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SORTING OR STEERING:
EXPERIMENTAL EVIDENCE ON THE ECONOMIC EFFECTS OF HOUSING DISCRIMINATION

Peter Christensen
Christopher Timmins

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ABSTRACT

Housing discrimination is illegal. However, paired-tester audit experiments have revealed evidence of discrimination in the interactions between potential buyers and realtors, raising concern about whether certain groups are systematically excluded from the beneficial effects of healthy neighborhoods. Using data from HUD's most recent Housing Discrimination Study and micro-level data on key attributes of neighborhoods in 28 US cities, we find strong evidence of discrimination in the characteristics of neighborhoods towards which individuals are steered. Conditional upon the characteristics of the house suggested by the audit tester, minorities are significantly more likely to be steered towards neighborhoods with less economic opportunity and greater exposures to crime and local pollutants. We find that holding locational preferences or income constant, discriminatory steering alone may contribute substantially to the disproportionate number of minority house- holds found in high poverty neighborhoods in the United States. The steering effect is also large enough to fully explain the differential in proximity to Superfund sites among African American mothers. These results have important implications for studies of "neighborhood effects" and confirm an important mechanism underlying observed correlations between race and pollution in the environmental justice literature. Our results also suggest that the basic utility maximization assumptions underlying hedonic and residential sorting models may often be violated, resulting in an important distortion in the provision of local public goods.

Peter Christensen
University of Illinois
431 Mumford Hall
1301 W. Gregory
Urbana, Illinois 61801
pchrist@illinois.edu

Christopher Timmins
Department of Economics
Duke University
209 Social Sciences Building
P.O. Box 90097
Durham, NC 27708-0097
and NBER
christopher.timmins@duke.edu

1 Introduction

The choice of residential location is a critical economic decision for households in the United States. It affects the neighborhood with which one interacts on a daily basis. This can have important implications both in the short-run and long-run, and impacts can even accumulate across generations. Over the past decade, a growing body of evidence has found neighborhood poverty (Kling et al., 2007), employment (Bayer et al., 2008), school quality (Chetty et al., 2011), violent crime (Kling et al., 2005), and health outcomes from pollution exposures (Currie et al., 2015) to be important, elevating concern about whether certain groups are systematically excluded from beneficial neighborhood effects or disadvantaged by segregation or discriminatory steering. A large body of observational research has also documented that patterns of residential sorting are strongly correlated with economic disparities and pollution exposures between racial groups in the United States (Alexander and Currie, 2017, Currie, 2011, Mohai et al., 2009). It has, however, been extremely challenging to disentangle the effect of discrimination (steering) from preference-based sorting in evaluating these persistent disparities.

This paper studies the effect of racial discrimination on residential location choices in the United States housing market. Specifically, we present experimental evidence on discriminatory behavior of realtors and housing providers from a nation-wide paired-actor study that was conducted by the Urban Institute in conjunction with the Department of Housing and Urban Development (Turner et al., 2013). The 2012 Housing Discrimination Study utilized a matched-pair block randomized design that simulates the housing search process for a matched pair of "testers" who are assigned attributes that make them equally qualified to purchase a particular house or rent a particular unit. Paired testers are matched to an advertised listing and randomly assigned to a realtor; different aspects of their search experience are then documented. According to evidence from a series of four studies executed between 1977 and 2012, incidence of the most blatant forms of housing discrimination has declined dramatically in the period following the Fair Housing Act (FHA) of 1968, but it is less clear that more subtle forms of discrimination have also fallen.[1]

With respect to locational choice, prior studies have described the process of steering buyers into same-race neighborhoods and exacerbating historical racial segregation in the housing market (Galster and Godfrey, 2005, Yinger, 1995). Our paper builds upon these segregation studies by testing for evidence of systematic differences in key local attributes that have been shown to affect both economic and non-economic outcomes. The HUD study provides detailed information on the price, characteristics, condition, and the exact locations of homes that are shown and recommended to white versus minority buyers. While discriminatory behavior on the part of real estate agents and housing providers is just one of several channels through which racial discrimination can constrain housing options of minorities (Aaronson et al., 2017, Zhao et al., 2005, Ondrich et al., 2003, 1998, Yinger, 1995), this channel is crucial for disentangling the effect of illegal discrimination (steering) from preference-based sorting in determining differences in access to local amenities/advantages across racial groups. We formalize this argument by examining the effect of discrimination on location choice using a theoretical model of housing search, which motivates the identification of discriminatory behavior in reduced-form tests as well as the welfare implications of a housing search with discrimination constraints.

Our results indicate that systematic differences in the homes shown to minority versus white testers impart a number of critical disadvantages. Minority testers are (relative to their white counterparts) systematically recommended homes in neighborhoods with higher poverty rates, fewer college educated families, and fewer skilled workers. Important for the analysis of environmental injustice, they are also steered towards neighborhoods with higher concentrations of Superfund sites and releases from the Toxic Release Inventory (TRI). These disparities are consistent across specifications, are stronger in the case of African American testers, and become more pronounced when tester pairs signal preferences for the neighborhood characteristic in question. In addition, African Amer-

[1]Housing discrimination is illegal according to the Fair Housing Act of 1968, which was amended in 1988. Blatant forms of discrimination include denial of appointments with a housing provider or refusal to show an advertised house. Less blatant forms include disparities in the number of houses shown or in the condition of the houses that are recommended.

ican testers are more likely to be recommended houses in neighborhoods with higher assault rates and lower percentages of skilled workers. While only statistically significant for African Americans with children, all minority groups are also more likely to be recommended houses in neighborhoods with lower quality schools. We also find that minority testers are less likely to be recommended houses in white neighborhoods, however, evidence suggests that segregation-based steering (i.e., directed by neighborhood race) cannot explain the disparities in pollution exposures resulting from discrimination. We find that differences are magnified for mothers and are large enough to fully account for higher rates of sorting among African American mothers into homes near Superfund sites, as has been found in previous research on in utero pollution exposures (Currie, 2011). Finally, we discuss the implications of discrimination of the sort revealed in this study for measures of marginal willingness to pay for an important set of local public goods (e.g., to avoid exposure to air toxics). The distortionary impact of discrimination has important consequences on the political incentives underlying the provision and allocation of local public goods.

This paper proceeds as follows. Section 2 summarizes a number of relevant literatures, including those that describe experimental approaches for broadly measuring discrimination; the evaluation of housing discrimination studies; "neighborhood effects" and their effects on long-run outcomes; and hedonics, residential sorting models, and related non-market valuation techniques. Section 3 describes the 2012 Housing Discrimination Study (HDS), which is the source of our paired tester audit study data. In Section 4, we develop a model of housing search to characterize the welfare effects of discrimination. Section 5 describes our data with a particular focus on spatial attribute information that we connect to the houses in HDS 2012. Section 6 reports results that characterize the extent of discrimination in the space of neighborhood attributes, and discusses some of the potential mechanisms that might be driving discrimination. Section 7 concludes.

2 Prior Literature

2.1 Experimental Approaches to Measuring Discrimination

A large and growing literature utilizes field experiment techniques for detecting discrimination. Bertrand and Duflo (2016) summarize this literature, focusing on the difference between audit and correspondence studies. Audit studies typically utilize a matched-pair randomized design, where a pair of actors or "testers", differing only in the characteristic of interest (e.g., race), is sent into the field to carry out an economic activity. In a correspondence study, fictitious applicants correspond only by mail or Internet. In partnership with university researchers and institutions, the United States Department of Housing and Urban Development has conducted four major, multi-city audit studies that are designed to measure the incidence of discrimination against African American, Hispanic, and Asian and Native American minority testers (relative to a white control) in the context of a rental housing or real estate search. The first such study was conducted in 1977, with successive iterations occurring in 1989, 2000, and 2012. Audit studies have similarly been used to study bargaining at car dealerships (Ayres and Siegelman, 1995), gender discrimination in hiring at restaurants (Neumark et al., 1996), and the combined effects of race and criminal record on hiring (Pager, 2003).

Audit studies are designed to fully simulate engagements between individuals in a market, often involving a series of in-person interactions and involving a full representation of racial identity. As a result, they provide a more complete characterization of discriminatory behavior as it operates in many markets. However, this also makes them much more expensive to implement at powered scales (and therefore less common). Siegelman and Heckman (1993) and Heckman (1998) describe other limitations of audit studies – for instance, it is unlikely that testers will be identical in all respects except for the attribute of interest. Moreover, testers are aware of their role and may act in such a way as to try to sway the results towards or against finding evidence of discrimination. The investigator retains more control in a correspondence study, as testers do not actually exist and their attributes can therefore be more easily controlled.[2]

2.2 Discrimination in the Housing Market

Within the economics literature, HDS audits have been utilized to study the persistence of discrimination and underlying behavioral mechanisms such as animus-based versus statistical discrimination (Guryan and Charles, 2013, Dymski, 2006).[3] An additional hypothesis posits that real estate agents may have an incentive to discriminate against people of color in order to avoid losing a prejudiced white customer base. Under this hypothesis, Yinger (1995) suggests that realtors will discriminate more in neighborhoods that are at risk of being "flipped" and or disproportionately against minority families with children if their white customers are particularly sensitive to school integration.

The consistency of the HUD design (especially 1989, 2000, 2012) has allowed for comparisons of discriminatory behavior over time, with results generally indicating a decline in exlusionary practices over the past five decades (Turner et al., 2013, 2002). Using data from a paired-tester audit study in Boston in 1981 that considered white and black renters, Yinger (1986) finds that black renters are informed about 30% fewer rental units than their white counterpart, who is also invited to inspect 57% more apartments.[4] Page (1995) builds upon this study by employing a Poisson model to describe the number of houses shown. Using HDS 1989, she finds that black and Hispanic testers are shown 80% to 90%, respectively, of the number of units shown to white testers. Results are similar for rental and sales properties and are best explained, for black testers, by the white customer or statistical discrimination mechanisms. A series of subsequent papers

[2]One problem that might arise in both audit and correspondence studies is the potential for those being audited to check the online profile of the tester or fictitious applicant, particularly in markets where there is a high return to gathering such information (e.g., high skilled labor). To address this problem in a correspondence study, Acquisti and Fong (2015) create an online presence for their fictitious applicants in an analysis of discrimination in the labor market. In parallel analyses of labor and rental markets, Bartoš et al. (2013) create websites for applicants and keep track of how often they are accessed.

[3]The common theme in these papers is measuring discrimination at the initial point of contact when the realtor recommends rental units or homes for purchase, and when customers are invited to inspect a property. Studies differ in the measures of discrimination they use and in the minority groups they consider.

[4]Yinger argues for the inclusion of tester-pair fixed effects to control for unobservables that are common to a particular audit experiment (i.e., office conditions on the day that the two testers visited a particular realtor), and these have henceforth been common in the literature.

find similar evidence of realtor predjudice, statistical discrimination, and catering to a white customer base (Ondrich et al., 1998, 2003, Zhao et al., 2005). The latter two papers introduce the fixed-effects logit model, controlling for trial fixed effects while looking for evidence of discrete instances of discrimination, and controls for testers' *actual* characteristics, recognizing that some elements of these might show through during the audit.

Yinger (1997) builds on the analysis of Courant (1978) to develop a model of housing search, where realtors' discrimination affects the surplus 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.[5] Since the HDS research design focuses on discrimination that occurs at the point of initial contact with the realtor – i.e., the point at which recommendations are given and the choice set is narrowed – the results of HDS analyses describe one particular form of housing market discrimination that could be compounded by other forms of discrimination in the process of searching for, financing[6], and purchasing a home. Prior literature has included arguments in favor of and against the reliable extension of inferences from partial audit studies to estimate the full extent of compounded impacts, though it is clear that the direct results of the HDS must be interpreted as a lower bound.

According to the comparative work done across HDS studies, the single persistent form of discrimination in the housing market is "discriminatory steering" of minority testers into minority neighborhoods (Dymski, 2006, Galster and Godfrey, 2005, Yinger, 1995). These studies provide important motivation for research on the characteristics of

[5]Yinger (1997) does not account for differences in the attributes of houses or neighborhoods shown to African American testers

[6]There is a large body of evidence that documents the presence of discrimination in mortgage and other lending markets (Dymski, 2006). It is possible (indeed likely, based on prior evidence) that discrimination also occurs in the mortgage lending industry. Official government guidance for mortgage lenders in the 1930's suggested that neighborhoods with a high percentage of people of color constituted risky loans, drawing a red line around those areas and steering funds away (Aaronson et al., 2017). If minority home buyers were steered towards those neighborhoods, red-lining would make home-ownership more difficult, or at least more expensive.

neighborhoods that define buyer/renter choice sets, though the prior work has emphasized the role of discrimination in perpetuating segregation rather than the intersection between discriminatory steering and neighborhood effects.

2.3 Neighborhood Effects

If housing market discrimination alters an individual's choice set and ultimately influences neighborhood choice, then a growing body of evidence on neighborhood effects indicates that it could have impacts on labor market outcomes, educational attainment, criminal activity, physical safety and environmental health. Much of the experimental evidence on neighborhood effects has come from the from the "Moving to Opportunity" (MTO) program, which provided housing vouchers to public housing residents that could be used to secure a residence in a neighborhood with a lower than 10% poverty rate.[7] MTO has demonstrated that the the poverty level of a neighborhood is a key determinant of long-run outcomes – poverty levels likely capture a set of mechanisms underlying human capital formation, such as levels of crime and public safety, the quality of schools, pollution exposures, and other types of spillovers within neighborhoods.

In an intent to treat analysis, Kling et al. (2005) find that female youth are less likely to commit violent or property crimes with MTO treatment assignment. Incidence of participation in violent crime also falls for males assigned MTO treatment, but after a short-term drop, property crime rises again for this group. Other papers have focused on other health and economic outcomes. Sanbonmatsu et al. (2006) look four to seven years after the MTO treatment and find little to no evidence of impacts on test scores for children treated by MTO. Kling et al. (2007) similarly find little evidence of impacts on physical health or economic outcomes of adults. They do, however, find evidence of strong mental health benefits for adults and female youth. These effects are offset by adverse effects on male youth. Ludwig et al. (2013) take a longer view (i.e., 10-15 years after the MTO treatment) and find no evidence of improvements in adult economic outcomes, but large improvements in some health outcomes (e.g., incidence of obesity

[7] A second treatment group was randomized to receive a Section 8 voucher with no constraints on use and a third treatment group simply retained access to public housing.

and diabetes). Focusing on outcomes for children, they find no evidence of impacts on educational attainment, but do find some health benefits for girls. The program appears, however, to have been detrimental to the health of boys.

Other research has focused on the duration of time spent in different types of neighborhoods. Clampet-Lundquist and Massey (2008) find evidence that time spent in high poverty neighborhoods affects economic self-sufficiency (i.e., earnings, employment, TANF, and food stamps). More recently, Chetty et al. (2016) analyzed the age at which a child experiences a switch in neighborhood attributes with MTO, finding that the duration of exposure to a low poverty neighborhood plays an important role in the size of the beneficial effect, which offsets the negative impacts of "disruption". Specifically, those who are randomly assigned to the experimental voucher prior to age 13 experienced a 31% increase in income in their mid-20's relative to a control group; those assigned after age 13 experienced an insignificant drop relative to the control, suggesting that benefits accrued were insufficient to cover the costs of the move.

There is a mostly separate body of evidence demonstrating that neighborhood pollution exposures have substantial impacts on health outcomes. Currie and Neidell (2005) find that pollution levels from nearby toxic plants have important effects on infant health, which correspond to a 3% increase in the incidence of low birthweight within 1 mile of a plant.[8] In utero exposure to pollution from nearby traffic congestion also substantially affects birthweight (Currie and Walker, 2011). A separate study finds that carbon monoxide has a strong effect on the infant mortality rate in California, with the drop observed over the course of the 1990's estimated to have saved 991 infant lives (Currie and Neidell, 2005). Using the universe of health records of children born in New Jersey between 2006 and 2010, Alexander and Currie (2017) find that the two-fold differential in asthma rates between African American and other racial groups disappears when the sample is split to examine differences within our outside majority African American zip codes.

[8] In prior research at the county level, Currie and Schmieder (2009) demonstrate that fugitive emissions of toxic pollutants such as cadmium and toluene have important impacts on infant birthweight. Using a twin study, Black et al. (2007) find that a 7.5 percent increase in birth weight results in a 1.8 percent increase in earnings among men and a 1 percentage point increase in high school completion among women.

A more recent literature has exploited long-run panel data to more directly examine the impact of exposure to environmental nuisances while in utero on long-run economic outcomes. In a county-level study, Chay and Greenstone (2003) show that a 1% reduction in exposures to Total Suspended Particulates during the recession of the 1980-1981 resulted in a 0.35% effect in infant mortality. Sanders (2012) utilizes the same natural experiment to measure the effect of pre-natal TSP exposure on long-run educational outcomes, finding that a one standard deviation decrease in particulate matter exposure results in a reduction in high school test scores equal to 2% of a standard deviation. Instrumenting for changes in pollution using county-level changes in manufacturing employment, that number rises to 6%.[9] In a cohort study in Florida, Persico et al. (2016) find that children conceived to mothers living within close proximity (within 2 miles) of an untreated Superfund site are more likely to repeat a grade (+7.4 pp), to be suspended from school (6.6 pp), and have lower test scores (-0.06 std dev) than siblings who were conceived after clean-up. Children conceived to mothers living at closer proximity (within 1 mile) are 10 percentage points more likely to be diagnosed with a cognitive disability. Barreca et al. (2017) looks at the long-run impacts of exposure to SO_2 with variation induced by the US Acid Rain Program and proximity to regulated plants. Strong impacts on mortality are found, and causal mechanisms are supported by cause of death data.[10]

There is an active discussion about the impact of neighborhood effects on labor market outcomes and earnings. Chetty et al. (2011) examines the impacts at age 27 of random assignment to classrooms for 11,571 K-3 students and their teachers in Tennessee. More experienced kindergarten teachers and better test scores of peers both increase earnings. In addition to the direct effects of disparities in the allocation of public goods (e.g., school quality, pollution abatement, public safety), empirical evidence suggests that spillovers, interactions and other positive/negative externalities can also have important neighborhood effects. Controlling for sorting, Bayer et al. (2008) find evidence that similar individuals living in the same census block are also more likely to work in the same census

[9] Local exposure to PM2.5 has been shown to have large effects on the contemporaneous productivity in outdoor workers (Chang et al., 2016).

[10] Barreca (2010) analyzes the effect of exposure to malaria while in utero on lifetime education attainment and adult poverty rate.

block, suggesting a strong neighborhood referral effect. Good matches lead to more hours worked and higher earnings.

2.4 Sorting and the Provision of Local Public Goods

It may be that disparities in neighborhood effects observed between race groups result from the locational choices of households. For instance, Currie (2011) provides some evidence that the mothers who are most likely to live within the vicinity of a Superfund site after cleanup are more likely to be white and college educated. Similarly, white mothers are less likely to reside within the vicinity of a plant that emits toxic pollutants after emissions are disclosed. While these estimates suggest differential patterns of sorting in response to changes in the level or information about pollution exposures, it is not clear whether all households in these samples had access to the same choices. The hedonics and sorting literatures have typically ignored housing market discrimination because it cannot be identified from observational data in housing markets. However, if discrimination is at play, then we cannot expect all housing units to be freely chosen. This distortion would bias estimates of the value of different amenities. In the simplest terms, we may understate a minority group's willingness to pay for pollution reductions if those households live in a polluted neighborhood not by free choice but because of discrimination.

The most commonly used methods for valuing local public goods and amenities rely on the observed decisions that individuals make in housing markets. Rosen (1974) provides the theory for recovering preferences from residential location decisions. Simply put, the hedonic gradient reveals the slope of the individual's utility function in the space of amenities and house prices. That slope represents marginal willingness to pay under the assumption that individuals are free to choose where to live (i.e., decisions were not constrained by discrimination). This same assumption is required for a class of models of efficient public goods provision beginning with Tiebout (1956). While the hedonic literature uses the equilibrium outcome of those sorting decisions, a structural literature builds models that instead derive preference estimates from the sorting decisions themselves. Sorting models have also been used to predict the outcomes of urban policies, especially when those policies are large and likely to result in equilibrium feedback effects. Reviews of the hedonics and sorting literatures are now available. See Champ et al. (2003) or Palmquist (2005) for a review of the hedonics literature, and the survey of the sorting literature in Kuminoff et al. (2013).

3 2012 Housing Discrimination Study

The 2012 Housing Discrimination Study was conducted in 28 metropolitan areas, with sampling designed to represent the racial/ethnic composition of the national housing market based on the geographic distribution of each minority group as documented in the 2010 US population census. The 2012 HDS utilized a matched-pair block randomized design, where recruitment and assignment was conducted in each of the 28 metropolitan area field offices. Testers were blind matched to a partner based on their age and gender. They were both then provided with a profile of characteristics to use throughout the study: income, assets, debt levels, family circumstances, job characteristics, education levels, and housing preferences. The design involves randomly sampling the distribution of rental and real estate advertisements available for the market at the time of the study. Upon each draw of a listing and corresponding local real estate office or rental housing provider, a pair of testers is randomly assigned and undergoes a housing search process.[11] Income, asset and debt levels are assigned to make testers unambiguously well-qualified for the advertised listing.[12] Housing preferences and family/job characteristics are assigned to match the characteristics of the advertisement.

[11] Testers meet independently with a local test coordinator to review test protocols and receive an assigned listing/office.

[12] 2012 HDS documentation states that the assignment of qualifications errs on the side of making minority testers were slightly better qualified than their white counterparts for an advertised listing.

4 Model

4.1 Model of Discrimination in Housing Search

In this section, we develop a model of housing search, paying particular attention to interactions with the real estate broker. A homebuyer with income y_i can observe many attributes of houses (X_k) along with neighborhood characteristics (N_k) and price (p_k).[13] Each individual will have a vector of preference parameters $\phi_i = [\alpha_i, \beta_i, \gamma_i]$ that determine the utility derived from house k:

$$U_{i,k} = \alpha_i ln(y_i - p_k) + X_k'\beta_i + N_k'\gamma_i + \epsilon_{i,k} \tag{1}$$

where

$$\alpha_i = a_0 + Z_i'a_1 + u_i^a$$

$$\beta_i = b_0 + Z_i'b_1 + u_i^b$$

$$\gamma_i = g_0 + Z_i'g_1 + u_i^g$$

Z_i is a vector of observable attributes of tester i other than income, and

$$\bar{u} = \begin{pmatrix} u_i^a \\ u_i^b \\ u_i^g \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \Sigma\right)$$

where the distribution of individual preference parameters is defined by the underlying parameter vector $\theta = [a_0, a_1, b_0, b_1, g_0, g_1, \Sigma]$. $\epsilon_{i,k}$ is an idiosyncratic shock specific to the individual and house. Assuming that it is distributed Type I Extreme Value, we have a

[13]We assume a buyer with access to a real estate search tool, which provides information about house and neighborhood attributes. X_k may include housing type (house, condominium, townhouse, mobile home), total rooms, bathrooms, bedrooms, square footage, lot size, and year built. N_k might include crime rate, air pollution and other environmental nuisances, school quality, and characteristics of the local population including poverty rate, educational attainment, race and income.

closed form solution for the probability that individual i would choose house k:

$$P_{i,k} = \int \frac{\alpha_i ln(y_i - p_k) + X_k'\beta_i + N_k'\gamma_i}{\sum_{l\in\Gamma_i^*}(\alpha_i ln(y_i - p_l) + X_l'\beta_i + N_l'\gamma_i)} dF(\bar{u}) \tag{2}$$

where Γ_i^* includes the set of all houses in i's feasible set (defined by income). The expected utility from i's choice set, Γ_i^*, is given by:

$$EU^* = \int ln\left(\sum_{l\in\Gamma_i^*} e^{\alpha_i ln(y_i - p_l) + X_l'\beta_i + N_l'\gamma_i}\right) dF(\bar{u}) \tag{3}$$

A buyer i presents information on personal income (y_i) and other observable attributes (Z_i)[14] to a realtor. We assume that the realtor knows the conditional distribution of preferences from which the tester's preferences are drawn, $F(\phi|Z_i, y_i, \theta)$, and may use this information in some capacity when selecting a set of recommended homes to show to buyer i. This study focuses on bias in the definition of that set of recommended homes.

$$\Gamma_i^*|F(\phi|Z_i, y_i, \theta) \to \tilde{\Gamma}_i \tag{4}$$

The set of recommendations that the realtor provides to a buyer i will yield the following expected utility:

$$EU' = \int ln\left(\sum_{l\in\tilde{\Gamma}_i} e^{\alpha_i ln(y_i - p_l) + X_l'\beta_i + N_l'\gamma_i}\right) dF(\bar{u}) \tag{5}$$

Denote the number of homes in $\tilde{\Gamma}_i$ by n_i. Previous work (Yinger, 1997) has focused on the number of recommended homes. Indeed, in our model the smaller is n_i, the smaller will be EU' by construction – i.e., more recommendations are always better. However, the previous equation makes clear that EU' will also be lower the more $\tilde{\Gamma}_i$ deviates from individual i's optimal choice, conditional upon the size of the choice set.

Given the advertised house "chosen" by the tester (j^*), it is possible that the realtor

[14]In particular, we focus on race, but a richer model is possible with other financial information and borrowing constraints, household characteristics, and current home ownership status. We abstract away from those characteristics in this parsimonious model of utility, but they are implicitly included in the paired-teseter experimental design and empirical tests (being held constant across testers).

could update her impressions of the tester's preferences based in the following formula:

$$h(\phi|k^*, y_i, Z_i, \theta) = \frac{P(k^*|y_i, Z_i, \phi)g(\phi|y_i, Z_i, \theta)}{P(k^*|y_i, Z_i, \theta)}$$

$$\bar{\phi}_{k^*} = \int \phi h(\phi|k^*, y_i, Z_i, \theta)d\phi$$

Choosing a recommendation set based on these updated preferences, $\bar{\phi}_{k^*}$, will unambiguously improve expected utility of the tester, conditional upon the number of recommendations. In the analysis below, we test whether realtors incorporate individual testers' expressed preferences and whether the tendency to do so differs with tester race.

4.2 Empirical Models: Reduced Form Analysis

Ultimately, we are interested in how the change in expected utility, $\Delta EU = EU^* - EU'$, varies with race holding all other tester attributes fixed. Relative to a fully randomized design, the match-pair design employed by HDS 2012 eliminates the noise in the behavior of brokers that might arise as a result of heterogeneity in the advertisements, providers, and characteristics that are assigned to testers of different races. In particular, the HUD experiment is explicitly designed to set all preferences, including those stated and conveyed through the characteristics of advertisements and otherwise by testers, equal for tester pairs ($i = minority$, $j = white$) within a given trial f:

$$(y_i - y_j)|trial_f = 0$$

$$(\alpha_i - \alpha_j)|trial_f = 0$$

$$(\beta_i - \beta_j)|trial_f = 0$$

$$(\gamma_i - \gamma_j)|trial_f = 0$$

Given the matched-pair block randomized design, within-trial differences in the selection of homes ($\Gamma_i^* \to \tilde{\Gamma}_i$) recommended to testers of different races reduce to:

$$\Gamma_i^*|(trial_f, z_i^{race}) \to \tilde{\Gamma}_i \tag{6}$$

and the null hypothesis of a test of differences in the recommended sets ($\tilde{\Gamma}$) will take the general form:

$$H_0 : \tilde{\Gamma}_i - \tilde{\Gamma}_j|trial_f = 0 \tag{7}$$

where $i = minority, j = white$. These differences translate into differences in welfare via the utility function described above. We know that ΔEU is greater the smaller is the recommended set of homes (holding constant the attributes of those homes relative to the individual's optimum), and ΔEU is greater the more the recommended set deviates from the tester's optimum, conditional upon the number of recommended homes. Our reduced-form estimates test for overall differences in the choice set constraints placed on minority versus white testers.

In addition to our focus on the mechanism through which housing discrimination during the search process could result in advserse neighborhood effects for minority buyers, a major departure from past research on housing market discrimination in the search process is our use of the characteristics of advertised homes presented to an agent, which are an important channel for signaling the preferences over $(\alpha_i, \beta_i, \gamma_i)$ of a tester. In the HDS design, testers are instructed to limit all discussion about housing preferences (β_i) or neighborhood preferences (γ_i) to what is conveyed by the advertised listing that they have been assigned.[15] The listing therefore provides a key indicator of the tester's optimal choice, and from the realtor's perspective, is the best indicator of the tester's preferences for a given neighborhood characteristic (γ_i). Importantly, the advertised house provides us with control over the information about the tester's preferences conveyed in the experiment, and allows us to measure its impact on the recommended choice set.

Our baseline specification tests for differences in the neighborhood attributes of homes recommended to minority testers relative to their paired white counterparts using a set

[15] Advertised listings are drawn randomly from the full set of advertisements and assigned to tester pairs based on income levels.

of regressions that take the following general form:

$$A_{i,k,f} = \psi_1 Race_i + \psi_2\, Trial_f + \tilde{A}'_{i,k,f}\psi_3 + \ \mathrm{W}'_{i,k,f}\psi_4 + \nu_{i,k,f} \tag{8}$$

where $A_{i,k,f}$ is the attribute of interest of house k shown to tester i in trial f. *Race* is an indicator of the self-identified race of tester i. *Trial* is a vector of fixed effects that controls for differences across trials (and housing providers). $\tilde{A}_{i,k,f}$ controls for the corresponding attribute of the advertised home (and possibly other attributes of that home) that tester i brings to the appointment and is the primary piece of information upon which a realtor can use to infer the preferences of that tester. $W_{i,k,f}$ is a vector of controls containing characteristics of the actor who is serving as a tester,[16] characteristics that are assigned to the tester,[17] and characteristics of the search.[18]

5 Data and Sample Balance

5.1 Data from the HDS

The 2012 HUD buyer study is designed to elicit an information set based on a housing search process using scripted preferences.[19] The process results in data on the locations and attributes of advertised listings (assigned to buyers) and a set of recommended listings that results from the search. Figure 2 illustrates the search process for trials in Chicago and in Los Angeles, each involving a white and a paired Asian tester. In both of these cases, the housing search process yielded two independent sets of listings that were recommended to the testers. In each map, the black dot indicates the advertised

[16]Actor Characteristics: tester income, tester household income, gender of tester, age of tester, month of test, total number of homes recommended to tester, educational attainment of tester, and current lease assigned to tester.

[17]Assigned Characteristics: household members, current home ownership status, current lease type, car ownership status, reason for moving, years in current residence, length of employment at current job, and reason tester can afford down payment.

[18]Search Characteristics: month of test, sequence of tester appointments, time of the appointment (am/pm), type of recommended building, total number of homes recommended to tester, and availability of advertised home as stated by agent.

[19]Buyers are instructed to express zero geographic preference aside from that which might be inferred from their interest in the advertised listing.

listing that was requested by each tester. Red dots indicate houses recommended to the white tester, and blue dots indicate houses recommended to the Asian tester. Green dots indicate houses that were recommended to both testers. There are a few things to notice from these maps. The first is that recommended properties for both testers tend to be in relatively close geographic proximity to one another, suggesting that the common advertised house carries some weight in the recommendation process. The second thing to notice is that, while all of the recommendations are relatively close by, they do exhibit some spatial clustering by race. Third, we note that there is some overlap in recommended houses. In Los Angeles, 5 out of 23 total recommendations are shared between the two testers. However, this is not always the case – the white and Asian tester only share one common recommendation out of 15 total recommended houses in Chicago.

The full sample of properties from the buyer study contains 6,962 advertised listings and 21,496 recommendations. Basic characteristics and price information are taken from the HUD study data files. The HUD data files also contain extensive data on the true and assigned characteristics of testers, the timing and sequence of appointments, characteristics of the agents and representatives, and the quality of interactions between testers and agents during the study. Table 1 reports descriptive statistics on the general characteristics of testers recruited into in the sample. The average age of testers in the study is 41 and about two thirds of them are female. Home-owners and renters are well-represented amongst those working as testers, though the majority are renters at the time of their participation in the study. The median tester in the sample has a bachelor's degree and more than half of the sample earns less than $30,000 per year in personal income.

5.2 Data on Outcomes

We geocode the addresses of advertised and recommended homes reported in the 2012 HDS and merge them with contemporaneous data at the census block group level from the American Community Survey (ACS). The 2008-2012 5-year moving average ACS provides data on the share of white, African American, Asian, and Hispanic households at the census block group level. We also obtain ACS data on the share of households at or below the poverty line, the share of households with at least one member with a college degree, and the share of households with at least one member who is employed in a high skilled occupation (defined as management, business, science, and arts occupations).

Advertised and recommended homes are also merged with information about local pollution exposures/sources from monitoring programs conducted by the US Environmental Protection Agency (EPA). For each home in the sample, we create measures of: (1) the number of Superfund sites within a 5km radius using the exact location and extent of sites throughout the United States,[20] (2) the risk of exposure (in 2012) to industrial chemical releases from facilities monitored by the EPA's Toxics Release Inventory,[21] and (3) particulate matter (PM2.5) concentrations taken from satellite data.[22]

Finally, we merge information about crime (count of violent assaults)[23] and school quality ("GreatSchools" ratings)[24] that are scraped from the platform of a major online realtor service. Data were scraped for each property using the addresses of houses listed in the HUD study and both measures relate to the property-level characteristic of the home. The GreatSchool rating measures the quality of the school that a home is districted for or, in cases of no location-based assignment, takes the average of nearby schools. Data collection for these variables was conducted in December 2017 and measures relate to the time of collection. Neighborhood and district-level data for 2012 were not available for HDS markets. Differences in these outcomes therefore reflect school ratings and neighborhood assault counts 5 years after a housing search was conducted.

[20]The exact location and extent of Superfund sites is identified using data processed by the Socioeconomic Data and Applications Center at Columbia University: http://sedac.ciesin.columbia.edu/data/collection/superfund/sets/browse

[21]https://www.epa.gov/sites/production/files/2018-01/documents/rsei_methodology_v2.3.6.pdf

[22]PM2.5 can be an important factor in mortality from cardiovascular and respiratory diseases. Satellite data are taken from Van Donkelaar et al. (2016), who use Aerosol Optical Depth (AOD) retrievals from the NASA MODIS, MISR, and SeaWiFS to recover ground-level PM2.5 concentration. Data have a grid cell resolution of 0.01 degree.

[23]Assault counts are drawn from multiple sources, including CrimeReports.com, EveryBlock.com and SpotCrime.com.

[24]GreatSchools is a private ratings service that combines information on test scores, student progress, and "other factors that make a big difference in how children experience school" to generate a score on a 1-10 scale. Details on the GreatSchools rating system can be found at https://www.greatschools.org/gk/ratings. District boundaries are provided by Boundaries by Maponics.

5.3 Advertised Homes

Table 2 reports characteristics of the advertised listings that are assigned to testers as part of the study. These advertised listings are presented to real estate agents to initiate a search in the first stage of a trial. They are not representative of the set of all homes. More than 70% of the listings assigned to testers are single-family homes. The remaining listings are primarily for town-homes (13%) and some multi-family buildings (10.4%). The average list price of advertised homes in the sample is just over $300,000. The racial composition of the census block group of an advertised listing has, on average, 67% White, 9% African American, 7% Asian, and 15% Hispanic (and 2% other). On average, advertised listings are in neighborhoods where 9% of the households have incomes at or below the poverty line, 50% have at least one member with a college degree, and 47% have a member that is in a high skilled job.

5.4 Balance Tests

Tables 3 and 4 report the results of balance tests for within-tester pairs, including (1) true characteristics of testers (i.e., actor characteristics), (2) characteristics assigned to testers, and (3) characteristics of advertised homes. Tests for balance suggest that paired actors are not perfectly equivalent in all real-life dimensions, but do not reveal strongly significant differences in characteristics. African American actors have a lower likelihood of being homeowners than their white tester counterpart (15% lower, significant at p<10%). The number of African American testers with personal incomes in the $20,000-29,999 range is lower than their white counterparts (21% lower, significant at p<5%), but is higher in both the $10,000-19,999 and the $30,000-39,999 ranges. Similar differences in bin matching are also present for other groups. Hispanic actors tend to have a lower probability of having a bachelor's degree (25% lower, significant at p<10%), but a higher probability of having an associate's or a graduate/professional degree (non-significant). Asian actors are more likely than their counterparts to have a high school diploma (12% higher, significant at p<10%).

The HUD design intentionally constructs assignment profiles that err on the side of providing minority testers with slightly higher qualifications. For example, minority testers in all groups have been employed for 1-2 years longer and have lived for 1-2 years longer at their current address than their white counterparts. All actor and assigned characteristics are included as controls in the tests for discrimination. Balance tests reveal that advertisements for single-family homes are assigned at slightly higher rates and multi-family advertisements at slightly lower rates to Asian testers. There is no evidence of differences in the pollution levels, block group characteristics, or listing prices of homes assigned within tester pairs.

6 Results

This section reports the results of a series of tests of hypotheses that arise from the model presented above. Specifically, we test for effects of the tester's race on choice set size and composition while also exploring the role of the information provided by the tester in the form of the advertised house.

6.1 Are Minority Buyers Given Fewer Choices in a Search?

The model of housing search presented above shows that the expected utility of a buyer's choice set will be unambiguously lower when fewer homes are offered as available choices. A first-order question regarding the effect of housing discrimination concerns the effect of realtor behavior on the number of recommendations provided to the minority tester relative to a white counterpart.

Table 5 reports estimates from two highly related variants of this test. A row in the table presents estimates of differences between a minority tester and a white tester, where minority is defined as self-identified as African American, Hispanic, or Asian. The first two columns test for differences in the total number of recommendations provided to minority testers relative to the white tester in the same trial, whereas the third and fourth columns test for differences in the availability (communicated by the agent) of the advertised home. Columns 2 and 4 add controls for differences that may be due to a buyer's implied preference for price (α_i) and neighborhood characteristics (γ_i) using the listing price and racial composition of the neighborhood where the advertised listing is located. While point estimates indicate that African American and, to a lesser extent, Asian buyers receive fewer recommendations than their white counterparts, this difference is not statistically significant. Neither are any of the differences in the likelihood of the advertised home being available statistically significant. This is important, as refusing to suggest a property or making a claim that a particular property is unavailable is a more blatant form of discrimination that had been prevalent in previous HDS studies. While differences may still persist, they are not statistically significant in this sample. This test does not, however, imply anything about differences in the *quality* of the houses or neighborhoods that are being recommended.

6.2 Are Minority Buyers Steered into Minority Neighborhoods?

We begin our discussion of steering by examining the channel that has been the focus of previous research (Yinger, 1995, Galster and Godfrey, 2005). In particular, we consider the extent to which the racial composition of neighborhoods differs for homes recommended to minority testers relative to a white counterpart. Table 6 reports estimates of differences in the share of white households in the census block group that contains a home recommended to a minority versus a white tester. Columns I - V introduce additional controls for attributes of the advertised house, which capture the implied preferences of the testers for housing price (α_i) and neighborhood characteristics (γ_i), such as neighborhood racial composition and the share of households below the poverty line. In each case, African Americans are recommended homes in neighborhoods with a lower share of white households compared with those recommended to their white counterparts. This difference does not change when we control for the neighborhood racial composition, poverty rate, or price of the advertised listing that a tester presents to their agent.[25]

[25] In Appendix Tables 16-21, we report results of tests that examine steering into neighborhoods by the share of households from each of the three minority groups in the HDS study. These results demonstrate that African American testers are more likely to be steered towards neighborhoods with a higher share of African American households, but evidence of steering into same-race neighborhoods is not as evident for the other groups.

These estimates confirm the results documented in prior studies on steering and segregation, providing strong evidence that a tester's race directly influences the racial composition of the neighborhoods that define his choice set. This occurs in the absence of any explicit information about preferences for demographic or other neighborhood characteristics (γ_i) and is directly attributable to a buyer's race (Z_i). The effect persists irrespective of information about neighborhood preferences (γ_i) implied by an advertised listing presented to an agent.

Digging deeper, the estimates presented in Table 7 indicate that the results found in Table 6 are primarily driven by steering of African American buyers away from *high income* white neighborhoods. The steering effect is strong in high income white neighborhoods and is present for the minority group as a whole. It persists when we control for the listed price, the neighborhood racial composition, and the poverty rate of the advertised listing. These differences become much smaller for African American testers in medium-income white neighborhoods and disappear for the group of minority testers as a whole. The effect actually reverses for low-income white neighborhoods, such that Hispanic and Asian testers are *more* likely than their white counterpart (with the same income) to receive recommendations in a low-income white neighborhood.

6.3 Are Minorities Disadvantaged by Neighborhood Steering?

This section presents the core set of tests of our study, which extend the examination of discriminatory steering to analyze a set of key neighborhood characteristics that have been shown to have effects on critical short- and long-run outcomes. Evidence from revealed preference studies in housing markets also indicates that buyers have strong preferences for these characteristics. We therefore assume that the average buyer in the sample of HUD markets will have preferences for these neighborhood attributes and that discriminatory constraints along these dimensions will have a non-trivial impact on expected utility. We test for the effect of discriminatory behavior on recommendations of homes with each of the following neighborhood characteristics described above.

The two panels of Table 8 present core results from tests of differences between the homes recommended to minority versus white testers along key neighborhood dimensions. All estimates include controls for characteristics of advertised homes, and for tests that use census block and pollution variables we report sharpened q-values using a Hochberg adjustment to control for the family-wise false discovery rate (Benjamini and Hochberg, 1995).[26] We find substantial disparities in the attributes of neighborhoods recommended to minority testers relative to their white counterparts. The first panel of Table 8 shows that minority testers (as a whole) are recommended homes in census block groups with higher poverty rates (1.25%) and fewer high skilled neighbors (-2.28%).[27] Considering the average values of these neighborhood attributes over all houses in the set of advertised listings (8.9% and 46.7%), these impacts are substantial (particularly so for poverty). We do not find statistically significant differences in the percentage of college educated residents in neighborhoods recommended to minorities when considered as a whole.

Below the estimates of differences between white testers and minorities, we report differences by racial group. Overall, these estimates indicate that African American testers are shown homes that are in census block groups characterized by higher poverty rates (+1.24%), lower shares of skilled workers (-2.72%), and lower shares of college educated neighbors (-3.04%), although the result for poverty is not statistically significant at traditional levels. The disparities between white and Hispanic testers are even larger in terms of the poverty rate and high-skill neighbors but smaller and insignificant for college share. Differences between white and Asian testers are markedly lower and are not significant along any of the dimensions of neighborhood capital that we study.

Column 4 of the first panel describes school quality as measured by the "GreatSchools" index. While the houses recommended to every minority group reflect a lower school quality than that of the houses recommended to their paired white testers, none of these differences are statistically significant; note, however, that our sample size is approximately halved owing to difficulties with merging HUD house addresses with information

[26] Hochberg-adjusted p-values are provided for tests of differences between minority and white testers (census block and pollution variables) at the bottom of Table 8. Standard test statistics are reported for assault counts and school ratings.

[27] High skill is share of census block group employed in American Community Survey defined Management, business, science, and arts occupations.

scraped from the online realtor platform. Appendix Table 22 demonstrates that, when we consider tester households separately by the presence of children, the effect school quality for African American households with kids is indeed negative and significant at $p < 0.1$. This echos results from previous research which had described realtors as being motivated to discriminate out of a fear of backlash from white customers responding to the integration of a neighborhood school.

The second panel of Table 8 focuses on neighborhood disamenities – assaults and three environmental nuisances – proximity to Superfund sites, air toxics (as measured by the EPA's RSEI), and PM2.5, an important criteria pollutant with substantial long run health effects. Considering all minority groups as a whole, we see statistically significant differences in the proximity to Superfund sites and air toxics relative to the houses recommended to white testers. The difference in assaults is positive, although not statistically significant. However, considering only African Americans, we find the difference in assaults to be positive and statistically significant. The magnitude of that difference (+23.80) is large compared to the average number of assaults across all advertised houses (93). The same is true for Superfund proximity (a difference of +0.12 relative to an average of 0.33) and air toxicity (a difference of +915.45 relative to an average of 6,071). Asians show similar statistically significant differences for Superfund proximity and air toxics. Point estimates for Hispanics are positive, but estimates are smaller in magnitude and statistically insignificant.

In contrast to air toxics, results with respect to particulate matter show very little difference across testers. The average value of particulate matter in the sample of advertised houses is 9.283. Asian testers do exhibit a statistically significant difference with their white counterparts of -0.1283, but this difference is very small in magnitude. None of the other race groups exhibit statistically significant differences within tester pairs. We suspect that this is due to an important difference between particulate matter and air toxics. In particular, spatial variation in particulate matter concentrations occurs over large geographies, whereas air toxics can vary from neighborhood to neighborood. Because realtors do tend to recommend houses within relatively small buffers around the advertised house to both testers within a pair, the scope for steering with respect to particulate matter is far lower than that with respect to air toxics.[28]

Table 9 reports differences for the subsample of testers (37%) who are assigned an identity of mother (female with children). We find that the differences are magnified for this group. In particular, we find that minority mothers are steered into neighborhoods with a +4.81% higher poverty rate than white mothers and that this difference is particularly stark for African American (+5.23%) and Hispanic (+5.60%) mothers. Recall that the average poverty rate in the neighborhoods surrounding the set of advertised houses is only 8.9%. Differences in the skill level and share of college educated households in neighborhoods recommended to African American and Hispanic/LatinX mothers are also much larger than the differences for the average tester. Homes recommended to African American mothers have a 35% higher incidence in nearby assaults (+33), a 52% higher number of nearby Superfund sites (+0.17), and a 37% higher (+2,269.92) level of exposure to air toxics than white mothers. The exception is for elementary school quality – we find some evidence that homes recommended to Hispanic/LatinX mothers have higher school quality (+0.84).[29]

6.4 Is there a Single Behavioral Mechanism Underlying Discriminatory Steering?

The HDS study was not designed to provide the experimental variation of the sort that would be needed to identify behavioral mechanisms underlying discriminatory steering in the housing market. However, the differences that we identify in discriminatory steering do provide valuable information about realtor behavior. For instance, it is possible that

[28]Appendix Table 24 demonstrates that these differences do not change when we control for the preferences of different types of buyers in the study (using preferences implied by the characteristics of advertised listings) or for the price of the advertised home. Three columns appear under each neighborhood characteristic. Moving from the first to the second column adds in controls for the corresponding characteristic of the advertised house, the racial composition of the advertised house, and the price of the advertised house. In each case, the coefficient on tester race does not change in a significant way.

[29]Appendix Table 23 breaks down effects by race and gender. We find similar results with respect to school quality in that effects are large, negative and significant for female African American testers as a whole. We also see that the impact of African American race on the poverty rate of recommended neighborhood is stark for males. Other gender effects are not, however, uniform across all neighborhood attributes and races.

steering of African Americans away from white neighborhoods is driven by a racial animus and a desire to segregate that population as other studies have posited. However, a strict interpretation of racial animus is inconsistent with the findings presented in Table 7, which demonstrate that steering does not occur solely into same-race neighborhoods and but rather depends on the interaction between race and neighborhood income.[30]

Another explanation that might explain neighborhood effects as well as this income component could be that realtors discriminate by discounting African American testers' financial credentials, steering them towards lower income neighborhoods where houses are also lower priced. However, as seen in Table 10, we do not find any evidence that minority testers receive recommendations for lower priced homes relative to their white paired testers. Looking at point estimates alone, it appears that homes recommended to Hispanic/LatinX buyers may be moderately less expensive than those recommended to their white counterparts, but that African American and Asian buyers receive recommendations that may somewhat more expensive on average.

We perform an additional test to rule out this potential mechanism in Appendix Table 24. Three columns correspond to each neighborhood characteristic in this table – for each characteristic, the third column incorporates an additional control into the main regression specification that measures the average neighborhood characteristic for all houses in the sample that fall in the same \$20,000 price bin as the recommended house.[31] We are therefore testing whether, within a set of houses of similar price, are minority testers recommended houses with systematically different attributes. The main results in our table are invariant to this additional control.

Finally, the steering behavior that we observe could also be driven by a form of statistical discrimination where realtors believe that the preferences of an individual buyer are the same as those of other members of their racial group. Alternatively, realtors could simply believe that buyers have a preference for neighborhoods with households from their own race group. Realtors that employ these forms of statistical discrimination rely

[30]In other results, we do not find evidence of clear differences in steering behavior among realtors of the same group as the buyer (versus different group). Results available in an online appendix.

[31]Note that limitations on our ability to match scraped school quality and assault data to the HUD data reduce our sample size by enough that we cannot perform this test for those two outcome variables.

more heavily upon the demographic composition of a neighborhood than the information provided about the preferences of an individual tester. We test for this behavior in a set of specifications that regress the racial composition (share of white, black, Hispanic/LatinX, or Asian households) of the recommended neighborhood on the interaction between tester race and the share of white households in the neighborhood of the advertised listing presented to an agent. Table 11 presents results from these tests, with the four columns pertaining to the respective share of white, black, Hispanic/LatinX, and Asian households in the neighborhood of the recommended home. The results show that the steering effect is stronger for African American buyers who present listings in neighborhoods with a higher percentage of white households. The effect is of the same sign but not as large and is not significant for Hispanic/LatinX buyers. Not only do we find that realtors do not take into account own-race preferences of African American buyers when making recommendations – they actively work in opposition to those preferences. This implies a mechanism that goes beyond simple statistical discrimination.

6.5 The Welfare Effects of Realtor Behavior

The results described above provide evidence that minorities receive housing recommendations in neighborhoods that could disadvantage them in numerous dimensions. The magnitude of the effect of housing discrimination also depends on the information, preferences, and behavior of buyers. Therefore, obtaining precise estimates of welfare effects would require an experiment that examines discriminatory behavior within the context of real preferences of individuals making decisions in a housing market. This would clearly be an undesirable experiment to implement.

We expect that some buyers may be less informed about pollution exposures, school quality, or public safety in the neighborhoods where they are searching. In a review of the evidence on locational choice and persistent inequality, Currie (2011) discusses the potential effects of educational disparities in determining locational choices near Superfund cleanups or plants with publicly disclosed emissions of toxic chemicals. Our results suggest that if buyers who lack information are more likely to be steered by their realtor, then minority buyers are likely to be differentially steered and subsequently disadvantaged.

In order to more directly compare our results on discrimination with the findings from Currie (2011), we restrict the HDS sample to mothers and construct a test of homes recommended to white versus African American mothers within 2 km of Superfund sites (that had not been cleaned up in 2011). Currie (2011) finds that 1.74% of all mothers live within 2 km of a Superfund site and that African American mothers are +0.77 percentage points more likely to live within 2 km of a Superfund site, indicating a 43% difference in the likelihood of maternal exposures between the groups. In our HDS sample of cities with large minority populations, 24% of homes recommended to the sample of mothers fall within 2 km of a Superfund site. The test indicates that African American mothers are 10 percentage points more likely to receive a recommendation within 2km of a Superfund site (estimate is significant at $p<.1$), indicating a 42.5% higher likelihood than their white counterpart. These estimates suggest that the differences in maternal exposures from residential location could be entirely explained by discriminatory steering into homes that are within 2 km of a Superfund site.[32]

To provide additional context for our results, consider Chetty et al. (2016), who analyze the Moving to Opportunity (MTO) experimental voucher program. The MTO program provided vouchers for residents living in neighborhoods with a poverty rate of greater than 40% to obtain subsidies in neighborhoods with poverty rates of less than 10%. Chetty et al. (2016) find that the treatment was responsible for a 17 percentage point (intent to treat) or 36 percentage point (treatment on the treated) reduction in neighborhood poverty and subsequent impacts of this poverty reduction on income, college education, employment, marriage and fertility later in life. In the HDS sample, only 1% of recommended homes are in neighborhoods with poverty rates of greater than 40%, making it difficult to draw a direct comparison with a statistically powered test for the high poverty neighborhoods. Rather, a test of steering into low poverty block groups as defined

[32]We construct a similar test of differences in air toxics using our RSEI measure. On average, homes recommended to mothers in the HDS study have a RSEI level of 5313.1. Homes recommended to African American mothers have levels that are 2268.9 higher (estimate is significant at $p<.1$) than their white counterpart, indicating a 42.6% disparity in exposures.

by MTO[33] indicates that minority testers are 6% less likely to be recommended a home in these neighborhoods (significant at p<.1). African American testers are 6.3% less likely (not significant at p<.1) and Hispanic/LatinX testers are 11.1% less likely (significant at p<.05). African American testers with families are 12.1% less likely (not significant at p<.1) and Latino testers with families are 22.6% less likely to receive recommendations in neighborhoods with low poverty rates (significant at p<.1).[34] There are caveats with this comparison. In particular, we isolate the effect of housing discrimination occurring in a single stage of the housing search process; the steering effect that we identify is therefore likely a lower bound on the effect of total discrimination, though these estimates suggest that the impacts of discriminatory steering are both *statistically* and *economically* significant.[35]

For buyers who lack information about pollution exposures or other neighborhood attributes, adverse welfare impacts are likely to come directly from the short and long-run outcomes associated with multiple neighborhood effects. Another type of buyer may be well-informed, but may not have strong preferences for the neighborhood and pollution characteristics that we examine in this study. The strength of individual preferences will determine the effects in our model of expected utility. However, it is important to note that a minority buyer that does not have strong preferences for the neighborhood characteristics that we study will nonetheless experience different outcomes than a white buyer with the exact same preferences. Assuming that these buyers are more likely to be steered into neighborhoods with higher levels of poverty and pollution exposures, discriminatory steering will put them at a direct disadvantage.

For buyers who are well-informed about pollution exposures and neighborhood effects, discriminatory behavior will interact with preferences to produce an effect on expected utility. For instance, home buyers may sort on race, and minority buyers may pre-

[33]We define the MTO-consistent measure as a recommended home in a census block group where the share of families living below the poverty line is less than 10%.

[34]Full panel of results from this comparison are available upon request.

[35]Yinger (1997) examines the total effect of discrimination on the surplus from a housing search, including differences in assistance and encouragement, assistance with a loan application, and loan approval. The effects of discriminatory steering into higher poverty neighborhoods estimated in this study could be compounded by differences in information provided by a real estate agent about neighborhood conditions, differences in recommendations regarding an initial offer, or differences during the process of negotiations.

fer houses in neighborhoods populated by other minorities. We see from Figure 3 that neighborhood poverty, college education, high skill and school quality are all strongly correlated with race (although the same is less evident for assaults, Superfund proximity, and air toxics). Without knowing the relative strengths of preferences for different neighborhood attributes (including the racial mix of one's neighbors) we are unable to know for sure how the attributes of houses recommended by realtors interact to produce expected utility.[36] Returning to the model in Section 4, we can, however, say something about the impact of realtor behavior on the welfare of whites and minorities from housing search. In particular, the realtor's incorporation of the tester's *individual* preferences, expressed by the information inherent in her "choice" of advertised house, will unambiguously increase that tester's expected utility from housing search, *ceteris paribus*. Our data do allow us to test directly the extent to which this individual information is incorporated into realtors' recommendations, and in particular how this differs by tester race.

Table 12 reports estimates that test for these differences. For each recommended house attribute, a coefficient describes the interaction of the tester's race with the corresponding attribute value for the tester's advertised house. We see first that whites, who are the omitted racial group, have a strong positive and statistically significant relationship between each recommended house attribute and their preference for that attribute expressed through their advertised house. For African Americans, this relationship is significantly weakened for every neighborhood attribute with the exception of Superfund proximity. Hispanic testers have a significantly weaker relationship in the case of high skill, school quality and air toxics, and Asian testers have a weaker relationship in the case of assaults and all of the pollution variables. In the case of poverty, high skill and college education, Asian testers exhibit a stronger relationship than their white counterpart, and the same is true in the case of assaults for Hispanic testers. However, particularly for

[36] The seemingly obvious solution to this problem would be to estimate preferences for buyers of different race groups from observed housing transactions data – indeed, this is done commonly in the hedonics and residential sorting literatures. We highlight here, however, that such estimates will themselves likely be contaminated by constraints imposed by realtors of the sort discribed above. Put differently, discrimination is likely already "baked in" to utility parameters derived from revealed preference data. This is a broader problem for work in non-market valuation and allocation of funds to the provision of public goods; in the current context, it makes it difficult to draw strong conclusions about welfare effects from steering.

African Americans, individual preferences are ignored by realtors relative to the case of whites. This leads to a relative reduction in expected utility from the search process.

7 Conclusions

In this paper, we find strong evidence that contact with real estate agents differentially constrains the choice sets of minority buyers relative to a white counterpart. Building on prior literature, we show that while discrimination no longer has a significant effect on the number of recommendations a minority buyer receives, it does have strong impacts on the quality of the neighborhoods that constitute the recommended set. The implications of these constraints are quite clear – the constraints imposed by realtors in the search process provide all minority groups with houses to choose from that are worse in at least one (but typically many) dimensions.

This is a result with implications for several literatures in economics. First, it is important for studies of "neighborhood effects", which analyze the ways in which neighborhood attributes affect short and long-run (even multi-generational) outcomes in the dimensions of poverty, employment, schooling, criminal activity and public safety, and environmental health. Prior research has demonstrated clearly that residential location choices can affect short- and long-run outcomes; the steering behavior that we identify affects the neighborhood attributes in the household's choice set, and ultimately their house purchase decision, in an important way.

Second, our results demonstrate that minority homebuyers and renters may not be "free to choose" in the housing market, and that their observed behavior may not actually reveal their preferences. If households' choice sets are distorted by the recommendations provided by realtors, this can have important implications for how we interpret the results of non-market valuation analyses and for how perceived preferences are used to allocate public goods. Our results suggest that what might look on face value to be weak preferences for environmental quality on the part of minorities may actually be a reflection of the fact that they were presented with options that were disproportionately lower in environmental quality than were those given to similar white buyers. The results of non-market valuation studies based on supposedly unconstrained choices over housing units are the backbone of cost-benefit analyses and evaluation of environmental policies in the US. They also play a critical role in determining how governments allocate scarce funds to the provision of public services across communities.

Finally, our results provide evidence that even holding income disparities or differences in preferences constant, housing discrimination could play an important role in determining observed spatial correlations between race, income, and local disamenities. This has particularly important implications considering pollution, and policies relating to environmental justice. Under an executive order signed by Bill Clinton in 1994, the federal government is obligated to consider the distributional impacts of its policies with respect to pollution and disadvantaged groups. Understanding the origins of existing inequities has been the topic of a large and growing literature (Banzhaf et al., 2018). Discrimination has largely been overlooked by that literature, and our paper suggests that this may be an important oversight. This particular mechanism has important implications for the development of fair housing laws.

While we are able to identify the differential impacts of realtors on the housing search processes of whites and minorities, we note that the HUD audit data do not allow for direct tests of the behavioral mechanisms underlying these effects. We find that the differential constraints imposed by realtors occur irrespective of preferences demonstrated by testers in the form of their "choice" of advertised house, though we cannot disentangle mechanisms based on statistical discrimination from others based on, for example, racial animus or disregarding financial credentials. We propose an expanded research agenda in the economics of housing discrimination, including complementary experimental designs that are capable of more directly testing the behavioral mechanisms underlying discriminatory steering as in Knowles et al. (2001), List (2004), and Charles and Guryan (2008).

Perhaps an even more important avenue for experimental research involves the design of a research methodology that combines experimental identification of discriminatory behavior with individual preferences that are representative of decisions being made in the housing market. These could be used to obtain precise estimates of welfare effects. An important remaining question is the extent to which the constraints from discriminatory steering may be overcome by tenacity – buyers with a sufficiently high marginal utility for certain housing characteristics may choose to absorb additional search costs in order to expand their choice set. Unfortunately, studying this aspect is not possible in the audit study context. Neither is a study of the mortgage lending process, where we might expect the sorts of discriminatory effects we identify here to be amplified.

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Table 1. Descriptive Statistics for Tester Dataset

Variable	All Groups	White	African American	Hispanic	Asian
	Tester Characteristics (True Actors, Not Assigned)				
Age	40.910	41.485	41.494	42.070	36.398
Percent Male	0.388	0.415	0.375	0.284	0.420
Percent Rented Home	0.588	0.580	0.630	0.516	0.614
Percent Owned Home	0.305	0.296	0.312	0.421	0.217
Personal Income					
Under $10,000	0.244	0.275	0.241	0.125	0.249
$10,000 - $19,999	0.164	0.130	0.225	0.114	0.235
$20,000 - $29,999	0.237	0.293	0.136	0.249	0.184
$30,000 - $39,999	0.136	0.114	0.152	0.183	0.152
$40,000 - $49,999	0.096	0.086	0.105	0.117	0.090
$50,000 - $74,999	0.068	0.062	0.069	0.136	0.022
$75,000 - $99,999	0.009	0.013	0.008	0.000	0.004
$100,000 or more	0.003	0.002	0.004	0.011	0.000
Education					
Attended High School	0.003	0.000	0.002	0.000	0.018
GED	0.012	0.021	0.004	0.000	0.000
High School Diploma	0.035	0.020	0.045	0.037	0.079
Attended Vocational School	0.005	0.005	0.000	0.018	0.000
Vocational School Diploma	0.022	0.032	0.006	0.007	0.029
Attended College	0.162	0.130	0.182	0.308	0.108
Associate's Degree	0.078	0.059	0.101	0.136	0.054
Bachelor's Degree	0.358	0.404	0.283	0.183	0.484
Attended Graduate School	0.052	0.074	0.020	0.048	0.025
Graduate Degree	0.243	0.230	0.308	0.253	0.170
	Assigned Characteristics				
Monthly Rent	1,332	1,334	1,392	1,277	1,285
Percent Tester Went First	0.516	0.589	0.417	0.454	0.462
Percent Appointment in AM	0.416	0.410	0.425	0.428	0.422
Percent Car Owner	0.854	0.861	0.796	0.922	0.861
Length of Employment (Years)	4.091	3.345	4.936	5.203	4.507
Years at Residence	3.650	2.925	4.405	4.766	4.101
Lease Type					
Month-to-Month	0.569	0.558	0.565	0.581	0.620
Lease	0.431	0.442	0.435	0.419	0.380
	N = 2,260	N = 1,161	N = 512	N = 286	N = 294

Table 2. Home and Neighborhood Characteristics

	Characteristics of Advertised Homes				
Variable	All Groups	White	African American	Hispanic	Asian
Listing Price	306,701	302,935	304,661	304,812	328,761
Building Type					
Single family, detached	0.739	0.743	0.738	0.699	0.748
Duplex	0.017	0.017	0.013	0.018	0.018
Rowhouse or Townhouse	0.134	0.128	0.118	0.158	0.155
Multi-family structure	0.101	0.101	0.125	0.112	0.069
Mobile home	0.001	0.001	0.000	0.005	0.000
	Pollution Measurements				
Superfund Sites	0.330	0.314	0.340	0.350	0.361
Particulate Matter	9.283	9.378	9.253	9.055	9.293
RSEI	6,071	6,244	7,860	4,283	5,127
	Neighborhood Characteristics				
Assaults	93	88	96	95	104
Elem. School Quality	6.207	6.198	6.202	6.169	6.260
Poverty Rate	0.089	0.088	0.092	0.090	0.086
Percent College Graduate	0.501	0.504	0.501	0.494	0.501
Percent High Skill	0.467	0.467	0.467	0.463	0.472
Percent White	0.675	0.685	0.684	0.639	0.664
Percent African American	0.090	0.091	0.103	0.082	0.084
Percent Asian	0.067	0.065	0.061	0.073	0.079
Percent Hispanic	0.148	0.140	0.135	0.185	0.151
	N = 7,033	N = 3,612	N = 1,213	N = 1,028	N = 1,109

Table 3. Balance Statistics for Testers

	Tester Characteristics (True Actors, Not Assigned)		
Variable	African American	Hispanic	Asian
Age	-0.874	1.476	-2.060
	(0.996)	(1.858)	(1.833)
Percent Male	0.009	0.000	0.000
	(0.015)	(0.000)	(0.000)
Percent Rented Home	0.138	-0.044	0.083
	(0.100)	(0.124)	(0.114)
Percent Owned Home	-0.153*	0.033	-0.111
	(0.093)	(0.113)	(0.110)
Personal Income			
Under $10,000	-0.012	-0.107	-0.000
	(0.097)	(0.116)	(0.125)
$10,000 - $19,999	0.118	0.012	0.235**
	(0.076)	(0.116)	(0.102)
$20,000 - $29,999	-0.212**	-0.066	-0.113
	(0.086)	(0.151)	(0.107)
$30,000 - $39,999	0.126	0.147*	0.008
	(0.081)	(0.088)	(0.114)
$40,000 - $49,999	-0.002	0.011	-0.066
	(0.063)	(0.079)	(0.077)
$50,000 - $74,999	-0.023	0.006	-0.090
	(0.057)	(0.065)	(0.080)
$75,000 - $99,999	-0.028	-0.027	-0.012
	(0.022)	(0.041)	(0.018)
$100,000 or more	0.000	0.030	0.000
	(0.000)	(0.046)	(0.000)
Education			
Attended High School	0.000	0.000	0.020
	0.000	0.000	0.031
GED	0.011	-0.071	-0.028
	(0.017)	(0.050)	(0.044)
High School Diploma	0.036	0.041	0.116*
	(0.035)	(0.037)	(0.068)
Attended Vocational School	-0.007	0.015	0.000
	(0.011)	(0.034)	(0.000)
Vocational School Diploma	-0.014	-0.002	-0.012
	(0.030)	(0.035)	(0.018)
Attended College	0.100	0.109	0.082
	(0.080)	(0.138)	(0.103)
Associate's Degree	-0.017	0.088	-0.016
	(0.043)	(0.066)	(0.052)
Bachelor's Degree	-0.161	-0.251*	-0.032
	(0.110)	(0.147)	(0.104)
Attended Graduate School	-0.062	-0.043	-0.036
	(0.054)	(0.075)	(0.032)
Graduate Degree	0.106	0.114	-0.088
	(0.107)	(0.120)	(0.113)
	Assigned Characteristics		
Percent Tester Went First	-0.093	-0.231	-0.047
	(0.165)	(0.200)	(0.209)
Percent Appointment in AM	0.002	-0.014	0.028
	(0.041)	(0.038)	(0.038)
Percent Car Owner	0.010	0.000	-0.065
	(0.015)	(0.000)	(0.058)
Length of Employment (Years)	1.559***	2.050***	1.444***
	(0.270)	(0.328)	(0.238)
Years at Residence	1.511***	1.898***	1.551***
	(0.288)	(0.301)	(0.203)
Lease Type			
Month-to-Month	0.012	0.072	0.115
	(0.047)	(0.091)	(0.076)
Lease	-0.012	-0.072	-0.115
	(0.047)	(0.091)	(0.076)
	N = 512	N = 286	N = 294

Table 4. Balance Statistics for Homes

Variable	African American	Hispanic	Asian
	Characteristics of Advertised Homes		
Listing Price	6,976	-2,199	10,907
	(14,999)	(14,224)	(14,410)
Building Type			
Single-family Detached	0.009	0.006	0.029*
	(0.014)	(0.018)	(0.016)
Duplex	-0.001	-0.002	-0.005
	(0.007)	(0.007)	(0.011)
Rowhouse or Townhouse	0.005	0.007	0.007
	(0.014)	(0.016)	(0.021)
Multi-family Structure	-0.006	-0.006	-0.030*
	(0.011)	(0.013)	(0.017)
Mobile Home	-0.001	-0.001	-0.000
	(0.002)	(0.004)	(0.00001)
	Pollution Measurements		
Superfund Sites	-0.001	0.017	-0.0003
	(0.007)	(0.015)	(0.009)
Particulate Matter	-0.010	0.0001	0.015
	(0.016)	(0.023)	(0.022)
RSEI	-30	-108	89
	(74.130)	(148.209)	(203.457)
	Neighborhood Characteristics		
Assaults	−0.040	0.109	−0.153
	(0.255)	(1.569)	(0.254)
Elem. School Quality	0.001	0.019	0.025
	(0.031)	(0.032)	(0.050)
Poverty Rate	0.0005	0.001	-0.001
	(0.002)	(0.003)	(0.002)
Percent College Educated	-0.005	-0.003	0.0002
	(0.003)	(0.005)	(0.003)
Percent High Skill	-0.005	-0.002	0.0004
	(0.004)	(0.005)	(0.003)
Percent White	-0.0003	-0.007	0.004
	(0.004)	(0.004)	(0.003)
Percent Black	0.003	0.004	-0.003
	(0.003)	(0.004)	(0.003)
Percent Asian	-0.001	-0.0002	-0.001
	(0.002)	(0.002)	(0.001)
Percent Hispanic	-0.002	0.003	0.001
	(0.002)	(0.003)	(0.002)
	N = 1,213	N = 1,028	N = 1,109

Table 5. Differences in Recommendations and Availability of Advertised Properties

	Dependent variable:			
	Number of Recommendations		Home Availability	
Racial Minority	−0.2947	−0.2286	0.0068	0.0052
	(0.4530)	(0.4436)	(0.1714)	(0.1719)
African American	−0.5137	−0.4652	0.0928	0.0935
	(0.5747)	(0.5676)	(0.2052)	(0.2050)
Hispanic	0.2877	0.3700	−0.0008	−0.0076
	(0.5202)	(0.5101)	(0.2411)	(0.2433)
Asian	−0.2464	−0.1809	−0.0507	−0.0496
	(0.6209)	(0.6088)	(0.2153)	(0.2150)
Other	4.0317	3.9882	0.1336	0.1421
	(2.4750)	(2.4891)	(0.6590)	(0.6604)
Racial Comp Advert Home	*N*	*Y*	*N*	*Y*
ln(Price) Advert Home	*N*	*Y*	*N*	*Y*
Observations	21,385	21,363	6,656	6,629
Adjusted R^2	0.6315	0.6318	-0.2093	-0.2127

*p<0.1; **p<0.05; ***p<0.01

Note: All regression specifications control for the full set of actor characteristics, assigned characteristics, and search Characteristics. Actor characteristics: tester income, tester household income, gender of tester, age of tester, month of test, educational attainment of tester; Assigned Characteristics: household members, current home ownership status, current lease type, car ownership status, reason for moving, years in current residence, length of employment at current job, reason tester can afford down payment, current lease assigned to tester; Search Characteristics: month of test, sequence of tester appointments, time of the appointment (am/pm), type of recommended building

Table 6. Discriminatory Steering and Neighborhood Racial Composition

	Dep. Variable: White Household Share				
	I	II	III	IV	V
Racial Minority	−0.0123	−0.0122	−0.0124	−0.0127	−0.0127
	(0.0122)	(0.0122)	(0.0122)	(0.0121)	(0.0121)
African American	−0.0416**	−0.0415**	−0.0420**	−0.0425**	−0.0427***
	(0.0166)	(0.0166)	(0.0166)	(0.0165)	(0.0165)
Hispanic	0.0017	0.0017	0.0016	0.0017	0.0018
	(0.0165)	(0.0165)	(0.0165)	(0.0164)	(0.0164)
Asian	0.0131	0.0131	0.0131	0.0127	0.0127
	(0.0146)	(0.0146)	(0.0146)	(0.0146)	(0.0146)
Other	0.0643	0.0643	0.0653	0.0663	0.0662
	(0.0472)	(0.0472)	(0.0469)	(0.0469)	(0.0469)
Share White Advert Home	*N*	*Y*	*Y*	*Y*	*Y*
ln(Price) Advert Home	*N*	*N*	*Y*	*Y*	*Y*
Racial Comp Advert Home	*N*	*N*	*N*	*Y*	*Y*
Poverty Share Advert Home	*N*	*N*	*N*	*N*	*Y*
Observations	21,517	21,506	21,488	21,488	21,488
Adjusted R^2	0.7791	0.7792	0.7789	0.7788	0.7788

*p<0.1; **p<0.05; ***p<0.01

Note: All regression specifications control for the full set of actor characteristics, assigned characteristics, and search Characteristics. Actor characteristics: tester income, tester household income, gender of tester, age of tester, month of test, educational attainment of tester; Assigned Characteristics: household members, current home ownership status, current lease type, car ownership status, reason for moving, years in current residence, length of employment at current job, reason tester can afford down payment, current lease assigned to tester; Search Characteristics: month of test, sequence of tester appointments, time of the appointment (am/pm), type of recommended building, total number of homes recommended to tester, availability of advertised home as stated by agent

Table 7. Discriminatory Steering and Neighborhood Racial Composition by Income

	Dep. Variable: White Household Share by Income		
	High Inc	Mid Inc	Low Inc
Racial Minority	-0.0264^{***}	-0.0035	0.0173^{**}
	(0.0090)	(0.0085)	(0.0070)
African American	-0.0337^{***}	-0.0185^{*}	0.0099
	(0.0116)	(0.0112)	(0.0091)
Hispanic	-0.0146	-0.0037	0.0204^{**}
	(0.0121)	(0.0112)	(0.0095)
Asian	-0.0244^{**}	0.0155	0.0214^{**}
	(0.0107)	(0.0103)	(0.0087)
Other	0.0582	0.0185	-0.0106
	(0.0390)	(0.0408)	(0.0264)
ln(Price) Advert Home	*Y*	*Y*	*Y*
Racial Comp Advert Home	*Y*	*Y*	*Y*
Poverty Share Advert Home	*Y*	*Y*	*Y*
Observations	21,500	21,500	21,500
Adjusted R^2	0.7177	0.7064	0.6666

*p<0.1; **p<0.05; ***p<0.01

Note: All regression specifications control for the full set of actor characteristics, assigned characteristics, and search Characteristics. Actor characteristics: tester income, tester household income, gender of tester, age of tester, month of test, educational attainment of tester; Assigned Characteristics: household members, current home ownership status, current lease type, car ownership status, reason for moving, years in current residence, length of employment at current job, reason tester can afford down payment, current lease assigned to tester; Search Characteristics: month of test, sequence of tester appointments, time of the appointment (am/pm), type of recommended building, total number of homes recommended to tester, availability of advertised home as stated by agent

Table 8. Discriminatory Steering and Neighborhood Effects

	Dependent variable:			
	Poverty Rate	High Skill	College	Elem School
Racial Minority	0.0125**	−0.0228**	−0.0161	−0.2748
	(0.0060)	(0.0115)	(0.0113)	(0.2158)
African American	0.0124	−0.0272*	−0.0304**	−0.3831
	(0.0085)	(0.0151)	(0.0144)	(0.2951)
Hispanic	0.0216***	−0.0348**	−0.0184	−0.1728
	(0.0082)	(0.0149)	(0.0141)	(0.2872)
Asian	0.0005	−0.0059	0.0023	−0.3578
	(0.0076)	(0.0143)	(0.0153)	(0.2601)
Other	−0.0272	−0.0021	0.0050	−0.3279
	(0.0256)	(0.0458)	(0.0401)	(0.6681)
ln(Price) Advert Home	*Y*	*Y*	*Y*	*Y*
Racial Comp Advert Home	*Y*	*Y*	*Y*	*Y*
Outcome Advertised Home	*Y*	*Y*	*Y*	*Y*
Observations	21,342	21,342	21,342	10,743
Adjusted R^2	0.5237	0.6937	0.7560	0.7468
	Census Block Characteristics			
p-values	0.037	0.047	0.15	
sharpened q-values	0.094	0.094	0.15	

*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:			
	Assaults	Superfund	Toxics	PM
Racial Minority	9.4284	0.0997***	787.9887**	−0.0448
	(7.5721)	(0.0360)	(355.1028)	(0.0580)
African American	23.8039**	0.1206**	915.4476**	−0.0228
	(11.7093)	(0.0517)	(447.0242)	(0.0777)
Hispanic	1.7870	0.0620	421.2600	0.0075
	(9.4729)	(0.0419)	(586.4115)	(0.0728)
Asian	5.7019	0.1030**	955.7904**	−0.1283*
	(8.9305)	(0.0522)	(480.9247)	(0.0704)
Other	−10.3010	−0.1229	−664.3224	−0.0588
	(69.1959)	(0.1875)	(1, 726.1620)	(0.2170)
ln(Price) Advert Home	*Y*	*Y*	*Y*	*Y*
Racial Comp Advert Home	*Y*	*Y*	*Y*	*Y*
Outcome Advertised Home	*Y*	*Y*	*Y*	*Y*
Observations	10,875	21,354	21,354	21,354
Adjusted R^2	0.7954	0.8760	0.6888	0.9634
		Local Pollutants		
p-values		0.0056	0.026	0.44
sharpened q-values		0.017	0.053	0.44

*p<0.1; **p<0.05; ***p<0.01

Note: All regression specifications control for the full set of actor characteristics, assigned characteristics, and search Characteristics. Actor characteristics: tester income, tester household income, gender of tester, age of tester, month of test, educational attainment of tester; Assigned Characteristics: household members, current home ownership status, current lease type, car ownership status, reason for moving, years in current residence, length of employment at current job, reason tester can afford down payment, current lease assigned to tester; Search Characteristics: month of test, sequence of tester appointments, time of the appointment (am/pm), type of recommended building, total number of homes recommended to tester, availability of advertised home as stated by agent

Table 9. Discriminatory Steering and Neighborhood Effects (Mothers)

	Dependent variable:			
	Poverty Rate	High Skill	College	Elem School
Racial Minority	0.0481***	−0.0254	−0.0341*	0.5491
	(0.0117)	(0.0169)	(0.0192)	(0.4069)
African American	0.0523***	−0.0464*	−0.0605**	0.1576
	(0.0176)	(0.0267)	(0.0304)	(0.5639)
Hispanic	0.0560***	−0.0455**	−0.0361*	0.8435**
	(0.0144)	(0.0198)	(0.0201)	(0.4241)
Asian	0.0360**	0.0047	−0.0293	0.5426
	(0.0175)	(0.0236)	(0.0281)	(0.6429)
Other	0.0092	−0.0403	−0.0354	0.5679
	(0.0372)	(0.0578)	(0.0576)	(1.0661)
Observations	7,849	7,849	7,849	5,647
Adjusted R^2	0.4633	0.6629	0.7411	0.6891

Note: *p<0.1; **p<0.05; ***p<0.01

	Dependent variable:			
	Assaults	Superfund	Toxics	PM
Racial Minority	3.5671	0.1154*	897.0170	−0.0601
	(17.3998)	(0.0676)	(742.4506)	(0.1330)
African American	33.2016**	0.1795*	2,268.9180*	−0.0155
	(15.2890)	(0.1036)	(1,245.5460)	(0.1845)
Hispanic	−4.5340	0.0207	1,178.3650	0.1472
	(20.3963)	(0.0865)	(828.1420)	(0.1501)
Asian	14.3675	0.0478	648.8790	−0.1493
	(26.7642)	(0.0826)	(995.8417)	(0.1632)
Other	31.5753	−0.3719	2,472.9360	0.5972**
	(53.7138)	(0.2733)	(2,341.9910)	(0.2862)
Observations	5,615	7,850	7,850	7,841
Adjusted R^2	0.8214	0.8528	0.5922	0.9671

Note: *p<0.1; **p<0.05; ***p<0.01

Note: All regression specifications control for the full set of actor characteristics, assigned characteristics, and search Characteristics. Actor characteristics: tester income, tester household income, gender of tester, age of tester, month of test, educational attainment of tester; Assigned Characteristics: household members, current home ownership status, current lease type, car ownership status, reason for moving, years in current residence, length of employment at current job, reason tester can afford down payment, current lease assigned to tester; Search Characteristics: month of test, sequence of tester appointments, time of the appointment (am/pm), type of recommended building, total number of homes recommended to tester, availability of advertised home as stated by agent

Table 10. Discriminatory Steering and Home Price

	Dependent variable: log(Price)		
	1	2	3
Racial Minority	−0.0057	−0.0046	0.0043
	(0.1155)	(0.1164)	(0.1099)
African American	0.0659	0.0648	0.0823
	(0.1790)	(0.1792)	(0.1737)
Hispanic	−0.1657	−0.1622	−0.1594
	(0.1106)	(0.1114)	(0.1024)
Asian	0.0597	0.0598	0.0621
	(0.1070)	(0.1075)	(0.1003)
Other	−0.2234	−0.2189	−0.2554
	(0.2791)	(0.2766)	(0.2781)
Racial Comp Advert Home	*N*	*Y*	*Y*
ln(Price) Advert Home	*N*	*N*	*Y*
Observations	21,785	21,774	21,761
Adjusted R^2	0.7228	0.7226	0.7245

*p<0.1; **p<0.05; ***p<0.01

Note: All regression specifications control for the full set of actor characteristics, assigned characteristics, and search Characteristics. Actor characteristics: tester income, tester household income, gender of tester, age of tester, month of test, educational attainment of tester; Assigned Characteristics: household members, current home ownership status, current lease type, car ownership status, reason for moving, years in current residence, length of employment at current job, reason tester can afford down payment, current lease assigned to tester; Search Characteristics: month of test, sequence of tester appointments, time of the appointment (am/pm), type of recommended building, total number of homes recommended to tester, availability of advertised home as stated by agent

Table 11. Discriminatory Steering and Implied Preference for Neighborhood Racial Composition

	Dep. Variable: White Household Share			
	White Share	Black Share	Hispanic Share	Asian Share
Racial Minority x Ad White Share	−0.0175	0.0211**	0.0063	−0.0087
	(0.0143)	(0.0101)	(0.0089)	(0.0071)
Ad White Share	−0.0940	0.0834	−0.0443	0.0625
	(0.1288)	(0.0943)	(0.0670)	(0.0895)
African American x Ad White Share	−0.0559***	0.0498***	0.0228**	−0.0156*
	(0.0173)	(0.0131)	(0.0114)	(0.0094)
Hispanic x Ad White Share	−0.0145	0.0202	0.0040	−0.0105
	(0.0202)	(0.0130)	(0.0123)	(0.0100)
Asian x Ad White Share	0.0263	−0.0091	−0.0114	−0.0013
	(0.0199)	(0.0147)	(0.0129)	(0.0099)
Other x Ad White Share	0.0864	−0.0139	−0.0384	−0.0247
	(0.0563)	(0.0421)	(0.0349)	(0.0219)
Ad White Share	−0.1280	0.1048	−0.0302	0.0587
	(0.1306)	(0.0929)	(0.0674)	(0.0886)
Observations	21,342	21,342	21,342	21,342
Adjusted R^2	0.7781	0.7708	0.8452	0.7435

*p<0.1; **p<0.05; ***p<0.01

Note: All regression specifications control for the full set of actor characteristics, assigned characteristics, and search Characteristics. Actor characteristics: tester income, tester household income, gender of tester, age of tester, month of test, educational attainment of tester; Assigned Characteristics: household members, current home ownership status, current lease type, car ownership status, reason for moving, years in current residence, length of employment at current job, reason tester can afford down payment, current lease assigned to tester; Search Characteristics: month of test, sequence of tester appointments, time of the appointment (am/pm), type of recommended building, total number of homes recommended to tester, availability of advertised home as stated by agent

Table 12. Discriminatory Steering by Implied Preferences for Neighborhood Attributes

	Dependent variable: Recommended House Attribute			
	Poverty Rate	High Skill	College	Elem School
African American x Ad House Attribute	-0.0460^{***}	-0.0180^{**}	-0.0182^{**}	-0.0783^{***}
	(0.0160)	(0.0073)	(0.0072)	(0.0107)
Hispanic x Ad House Attribute	0.0176	-0.0186^{**}	-0.0049	-0.0205^{*}
	(0.0176)	(0.0077)	(0.0077)	(0.0118)
Asian x Ad House Attribute	0.0659^{***}	0.0390^{***}	0.0157^{**}	-0.0082
	(0.0188)	(0.0074)	(0.0075)	(0.0106)
Other x Ad House Attribute	-0.1472^{***}	-0.0285	-0.0028	-0.0529^{*}
	(0.0440)	(0.0274)	(0.0283)	(0.0290)
Ad House Attribute	0.1746^{***}	0.2733^{***}	0.3489^{***}	0.4343^{***}
	(0.0102)	(0.0093)	(0.0089)	(0.0119)
Observations	21,342	21,342	21,342	10,743
Adjusted R^2	0.3645	0.5777	0.6528	0.6329

*p<0.1; **p<0.05; ***p<0.01

	Dependent variable: Recommended House Attribute			
	Assaults	Superfund	Toxics	PM
African American x Ad House Attribute	-0.1315^{***}	-0.0287	-0.6713^{***}	-0.0044^{*}
	(0.0201)	(0.0470)	(0.0147)	(0.0023)
Hispanic x Ad House Attribute	0.1258^{***}	0.0719	-0.4651^{***}	0.0029
	(0.0191)	(0.0743)	(0.0163)	(0.0024)
Asian x Ad House Attribute	-0.0635^{***}	-0.2831^{***}	-0.3830^{***}	-0.0125^{***}
	(0.0190)	(0.1041)	(0.0327)	(0.0022)
Other x Ad House Attribute	0.1026	0.1572	-0.3376^{***}	0.0098
	(0.0732)	(0.2018)	(0.0714)	(0.0084)
Ad House Attribute	0.3020^{***}	0.2100^{***}	0.6772^{***}	0.3336^{***}
	(0.0106)	(0.0437)	(0.0147)	(0.0072)
Observations	10,888	21,354	21,376	21,354
Adjusted R^2	0.6650	0.8101	0.5876	0.9462

*p<0.1; **p<0.05; ***p<0.01

Note: All regression specifications control for the full set of actor characteristics, assigned characteristics, and search Characteristics. Actor characteristics: tester income, tester household income, gender of tester, age of tester, month of test, educational attainment of tester; Assigned Characteristics: household members, current home ownership status, current lease type, car ownership status, reason for moving, years in current residence, length of employment at current job, reason tester can afford down payment, current lease assigned to tester; Search Characteristics: month of test, sequence of tester appointments, time of the appointment (am/pm), type of recommended building, total number of homes recommended to tester, availability of advertised home as stated by agent

Figure 1. Markets in 2012 HUD Buyer Experiment

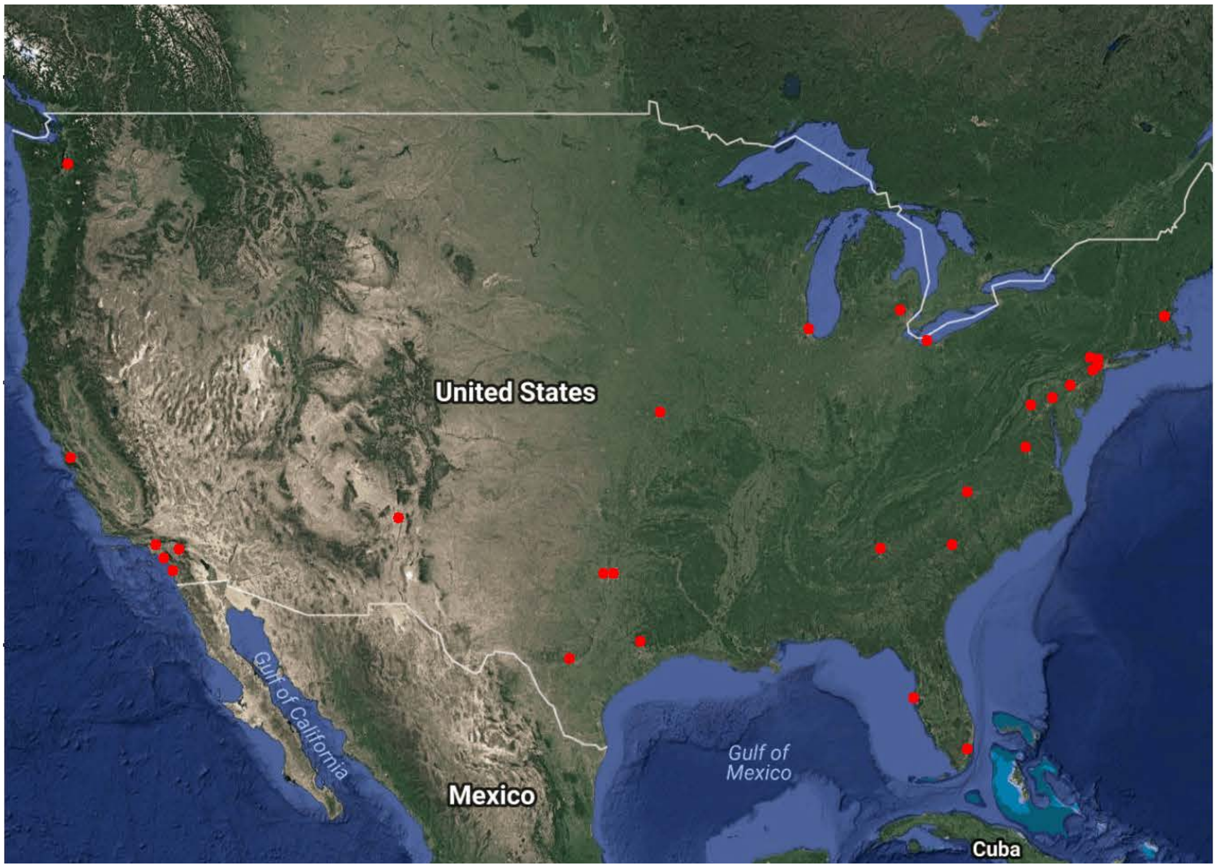
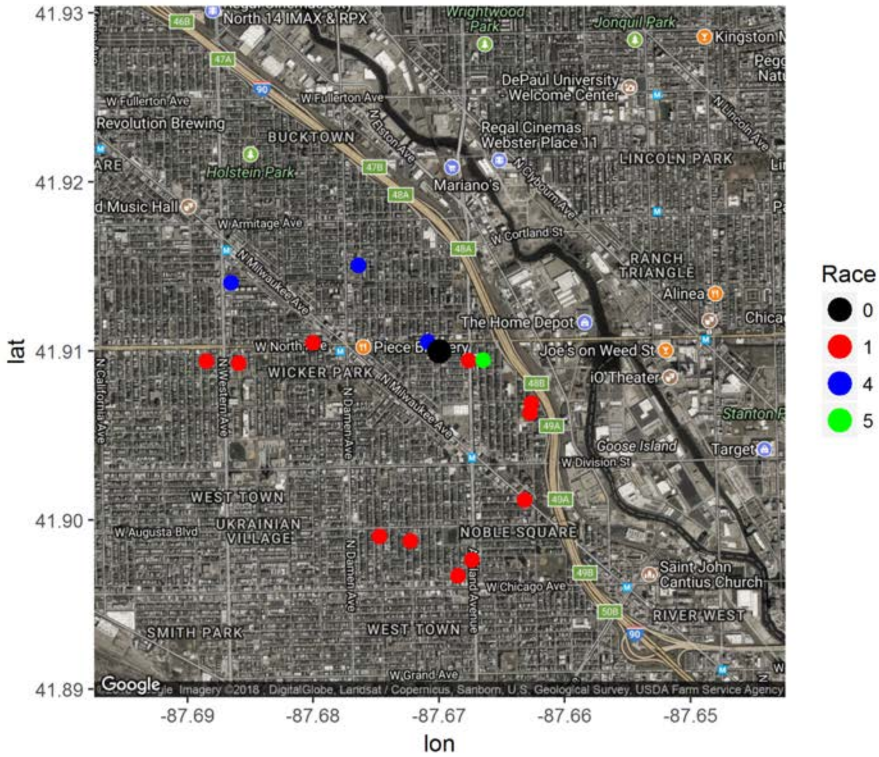


Figure 2. Trial Maps



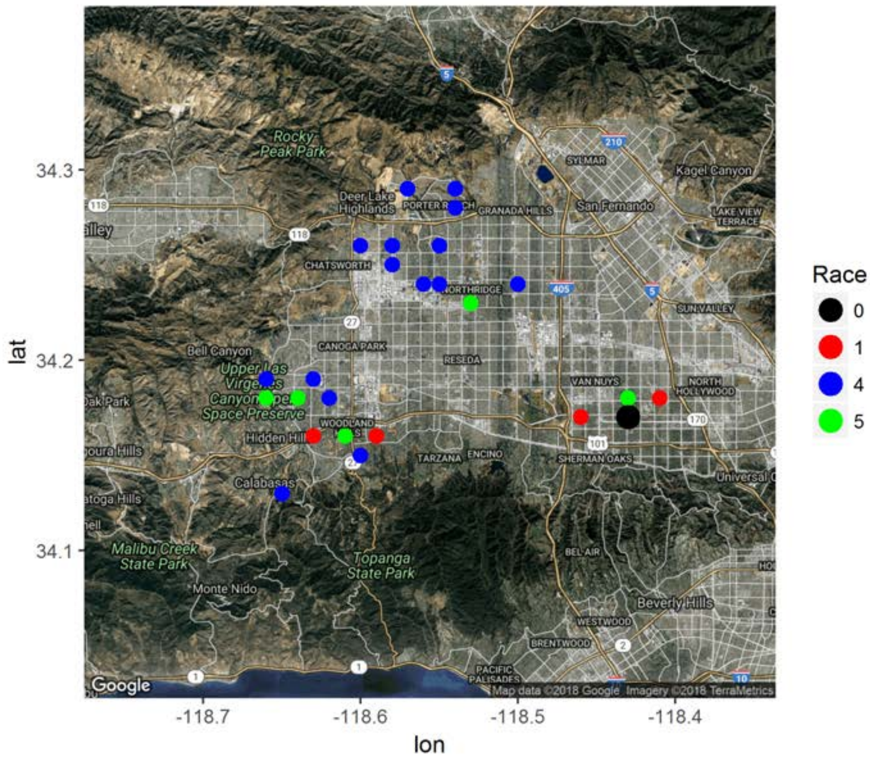
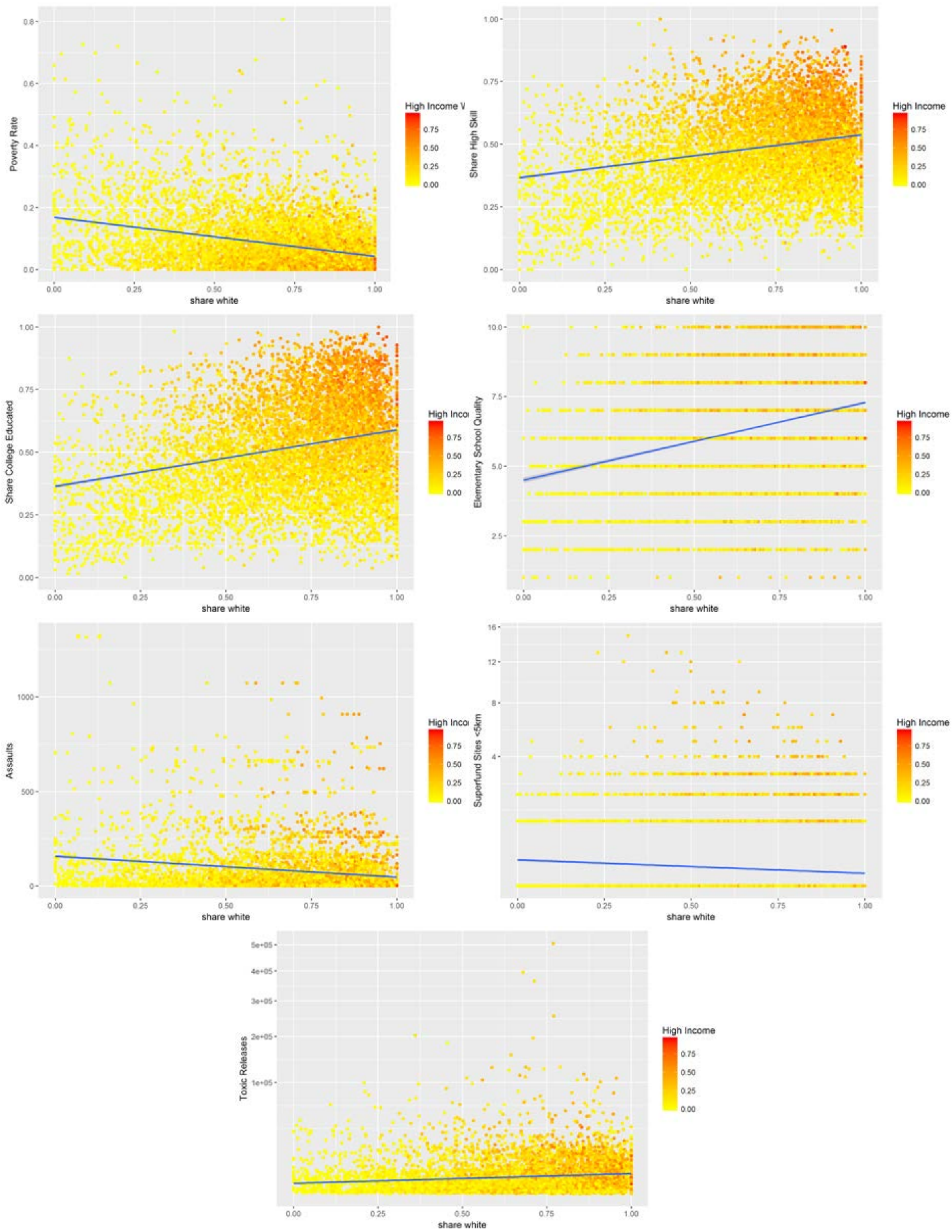


Figure 3. Correlation between white share of Block Group and Outcomes



8 Online Appendix

Table 13. Balance Table for Tester Data Omitting Matched Pairs

	Tester Characteristics (True Actors, Not Assigned)		
Variable	African American	Hispanic	Asian
Age	0.009	0.584	-5.087***
	(0.689)	(0.860)	(0.859)
Percent Male	-0.016	-0.127***	0.046
	(0.026)	(0.033)	(0.033)
Percent Tester Went First	-0.172***	-0.134***	-0.127***
	(0.027)	(0.033)	(0.033)
Percent Rented Home	0.050	-0.063*	0.034*
	(0.027)	(0.033)	(0.033)
Percent Owned Home	0.016	0.125***	-0.080**
	(0.025)	(0.031)	(0.031)
Personal Income			
Under $10,000	-0.035	-0.151***	-0.026
	(0.023)	(0.029)	(0.029)
$10,000 - $19,999	0.095***	-0.016	0.105***
	(0.020)	(0.025)	(0.025)
$20,000 - $29,999	-0.158***	-0.044	-0.109***
	(0.023)	(0.028)	(0.028)
$30,000 - $39,999	0.038**	0.069***	0.037
	(0.019)	(0.023)	(0.023)
$40,000 - $49,999	0.019	0.031	0.004
	(0.016)	(0.020)	(0.020)
$50,000 - $74,999	0.007	0.073***	-0.040**
	(0.013)	(0.017)	(0.017)
$75,000 - $99,999	-0.005	-0.013**	-0.009
	(0.005)	(0.006)	(0.006)
$100,000 or more	0.002	0.009**	-0.002
	(0.003)	(0.004)	(0.004)
Education			
Attended High School	0.002	-0	0.018***
	(0.003)	(0.004)	(0.004)
GED	-0.017***	-0.021***	-0.021***
	(0.006)	(0.007)	(0.007)
High School Diploma	0.025**	0.017	0.060***
	(0.010)	(0.012)	(0.012)
Attended Vocational / Technical School	-0.005	0.013***	-0.005
	(0.004)	(0.005)	(0.005)
Vocational / Technical School Diploma	-0.025***	-0.024**	-0.003
	(0.008)	(0.010)	(0.010)
Attended College	0.053***	0.178***	-0.021
	(0.020)	(0.025)	(0.024)
Associate's Degree	0.042***	0.076***	-0.005
	(0.014)	(0.018)	(0.018)
Bachelor's Degree	-0.121***	-0.221***	0.080**
	(0.025)	(0.032)	(0.032)
Attended Graduate / Professional School	-0.054***	-0.026*	-0.049***
	(0.012)	(0.015)	(0.015)
Graduate / Professional Degree	0.078***	0.023	-0.060**
	(0.023)	(0.029)	(0.029)
	Assigned Characteristics		
Percent Car Owner	-0.065***	0.061**	0.001
	(0.019)	(0.024)	(0.024)
Length of Employment (Years)	1.592***	1.858***	1.163***
	(0.105)	(0.132)	(0.131)
Years at Residence	1.480***	1.841***	1.177***
	(0.087)	(0.108)	(0.107)
Lease Type			
Month-to-Month	0.007	0.024	0.063*
	(0.027)	(0.034)	(0.033)
Lease	-0.007	-0.024	-0.063*
	(0.027)	(0.034)	(0.033)
	N = 512	N = 286	N = 294

Table 14. Balance Table for Homes Data Omitting Matched Pairs

Variable	African American	Hispanic	Asian
Listing Price	1,727	1,877	25,827**
	(10,082.410)	(10,729.450)	(10,418.710)
Time of Test (AM)	0.015	0.018	0.012
	(0.016)	(0.017)	(0.017)
Building Type			
Single-family Detached	-0.005	-0.044***	0.005
	(0.015)	(0.016)	(0.015)
Duplex	-0.004	0.001	0.001
	(0.004)	(0.005)	(0.004)
Rowhouse or Townhouse	-0.010	0.030**	0.027**
	(0.011)	(0.012)	(0.012)
Multi-family Structure	0.024**	0.011	-0.032***
	(0.010)	(0.011)	(0.010)
Mobile Home	-0.001	0.004***	-0.001
	(0.001)	(0.001)	(0.001)

Table 15. Steering and Neighborhood Effects Omitting Matched Pairs

	Dependent variable:					
	Neighborhood Capital			Pollution Exposures		
	Poverty Rate	College	High Skill	Superfund Prox	Toxic Releases	Respiratory
Racial Minority	0.0703***	0.0036	−0.0022	−0.0668***	−716.1090***	−0.0180**
	(0.0205)	(0.0031)	(0.0034)	(0.0114)	(247.4231)	(0.0081)
African American	0.0259	−0.0043	−0.0114**	−0.0726***	−656.5011**	−0.0300***
	(0.0276)	(0.0042)	(0.0046)	(0.0153)	(332.3424)	(0.0109)
Hispanic	0.0946***	0.0005	−0.0048	−0.0099	−418.0583	0.0267**
	(0.0298)	(0.0045)	(0.0050)	(0.0165)	(358.3695)	(0.0117)
Asian	0.0676**	0.0145***	0.0090*	−0.0996***	−969.8497***	−0.0245**
	(0.0284)	(0.0043)	(0.0047)	(0.0158)	(342.5564)	(0.0112)
Other	−0.1830**	−0.0047	−0.0095	0.0866*	564.3243	0.1353***
	(0.0864)	(0.0131)	(0.0144)	(0.0481)	(1, 041.7750)	(0.0340)
ln(Price) Advert Home	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Racial Comp Advert Home	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Outcome Advertised Home	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*
Observations	21,517	21,517	21,517	21,529	21,529	21,524
Adjusted R^2	0.3589	0.5198	0.5796	0.8174	0.5413	0.8927
Note:						*p<0.1; **p<0.05; ***p<0.01

Note: All regression specifications control for the full set of actor characteristics, assigned characteristics, and search Characteristics. Actor characteristics: tester income, tester household income, gender of tester, age of tester, month of test, educational attainment of tester; Assigned Characteristics: household members, current home ownership status, current lease type, car ownership status, reason for moving, years in current residence, length of employment at current job, reason tester can afford down payment, current lease assigned to tester; Search Characteristics: month of test, sequence of tester appointments, time of the appointment (am/pm), type of recommended building, total number of homes recommended to tester, availability of advertised home as stated by agent

Table 16. Differential Steering and Neighborhood Racial Composition: African American Share

	Dep. Variable: African American Household Share				
	I	II	III	IV	V
Racial Minority	0.0164**	0.0164**	0.0165**	0.0166**	0.0167**
	(0.0081)	(0.0081)	(0.0081)	(0.0081)	(0.0080)
African American	0.0396***	0.0397***	0.0399***	0.0401***	0.0404***
	(0.0123)	(0.0123)	(0.0123)	(0.0124)	(0.0123)
Hispanic	0.0127	0.0127	0.0127	0.0127	0.0127
	(0.0095)	(0.0095)	(0.0095)	(0.0095)	(0.0095)
Asian	−0.0065	−0.0065	−0.0064	−0.0064	−0.0063
	(0.0105)	(0.0105)	(0.0105)	(0.0105)	(0.0105)
Other	−0.0045	−0.0045	−0.0049	−0.0054	−0.0052
	(0.0337)	(0.0337)	(0.0336)	(0.0336)	(0.0336)
Share Black Advert Home	*N*	*Y*	*Y*	*Y*	*Y*
ln(Price) Advert Home	*N*	*N*	*Y*	*Y*	*Y*
Racial Comp Advert Home	*N*	*N*	*N*	*Y*	*Y*
Poverty Share Advert Home	*N*	*N*	*N*	*N*	*Y*
Observations	21,517	21,506	21,488	21,488	21,488
Adjusted R^2	0.7736	0.7738	0.7724	0.7724	0.7724
Note:					*p<0.1; **p<0.05; ***p<0.01

Note: All regression specifications control for the full set of actor characteristics, assigned characteristics, and search Characteristics. Actor characteristics: tester income, tester household income, gender of tester, age of tester, month of test, educational attainment of tester; Assigned Characteristics: household members, current home ownership status, current lease type, car ownership status, reason for moving, years in current residence, length of employment at current job, reason tester can afford down payment, current lease assigned to tester; Search Characteristics: month of test, sequence of tester appointments, time of the appointment (am/pm), type of recommended building, total number of homes recommended to tester, availability of advertised home as stated by agent

Table 17. Differential Steering and Neighborhood Racial Composition by Income: African American Share

	Dep. Variable: African American Household Share by Income		
	High Inc	Mid Inc	Low Inc
Racial Minority	0.0020	0.0098**	0.0051
	(0.0013)	(0.0041)	(0.0046)
African American	0.0052***	0.0176***	0.0178***
	(0.0018)	(0.0068)	(0.0065)
Hispanic	0.0005	0.0069	0.0055
	(0.0017)	(0.0046)	(0.0055)
Asian	0.0000	0.0030	−0.0094
	(0.0017)	(0.0047)	(0.0063)
Other	0.0013	−0.0084	0.0019
	(0.0054)	(0.0170)	(0.0202)
ln(Price) Advert Home	*Y*	*Y*	*Y*
Racial Comp Advert Home	*Y*	*Y*	*Y*
Poverty Share Advert Home	*Y*	*Y*	*Y*
Observations	21,500	21,500	21,500
Adjusted R^2	0.7297	0.7625	0.6704
Note:			*p<0.1; **p<0.05; ***p<0.01

Note: All regression specifications control for the full set of actor characteristics, assigned characteristics, and search Characteristics. Actor characteristics: tester income, tester household income, gender of tester, age of tester, month of test, educational attainment of tester; Assigned Characteristics: household members, current home ownership status, current lease type, car ownership status, reason for moving, years in current residence, length of employment at current job, reason tester can afford down payment, current lease assigned to tester; Search Characteristics: month of test, sequence of tester appointments, time of the appointment (am/pm), type of recommended building, total number of homes recommended to tester, availability of advertised home as stated by agent

Table 18. Differential Steering and Neighborhood Racial Composition: Hispanic/LatinX Share

	Dep. Variable: Hispanic Household Share				
	I	II	III	IV	V
Racial Minority	0.0038	0.0039	0.0040	0.0039	0.0038
	(0.0079)	(0.0079)	(0.0079)	(0.0079)	(0.0079)
African American	0.0152	0.0152	0.0154	0.0153	0.0151
	(0.0115)	(0.0115)	(0.0114)	(0.0115)	(0.0115)
Hispanic	−0.0010	−0.0009	−0.0008	−0.0009	−0.0009
	(0.0102)	(0.0102)	(0.0102)	(0.0102)	(0.0102)
Asian	−0.0073	−0.0073	−0.0073	−0.0074	−0.0074
	(0.0098)	(0.0098)	(0.0098)	(0.0098)	(0.0098)
Other	−0.0323	−0.0322	−0.0327	−0.0325	−0.0326
	(0.0305)	(0.0305)	(0.0305)	(0.0305)	(0.0304)
Share Hispanic Advert Home	*N*	*Y*	*Y*	*Y*	*Y*
ln(Price) Advert Home	*N*	*N*	*Y*	*Y*	*Y*
Racial Comp Advert Home	*N*	*N*	*N*	*Y*	*Y*
Poverty Share Advert Home	*N*	*N*	*N*	*N*	*Y*
Observations	21,517	21,506	21,488	21,488	21,488
Adjusted R^2	0.8452	0.8451	0.8452	0.8452	0.8452
Note:					*p<0.1; **p<0.05; ***p<0.01

Note: All regression specifications control for the full set of actor characteristics, assigned characteristics, and search Characteristics. Actor characteristics: tester income, tester household income, gender of tester, age of tester, month of test, educational attainment of tester; Assigned Characteristics: household members, current home ownership status, current lease type, car ownership status, reason for moving, years in current residence, length of employment at current job, reason tester can afford down payment, current lease assigned to tester; Search Characteristics: month of test, sequence of tester appointments, time of the appointment (am/pm), type of recommended building, total number of homes recommended to tester, availability of advertised home as stated by agent

Table 19. Differential Steering and Neighborhood Racial Composition by Income: Hispanic/LatinX Share

	Dep. Var: Hispanic Household Share by Income		
	High Inc	Mid Inc	Low Inc
Racial Minority	0.0016	−0.0012	0.0030
	(0.0019)	(0.0044)	(0.0048)
African American	0.0054*	0.0039	0.0055
	(0.0029)	(0.0054)	(0.0081)
Hispanic	−0.0017	−0.0049	0.0050
	(0.0026)	(0.0063)	(0.0063)
Asian	−0.0011	−0.0043	−0.0022
	(0.0027)	(0.0056)	(0.0052)
Other	−0.0165*	−0.0113	−0.0054
	(0.0085)	(0.0193)	(0.0114)
ln(Price) Advert Home	*Y*	*Y*	*Y*
Racial Comp Advert Home	*Y*	*Y*	*Y*
Poverty Share Advert Home	*Y*	*Y*	*Y*
Observations	21,500	21,500	21,500
Adjusted R^2	0.6518	0.8330	0.7123
Note:			*p<0.1; **p<0.05; ***p<0.01

Note: All regression specifications control for the full set of actor characteristics, assigned characteristics, and search Characteristics. Actor characteristics: tester income, tester household income, gender of tester, age of tester, month of test, educational attainment of tester; Assigned Characteristics: household members, current home ownership status, current lease type, car ownership status, reason for moving, years in current residence, length of employment at current job, reason tester can afford down payment, current lease assigned to tester; Search Characteristics: month of test, sequence of tester appointments, time of the appointment (am/pm), type of recommended building, total number of homes recommended to tester, availability of advertised home as stated by agent

Table 20. Differential Steering and Neighborhood Racial Composition: Asian Share

	Dep. Variable: Asian Household Share				
	I	II	III	IV	V
Racial Minority	−0.0087	−0.0087	−0.0087	−0.0085	−0.0085
	(0.0059)	(0.0058)	(0.0058)	(0.0058)	(0.0058)
African American	−0.0144*	−0.0143*	−0.0143*	−0.0142*	−0.0142*
	(0.0075)	(0.0074)	(0.0074)	(0.0074)	(0.0074)
Hispanic	−0.0143*	−0.0146*	−0.0147*	−0.0145*	−0.0145*
	(0.0086)	(0.0085)	(0.0085)	(0.0085)	(0.0085)
Asian	0.0014	0.0014	0.0015	0.0016	0.0016
	(0.0072)	(0.0072)	(0.0072)	(0.0072)	(0.0072)
Other	−0.0224	−0.0228	−0.0228	−0.0228	−0.0229
	(0.0178)	(0.0179)	(0.0179)	(0.0179)	(0.0179)
Share Asian Advert Home	*N*	*Y*	*Y*	*Y*	*Y*
ln(Price) Advert Home	*N*	*N*	*Y*	*Y*	*Y*
Racial Comp Advert Home	*N*	*N*	*N*	*Y*	*Y*
Poverty Share Advert Home	*N*	*N*	*N*	*N*	*Y*
Observations	21,517	21,506	21,488	21,488	21,488
Adjusted R^2	0.7438	0.7438	0.7438	0.7438	0.7437

Note: *p<0.1; **p<0.05; ***p<0.01

Note: All regression specifications control for the full set of actor characteristics, assigned characteristics, and search Characteristics. Actor characteristics: tester income, tester household income, gender of tester, age of tester, month of test, educational attainment of tester; Assigned Characteristics: household members, current home ownership status, current lease type, car ownership status, reason for moving, years in current residence, length of employment at current job, reason tester can afford down payment, current lease assigned to tester; Search Characteristics: month of test, sequence of tester appointments, time of the appointment (am/pm), type of recommended building, total number of homes recommended to tester, availability of advertised home as stated by agent

Table 21. Differential Steering and Neighborhood Racial Composition by Income: Asian Share

	Dep. Variable: Asian Household Share by Income		
	High Inc	Mid Inc	Low Inc
Racial Minority	−0.0021	−0.0036	−0.0023
	(0.0021)	(0.0030)	(0.0024)
African American	−0.0033	−0.0068*	−0.0040
	(0.0026)	(0.0036)	(0.0033)
Hispanic	−0.0034	−0.0047	−0.0055*
	(0.0033)	(0.0046)	(0.0032)
Asian	0.0013	−0.0002	0.0010
	(0.0026)	(0.0037)	(0.0030)
Other	0.0060	−0.0118	−0.0189*
	(0.0064)	(0.0126)	(0.0103)
ln(Price) Advert Home	*Y*	*Y*	*Y*
Racial Comp Advert Home	*Y*	*Y*	*Y*
Poverty Share Advert Home	*Y*	*Y*	*Y*
Observations	21,500	21,500	21,500
Adjusted R^2	0.6869	0.7234	0.6256
Note:			*p<0.1; **p<0.05; ***p<0.01

Note: All regression specifications control for the full set of actor characteristics, assigned characteristics, and search Characteristics. Actor characteristics: tester income, tester household income, gender of tester, age of tester, month of test, educational attainment of tester; Assigned Characteristics: household members, current home ownership status, current lease type, car ownership status, reason for moving, years in current residence, length of employment at current job, reason tester can afford down payment, current lease assigned to tester; Search Characteristics: month of test, sequence of tester appointments, time of the appointment (am/pm), type of recommended building, total number of homes recommended to tester, availability of advertised home as stated by agent

Table 22. Discriminatory Steering and Neighborhood Effects by Family Status

	Dependent variable:			
	Poverty Rate	High Skill	College	Elem School
Racial Minority - no children	0.0219***	−0.0116	−0.0127	−0.3683*
	(0.0059)	(0.0145)	(0.0094)	(0.2000)
Racial Minority - children	0.0069	−0.0300**	−0.0200**	−0.2581
	(0.0051)	(0.0119)	(0.0083)	(0.1603)
African American - no children	0.0067	−0.0136	−0.0153	−0.3460
	(0.0079)	(0.0217)	(0.0128)	(0.2815)
African American - children	0.0129*	−0.0355**	−0.0392***	−0.3971*
	(0.0067)	(0.0154)	(0.0109)	(0.2130)
Hispanic - no children	0.0431***	−0.0122	−0.0142	−0.3751
	(0.0086)	(0.0201)	(0.0139)	(0.2864)
Hispanic - children	0.0125*	−0.0463***	−0.0219*	−0.1011
	(0.0070)	(0.0155)	(0.0112)	(0.2195)
Asian - no children	0.0154*	−0.0060	−0.0048	−0.4556
	(0.0087)	(0.0205)	(0.0140)	(0.3168)
Asian - children	−0.0073	−0.0081	0.0009	−0.3632
	(0.0069)	(0.0151)	(0.0111)	(0.2307)
Observations	21,342	21,342	21,342	10,743
Adjusted R^2	0.5242	0.6939	0.7560	0.7467
Note:				*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:			
	Assaults	Superfund	Toxics	PM
Racial Minority - no children	9.4856	0.0876***	969.7851	−0.0358
	(9.8038)	(0.0339)	(738.2720)	(0.0476)
Racial Minority - children	8.5585	0.1031***	642.7901	−0.0461
	(7.9361)	(0.0298)	(648.3574)	(0.0418)
African American - no children	2.6265	0.0903**	1,257.8280	0.0085
	(14.0369)	(0.0460)	(1,002.0660)	(0.0646)
African American - children	26.9505**	0.1391***	700.6457	−0.0385
	(10.6483)	(0.0390)	(848.9701)	(0.0547)
Hispanic - no children	6.1774	0.0973*	647.7284	−0.0072
	(13.9678)	(0.0498)	(1,085.8530)	(0.0700)
Hispanic - children	−0.5538	0.0467	287.7887	0.0116
	(10.3165)	(0.0404)	(877.7155)	(0.0566)
Asian - no children	13.4485	0.0645	898.0889	−0.1329*
	(14.9905)	(0.0502)	(1,093.2040)	(0.0705)
Asian - children	−0.6546	0.1139***	862.4198	−0.1227**
	(10.6294)	(0.0399)	(871.2342)	(0.0562)
Observations	14,011	21,354	21,354	21,354
Adjusted R^2	0.7740	0.8760	0.6888	0.9634
Note:				*p<0.1; **p<0.05; ***p<0.01

Note: All regression specifications control for the full set of actor characteristics, assigned characteristics, and search Characteristics. Actor characteristics: tester income, tester household income, gender of tester, age of tester, month of test, educational attainment of tester; Assigned Characteristics: household members, current home ownership status, current lease type, car ownership status, reason for moving, years in current residence, length of employment at current job, reason tester can afford down payment, current lease assigned to tester; Search Characteristics: month of test, sequence of tester appointments, time of the appointment (am/pm), type of recommended building, total number of homes recommended to tester, availability of advertised home as stated by agent

Table 23. Discriminatory Steering and Neighborhood Effects by Gender

	Dependent variable:			
	Poverty Rate	High Skill	College	Elem School
Racial Minority - female	0.0113**	−0.0166	−0.0194**	−0.1953
	(0.0054)	(0.0137)	(0.0088)	(0.1698)
Racial Minority - male	0.0137**	−0.0313**	−0.0115	−0.4244**
	(0.0059)	(0.0136)	(0.0096)	(0.2041)
African American - female	0.0006	−0.0299*	−0.0346***	−0.4359**
	(0.0069)	(0.0179)	(0.0111)	(0.2171)
African American - male	0.0429***	−0.0093	−0.0177	−0.6545**
	(0.0092)	(0.0222)	(0.0148)	(0.3246)
Hispanic - female	0.0281***	−0.0143	−0.0164	0.1176
	(0.0076)	(0.0174)	(0.0122)	(0.2350)
Hispanic - male	0.0234**	−0.0587***	−0.0169	−1.2149***
	(0.0096)	(0.0226)	(0.0155)	(0.3305)
Asian - female	0.0119	0.0109	0.0027	−0.5705**
	(0.0077)	(0.0191)	(0.0125)	(0.2580)
Asian - male	−0.0123	−0.0211	0.0020	−0.0111
	(0.0082)	(0.0171)	(0.0133)	(0.2699)
Observations	21,342	21,342	21,342	10,743
Adjusted R^2	0.5244	0.6940	0.7560	0.7473
Note:			*p<0.1; **p<0.05; ***p<0.01	

	Dependent variable:			
	Assaults	Superfund	Toxics	PM
Racial Minority - female	15.5961*	0.0760**	1,070.8390	−0.0100
	(8.3619)	(0.0316)	(686.4393)	(0.0443)
Racial Minority - male	−1.8075	0.1323***	398.3885	−0.0928*
	(9.8444)	(0.0345)	(750.0684)	(0.0484)
African American - female	24.2386**	0.0874**	1,338.2690	−0.0196
	(10.8208)	(0.0398)	(867.6137)	(0.0559)
African American - male	16.0392	0.1941***	−44.5434	−0.0067
	(15.4184)	(0.0533)	(1,159.1290)	(0.0747)
Hispanic - female	7.7336	0.0341	519.4757	0.0867
	(11.4341)	(0.0440)	(956.7555)	(0.0616)
Hispanic - male	−9.3405	0.1375**	−12.8221	−0.1215
	(15.4764)	(0.0556)	(1,213.6880)	(0.0782)
Asian - female	13.8833	0.1101**	1,084.6720	−0.1020
	(12.0866)	(0.0447)	(974.6472)	(0.0628)
Asian - male	−8.0305	0.0843*	844.6461	−0.1373**
	(13.2213)	(0.0476)	(1,038.3110)	(0.0669)
Observations	14,011	21,354	21,354	21,354
Adjusted R^2	0.7739	0.8760	0.6888	0.9634
Note:			*p<0.1; **p<0.05; ***p<0.01	

Note: All regression specifications control for the full set of actor characteristics, assigned characteristics, and search Characteristics. Actor characteristics: tester income, tester household income, gender of tester, age of tester, month of test, educational attainment of tester; Assigned Characteristics: household members, current home ownership status, current lease type, car ownership status, reason for moving, years in current residence, length of employment at current job, reason tester can afford down payment, current lease assigned to tester; Search Characteristics: month of test, sequence of tester appointments, time of the appointment (am/pm), type of recommended building, total number of homes recommended to tester, availability of advertised home as stated by agent

Table 24. Discriminatory Steering and Neighborhood Effects: Robustness

	Dependent variable:								
	Poverty Rate			High Skill			College		
Racial Minority	0.0126**	0.0125**	0.0155**	−0.0222*	−0.0228**	−0.0220**	−0.0161	−0.0161	−0.0139
	(0.0061)	(0.0060)	(0.0064)	(0.0116)	(0.0115)	(0.0110)	(0.0113)	(0.0113)	(0.0120)
African American	0.0122	0.0124	0.0159*	−0.0271*	−0.0272*	−0.0281**	−0.0304**	−0.0304**	−0.0282*
	(0.0086)	(0.0085)	(0.0088)	(0.0151)	(0.0151)	(0.0137)	(0.0143)	(0.0144)	(0.0145)
Hispanic	0.0217***	0.0216***	0.0247***	−0.0326**	−0.0348**	−0.0294**	−0.0177	−0.0184	−0.0128
	(0.0084)	(0.0082)	(0.0087)	(0.0151)	(0.0149)	(0.0141)	(0.0140)	(0.0141)	(0.0146)
Asian	0.0009	0.0005	0.0019	−0.0061	−0.0059	−0.0063	0.0017	0.0023	0.0044
	(0.0077)	(0.0076)	(0.0081)	(0.0144)	(0.0143)	(0.0147)	(0.0152)	(0.0153)	(0.0163)
Other	−0.0268	−0.0272	−0.0245	−0.0004	−0.0021	0.0035	0.0043	0.0050	0.0185
	(0.0255)	(0.0256)	(0.0254)	(0.0462)	(0.0458)	(0.0453)	(0.0403)	(0.0401)	(0.0438)
Outcome Advert Home	*N*	*Y*	*Y*	*N*	*Y*	*Y*	*N*	*Y*	*Y*
Racial Comp Advert Home	*N*	*Y*	*Y*	*N*	*Y*	*Y*	*N*	*Y*	*Y*
ln(Price) Advert Home	*N*	*Y*	*Y*	*N*	*Y*	*Y*	*N*	*Y*	*Y*
Outcome by Price Bin	*N*	*N*	*Y*	*N*	*N*	*Y*	*N*	*N*	*Y*
Observations	21,364	21,342	20,133	21,364	21,342	20,133	21,364	21,342	20,133
Adjusted R^2	0.5224	0.5237	0.5310	0.6936	0.6937	0.7034	0.7558	0.7560	0.7664

Note: *p<0.1; **p<0.05; ***p<0.01

	Dependent variable:								
	Superfund Prox			Toxic Releases			PM		
Racial Minority	0.1006***	0.0997***	0.1004***	805.8466**	787.9887**	786.6876**	−0.0464	−0.0448	−0.0445
	(0.0362)	(0.0360)	(0.0361)	(356.5548)	(355.1027)	(354.3281)	(0.0581)	(0.0580)	(0.0580)
African American	0.1233**	0.1206**	0.1210**	946.0394**	915.4476**	959.5564**	−0.0233	−0.0228	−0.0165
	(0.0518)	(0.0517)	(0.0515)	(452.4100)	(447.0242)	(450.1002)	(0.0778)	(0.0777)	(0.0773)
Hispanic	0.0612	0.0620	0.0647	438.9166	421.2600	383.5972	0.0009	0.0075	0.0058
	(0.0424)	(0.0419)	(0.0415)	(589.4368)	(586.4115)	(588.9472)	(0.0729)	(0.0728)	(0.0730)
Asian	0.1029**	0.1030**	0.1022*	961.9641**	955.7904**	937.5928*	−0.1269*	−0.1283*	−0.1324*
	(0.0524)	(0.0522)	(0.0523)	(486.3646)	(480.9247)	(483.0982)	(0.0706)	(0.0704)	(0.0705)
Other	−0.1284	−0.1229	−0.1192	−663.3114	−664.3224	−707.4001	−0.0616	−0.0588	−0.0583
	(0.1880)	(0.1875)	(0.1874)	(1, 731.3800)	(1, 726.1620)	(1, 734.3390)	(0.2156)	(0.2170)	(0.2173)
Outcome Advert Home	*N*	*Y*	*Y*	*N*	*Y*	*Y*	*N*	*Y*	*Y*
Racial Comp Advert Home	*N*	*Y*	*Y*	*N*	*Y*	*Y*	*N*	*Y*	*Y*
ln(Price) Advert Home	*N*	*Y*	*Y*	*N*	*Y*	*Y*	*N*	*Y*	*Y*
Outcome by Price Bin	*N*	*N*	*Y*	*N*	*N*	*Y*	*N*	*N*	*Y*
Observations	21,376	21,354	21,354	21,376	21,354	21,354	21,376	21,354	21,354
Adjusted R^2	0.8760	0.8760	0.8762	0.6889	0.6888	0.6890	0.9634	0.9634	0.9634

Note: *p<0.1; **p<0.05; ***p<0.01

Note: All regression specifications control for the full set of actor characteristics, assigned characteristics, and search Characteristics. Actor characteristics: tester income, tester household income, gender of tester, age of tester, month of test, educational attainment of tester; Assigned Characteristics: household members, current home ownership status, current lease type, car ownership status, reason for moving, years in current residence, length of employment at current job, reason tester can afford down payment, current lease assigned to tester; Search Characteristics: month of test, sequence of tester appointments, time of the appointment (am/pm), type of recommended building, total number of homes recommended to tester, availability of advertised home as stated by agent