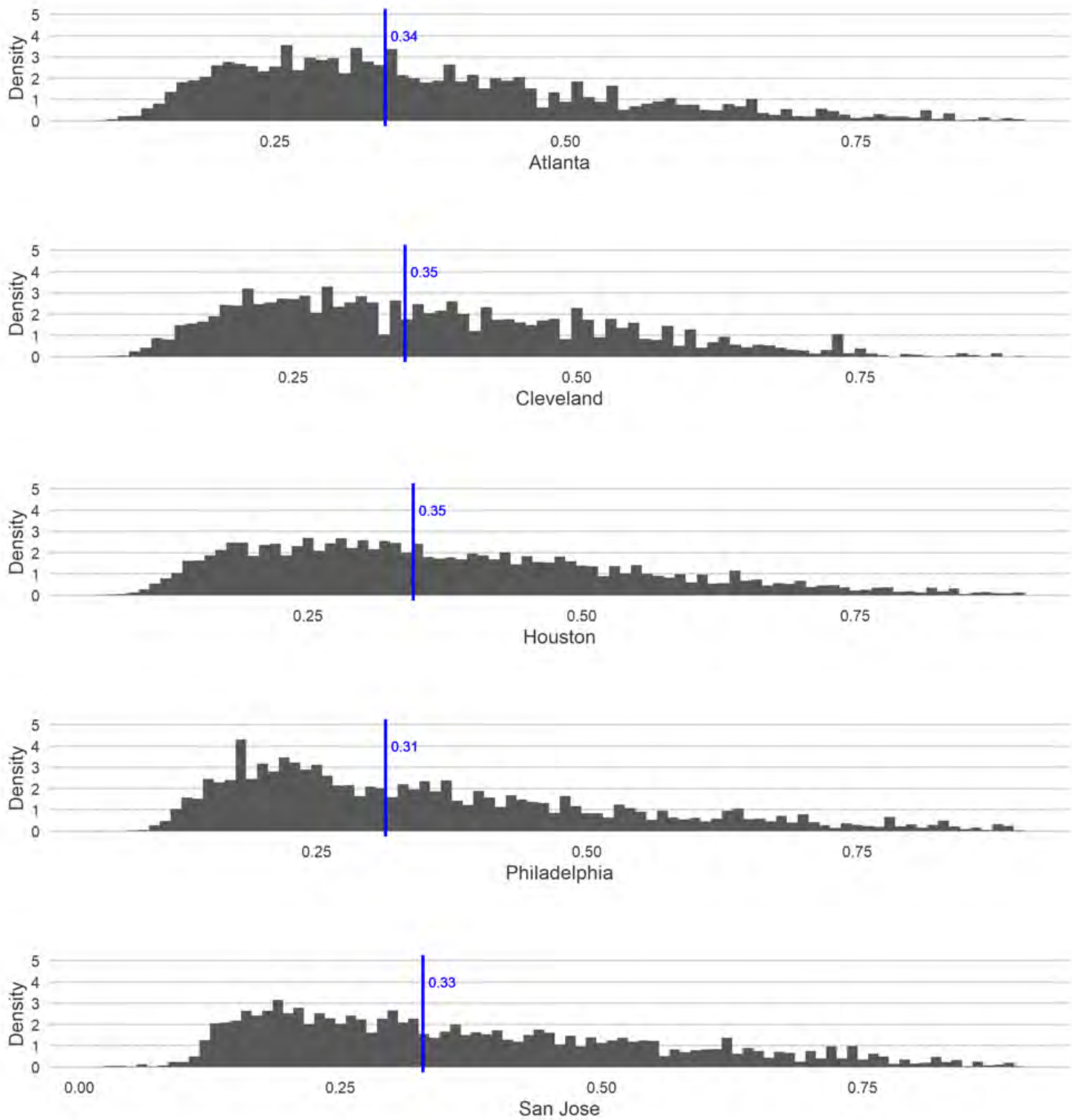
(i) Murders

(j) Murders

Notes: Figures plot differential constraints for renters of color (African American and Hispanic/LatinX) relative to White by attributes observed in rental listings collected in the experiment using estimates from Eq. 3. Increases in differential response correspond to increases in discriminatory constraints.

Appendix E: Rent-to-Income Ratio

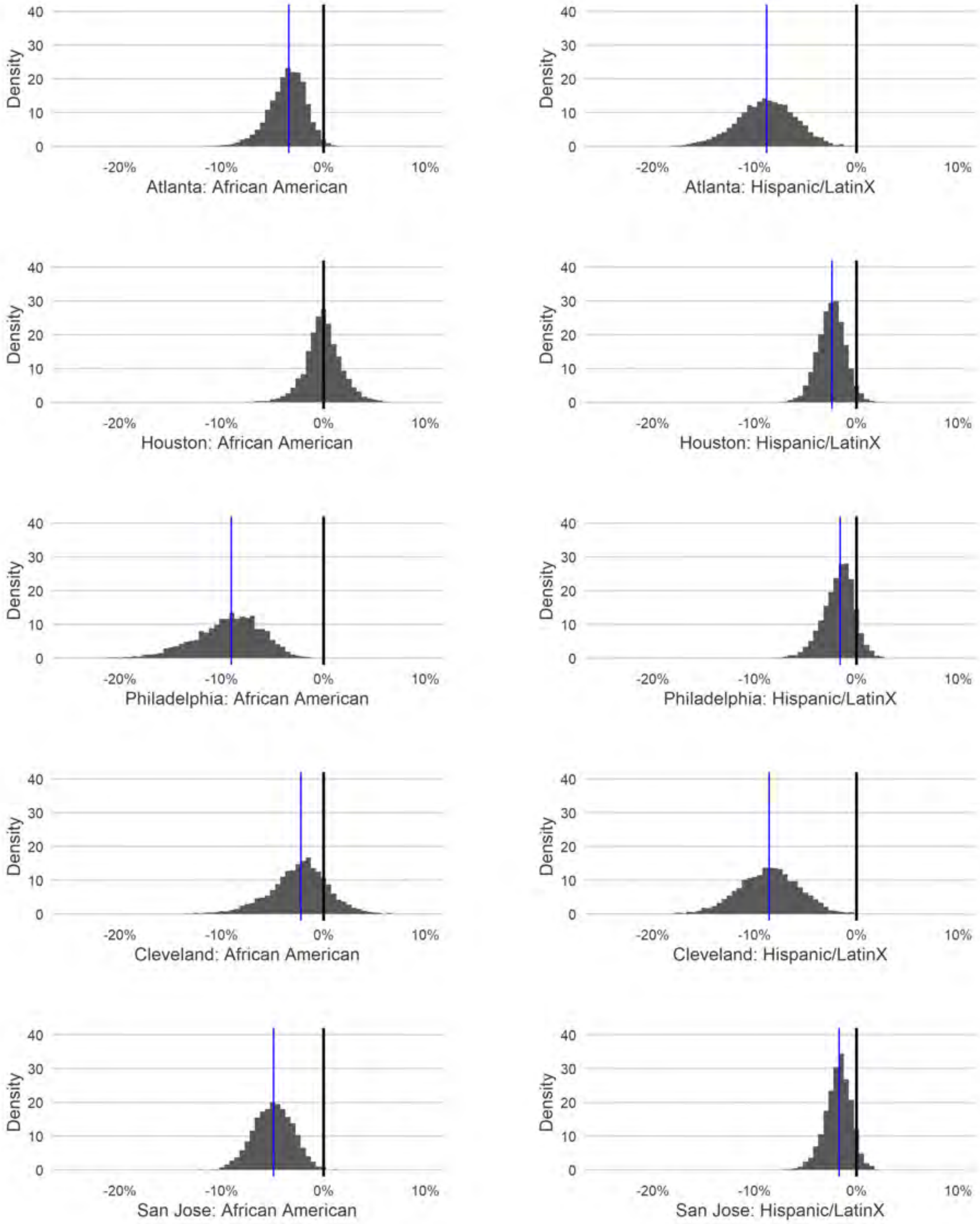
Figure E.1. Rent-to-Income Ratio by City



Note: Graphs plot the distributions of rent-to-income ratios using renter incomes from InfoUSA data and rental prices from XXX for each MSA. Blue vertical lines identify the mean for each distribution.

Appendix F: Damages by City

Figure F.1. Annualized Damages by City (Equivalent Variation)



Note: Graphs plot the distributions of renter welfare effects (compensating variation as a share of renter income) at different levels of renter income. Each plot illustrates a distribution of effects for the following renter income groups: $0-30,000, $30,000-60,000, $60,000-90,000, $90,000-120,000, $120,000-150,000. Blue and red vertical lines denote median effects for African American renters and Hispanic/LatinX renters, respectively. Effects were estimated using the baseline model XXX with all preferences.