Hidden Biases: Selective Advertising in the Rental Housing Market

by

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Abstract

A growing body of literature has documented persistent racial discrimination in rental housing markets, often using experimental (audit or correspondence) studies where fictitious identities request to view a housing unit. These methods are not designed to capture a subtle form of discrimination where landlords choose not to advertise certain units, instead reserving them for prospective tenants after an initial screening or other process to select renters on certain attributes. These selectively unadvertised units will not appear in the sample for an experimental analysis, potentially biasing the results of these studies. In this paper, we introduce an innovative method for detecting selective advertising. Our approach uses a large marketing dataset to track property units turnovers in 27 major U.S. metropolitan areas. We match this data with a rental listings dataset to identify turnover units that are not publicly advertised. By comparing the racial composition of occupants in listed versus "hidden" units and controlling for alternative factors that might account for racial sorting, we assess the extent of discrimination through selective advertising. We find that this form of discrimination against Black and Hispanic renters is particularly severe in neighborhoods with better amenities, where other forms of discrimination are more restricted, and in neighborhoods nearing "tipping points" in racial composition.

The authors would like to thank seminar participants at Carnegie Mellon, CU Boulder, UW Madison DemSem, University of Hong Kong, Chinese University of Hong Kong, Cornell, University of Waterloo, University of Buffalo, and the UEA North American Conference. Fred Freiberg provided valuable insights that inspired this work, and Cody Sondergoth provided outstanding research assistance. The authors acknowledge financial support from the US Department of Housing and Urban Development, Office of Policy Development and Research Contract #86614621F00017. The authors have no other relevant financial relationships or conflicts of interest to disclose.

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"Apart from misrepresenting the availability of apartments to African American testers, the manager also confided to a White tester that the landlord does not advertise available apartments because 'if you run ads, you get all kinds of things.'"
Freiberg and Squires (2015)

1. Introduction

Housing discrimination against color and race is illegal according to the Fair Housing Act of 1968 and its 1988 amendments, but racial discrimination still takes place at various stages of housing transactions, including home search (Christensen and Timmins, 2022; Ewens et al., 2014; Hanson and Hawley, 2011), negotiation over prices or rent (Bayer et al., 2017), home appraisal (Ambrose et al., 2022), and mortgage lending (Aaronson et al., 2021; Ambrose et al., 2021; Zhao et al., 2006; Frame et al., 2021). Among these, one of the most persistent forms of discrimination has been "discriminatory steering" of minority households into minority neighborhoods during the housing search stage (Dymski, 2006; Galster and Godfrey, 2005; Yinger, 1995). The discrimination that occurs at the initial search stage is concerning because it could eliminate the possibility of a successful housing transaction for the minority home seeker before the rest of the process even has a chance to unfold. . Experimental work using white and minority testers with similar characteristics posing as prospective home buyers or renters has sought to measure the extent of racial discrimination. However, there have been growing concerns that these experimental approaches may not be able to detect a particular subtle form of discrimination that occurs during the housing search stage. In particular, enforcement agents have found that landlords who have a preference for certain renter's characteristics may withhold advertising advertise units for which they wish to control tenant access. Instead, these landlords may rely on word-of-mouth, referrals from current tenants, or real estate agents to locate prospective renters who meet their standards. Some units might still be advertised to attract a pool of potential renters for initial screening, after which landlords may assign them to unlisted units if desired. This selective advertising approach is often cited as a reason why correspondence and audit studies may fail, as these practices are challenging to detect, posing significant obstacles for fair housing enforcement (Freiberg and Squires, 2015)..

In this paper, we introduce an innovative method for detecting selective advertising in rental markets. A landlord is considered to be selectively unadvertising if they choose to list some units while leaving others unlisted, AND if those unlisted units are more likely to be occupied by white renters, even after accounting for other factors that might influence racial sorting. Compared with audit and correspondence studies, this alternative strategy that we propose takes a data-intensive approach to finding broad evidence of selective advertising and learning about the contexts in which it is more likely to take place.

We present our analysis in several steps. First, using granular rental listing data merged with corresponding turnover data, we demonstrate that, unlike in owner-occupied markets, choosing not to list some available units is a common practice in the rental markets we study. While unlisting

on its own is not necessarily selective unadvertising, it creates opportunities for landlords to avoid listing certain units for discriminatory reasons.

We then show that, conditional upon knowing that the units in a building could have been listed (i.e., in the same building or by the same manager that has units that were listed), how do the attributes of the residents who end up in the units that were listed differ from those who end up in the unlisted units. This is after controlling for key neighborhood attributes (e.g., neighborhood race percentages) that might influence the sort of people who seek out apartments in that neighborhood. We find evidence that, indeed, Black and Hispanic renters are more likely to end up in the listed units. This result is consistent with an intentional policy of a landlord or property manager to save unlisted units for white renters, as has been suggested by evidence from fair housing enforcement and which would be illegal. It might also be evidence of landlords or property managers relying on some non-listing strategy to fill unlisted units that, while not intentionally designed to steer those units away from renters of color, has a disparate impact in that direction. For example, a property manager might request a letter of reference from an existing tenant rather than posting the listing on a commercial website. This would create a network based on the pool of existing residents, which could preserve the building's racial demographics.[1] A practice resulting in a disparate impact may still be illegal under HUD's "Discriminatory Effects" Rule.[2] The evidence of selective unadvertising highlights a disparate impact and suggests a new direction for targeting enforcement resources.

We also demonstrate how the extent of selective unadvertising varies based on tenants' income, family status, the neighborhood-level proportion of white tenants, and the degree of landlords' callback discrimination. Finally, we analyze the extent to which this practice hinders minorities' access to better amenities and neighborhoods with better opportunities.

To measure the extent in which selective advertising may lead to racial discrimination in housing, we required a setting in which we could compare the racial composition of tenants who end up in properties that were advertised to those in properties that were not. To address this challenge, we constructed a new dataset by merging, for the first time, two large data sources:

(i) Individual level turnover data compiled by Data Axle (a.k.a. InfoUSA) Residential Historical Files, which track the residential locations of hundreds of millions of individuals between 2006–2023 and provide information on race/ethnicity, gender, age, address, renter/owner status; and

[1] Note that our results are robust to the inclusion of tract-, building-, and manager-specific fixed effects. If one manager is more likely to use non-listing strategies to recruit tenants than other managers, this would be controlled for by including the manager fixed effects. Moreover, if word-of-mouth recommendations tend to come from tenants whom landlords "favor" and those tenants, in turn, recommend friends of the same race, we would expect to see the results we observe only if landlords disproportionately favored white tenants. This does not inherently indicate discriminatory intent on the part of landlords, but it suggests a possible avenue for racial bias, whether explicit or implicit. While intent is complex to demonstrate, our study highlights potential disparities in tenant selection that result from informal marketing practices. By examining this further, HUD could consider whether reliance on word-of-mouth recommendations alone aligns with fair housing principles, regardless of intent.

[2]https://www.hud.gov/press/press_releases_media_advisories/hud_no_23_054#:~:text=The%20Fair%20Housing%20Act%20prohibits,actions%20brought%20by%20private%20plaintiffs.

(ii) Rental listing data at the property unit level compiled by Dwellsy (www.dwellsy.com), which contain information on address, unit number, rent, listing time, and landlord or property manager between 2020–2023, with a focus on the class of professionally managed properties.

The merged dataset is unique in a number of aspects:

(i) The dataset includes never-before-linked building-unit and individual tenant-level information on tenure status, race, income, rents, property characteristics, and an indicator for if a property unit is publicly listed. This makes it possible for us to relate the racial characteristics of actual tenants to the landlords' advertising choice.
(ii) The dataset is large, containing more than 719,000 observations, covering a wide range of U.S. metropolitan areas between 2021–2023. This allows us to examine whether the discrimination is widespread and statistically significant.
(iii) The data provides granularity at the property unit level, enabling us to examine each multifamily building operated by the same landlord, as well as units across different buildings under the same management. This facilitates the use of fixed effects to control for determinants of the demographic composition of buildings that are driven by other property manager strategies aside from selective advertising. We analyze this behavior in 27 of the cities that have been the focus of the U.S. Department of Housing and Urban Development (HUD) Housing Discrimination Studies (HDS).[3]

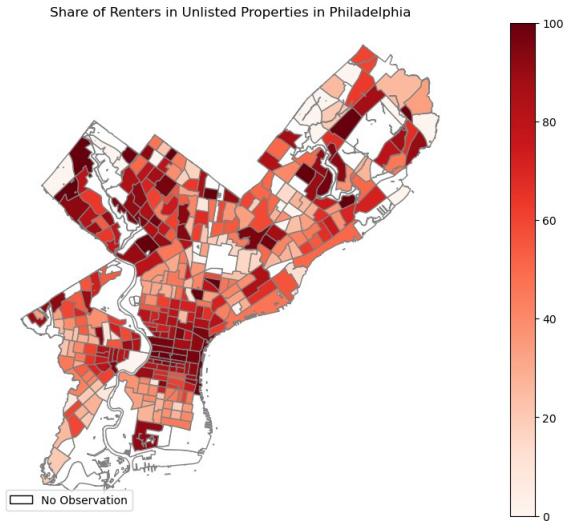
A unit is classified as unlisted if it undergoes tenant turnover without being listed beforehand. We restrict our sample, listed and unlisted, to properties (i.e., buildings) with at least one unit already listed on the Dwellsy platform. This ensures that any unlisted property is not due to the cost of adopting the Dwellsy software, as the fixed cost has already been incurred and the practical cost of listing additional units is minimal. Therefore, the decision not to advertise a unit on Dwellsy is likely strategic rather than unintentional. We expect that this will be a conservative approach for identifying unlisted units. For example, we will not identify instances where entire buildings are left unlisted, nor will we capture selective advertising in market segments that do not list on Dwellsy. In practice, this limits our analysis and conclusions to professionally managed properties. Exploring how results vary across other market segments is something that we hope to pursue in future research.

We start our analysis by examining the systematic difference in racial composition between listed and unlisted rental units. **Exhibit 1** (a) through (c) provides a heuristic introduction to this strategy using Philadelphia city as an example. **Exhibit 1** (a) and (b) show the spatial distribution of Black renters alongside the distribution of unlisted properties. In neighborhoods with more unlisted properties, there are fewer Black renters, suggesting that landlords might target White renters through informal networks or word of mouth. **Exhibit 1** (c) further shows that unlisted properties are more frequently found in areas with lower poverty rates, indicating that such selective (un)advertising is more likely to occur in neighborhoods with potentially better local amenities.

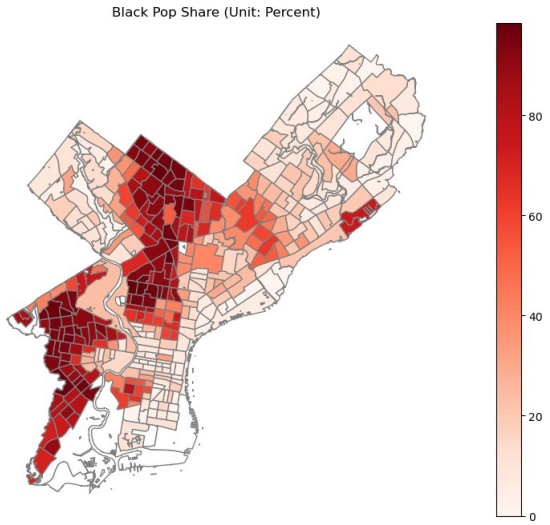
[3] HUD's Housing Discrimination Studies have used 27 cities chosen for the role that race plays in the local housing markets. We use these cities for our analysis, dropping Richmond, Virginia because of problems with missing data.

These patterns are not unique to Philadelphia. Across 27 major cities studied in the HDS, Black renters are, on average, 20 percent more likely than White renters to occupy listed apartments. Furthermore, unlisted units are disproportionately located in areas with lower poverty rates, higher rent, more educated populations, and better environmental conditions. Although descriptive, this evidence suggests racial disparities in local poverty rate – possibly related to the access to local amenities, potentially driven by selective advertising.

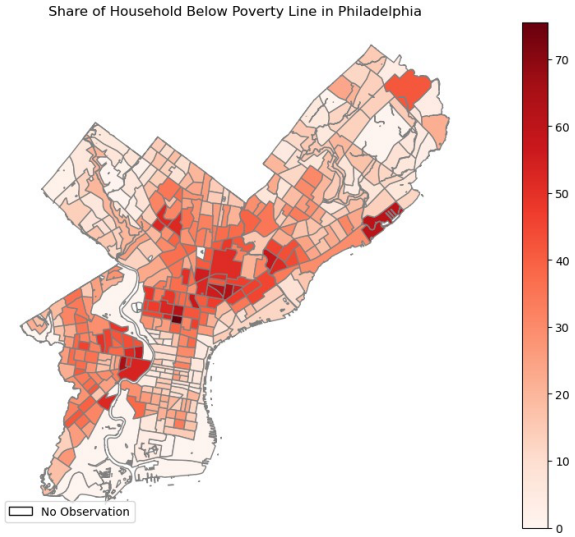
Exhibit 1 | Tract-Level Demographic Statistics for the City of Philadelphia



(a) Share of renters in unlisted units



(b) Black share of population



(c) Share of population in poverty

Motivated by this disparity, we aim to establish causal evidence and explore the consequences of selective advertising in rental markets. We begin by testing whether listed units are more likely to be rented to Black tenants, using a multinomial logit model. That model describes the outcome—the race of the eventual resident of a rental unit, which can take one of five discrete values—as a function of

whether or not that unit was listed along with controls for tract-level rent indices, the fraction of white renters, MSA fixed effects, and year fixed effects. We find that listed apartment units are 12.5 percent more likely to be occupied by Black tenants, 8.1 percent more likely by Hispanic tenants, and 40 percent less likely by Asian tenants compared to white tenants. These estimates remain robust to the inclusion of additional tract-level controls, suggesting that selective advertising is steering Black and Hispanic renters away from unlisted units. These results remain robust even with the inclusion of detailed neighborhood characteristics, such as the racial composition of renters, percentage of college graduates, local poverty rate, quality-adjusted Zillow rent indices, and local air quality—all of which help control for race-based sorting driven by non-discriminatory factors.

A legitimate concern is the possibility of non-selective unlisting. For instance, some landlords may not need to advertise a property if it is leased through corporate arrangements or subleased by an existing tenant. On this front, it is important to emphasize that evidence of selective advertising is not identified by the fraction of unlisted units, but rather by comparing the racial composition of listed and unlisted units within buildings already covered by Dwellsy. Unlisted units due to subleasing or corporate moves do not pose a threat to our strategy if these scenarios do not generate a systematic correlation between whether a property is listed and the racial composition of the tenants who subsequently occupy it. If they do—i.e., white tenants tend to sublease to other white tenants—then the question becomes to what extent are landlords using this as a tool to control the racial composition of their buildings.

Another potential concern is omitted variable bias. For instance, certain neighborhoods might experience higher turnover rates among specific racial groups due to factors such as immigration, company relocations, or college student turnover. In such cases, vacant units might be advertised internally rather than publicly. Alternatively, some managers may have relationships with alumni and/or corporate or community networks that could disproportionately attract tenants of a certain race, even without intentional steering.

To account for these unobserved factors, we estimate a linear probability model predicting a binary outcome—whether or not the eventual renter in a unit is Black. The advantage of the linear framework is that we can control for a rich set of fixed effects capturing unobservables at either the level of the census tract or the property manager (property managers may manage multiple buildings in different parts of the same MSA). This approach helps us mitigate bias from confounding factors at various levels, providing a cleaner identification strategy. For example, property manager fixed effects control for strategies used by the property manager that might have the inadvertent effect of steering more Black renters into these units. Tract fixed effects control for neighborhood characteristics that might induce more Black renters to seek apartments in places where there happen to be more listed units. Building fixed effects control for building characteristics that might attract a certain group renters more than others. In our most demanding specification, we find that, all else equal, Black renters are 48 percent more likely to occupy listed units than non-Black households when controlling for unobservables at the tract and property manager level.

Exploring heterogeneity in our results, we find that selective advertising targets not only minorities but also families with children. Across nearly all racial groups (except for Asians), families with children are more likely to rent listed units than those without children. Black and Hispanic families face discrimination through selective advertising regardless of whether they have children, but the discrimination is significantly greater for those with children. Notably, the level of discrimination against

white families with children is only slightly less than that experienced by minority families with children from the Black, Hispanic, or other racial groups.

We further explore the heterogeneity in the degree of selective advertising based on the percentage of the white population in a neighborhood. For Black renters, evidence of selective advertising becomes apparent when neighborhoods have a white population of approximately 60 to 80 percent (i.e., 20 to 40 percent minorities). This result is similar to that in Hanson and Hawley (2011), who find that rental discrimination, measured by landlords' response rates to email inquiries, is most severe in neighborhoods with a minority share between 5 to 20 percent, which corresponds to the tipping point range for white population outflows identified in Card et al. (2008).

Finally, we explore heterogeneity in the extent to which selective advertising varies with other documented forms of discrimination. In particular, we incorporate the estimated landlords call-back discrimination rates from a large-scale correspondence study of discrimination in rental markets in the 50 largest MSAs in the United States (Christensen et al., 2021). Results suggest that selective advertising substitutes for more direct forms of discrimination (e.g., failing to respond to inquiries to view units from identities of color). This is important, as it suggests that a great deal of discriminatory activity may be missed by more traditional measurement approaches.

Why does selective advertising matter? It is important because when minorities and families with children are steered away from potential rental units during their search, they lose not just an apartment but also the benefits associated with a particular location. Location is an asset: access to amenities and jobs provides a crucial context central to social inequality. We therefore explore the extent to which selective advertising may steer minorities away from neighborhoods with better amenities. We measure these amenities by income (poverty rates), education (percentage of the population with a college degree or higher), air quality (PM2.5), and a zip code-level quality-adjusted rent index.

We find that the detrimental steering effect on Black renters is mostly driven by neighborhoods with better amenities. Using quality-adjusted zip code-level ZORI rental indices as a proxy for local amenities, we find that listed apartment units are 37.4 percent more likely to be occupied by Black tenants compared to their white counterparts in neighborhoods where rents are above the average MSA level, and only 10.5 percent in neighborhoods where rents fall below the average MSA level. A closer investigation reveals that such steering is more likely to occur in neighborhoods with lower poverty rates, improved air quality, and more college graduates.

Thus, selective advertising not only limits Black renters' housing consumption options but also potentially restricts their access to better amenities. This is consistent with a report from the 2007 American Housing survey, which shows that Black households are 30 percent more likely than white households to report safety concerns with their drinking water, 60 percent more likely to report a serious crime in their neighborhood, and twice as likely to report being dissatisfied with the neighborhood elementary school. Our results suggest that at least part of this disparity is due to discrimination against Black renters at the very beginning of the rental search process.

Compared to traditional forms of discrimination in rental markets, such as the number of houses shown and landlords' callback responses, discrimination through selective advertising is more subtle and harder to detect. Yet this form of discrimination is potentially more harmful, as it limits renters' housing choices

at the very beginning stage of their rental search. We find that the degree of selective advertising is greater in areas where more blatant forms of discrimination (e.g., landlords' response rates to email inquiries) are more restricted. While recent HUD studies indicate a decline in some blatant forms of housing discrimination, our findings suggest that selective advertising may increasingly serve as a substitute for traditional forms of discrimination if it continues to go undetected.

2. Literature Review

2.1 Discriminatory Use of Information in Online Housing Markets

Our work is related to a literature that has explored the use of information in housing markets to achieve discriminatory outcomes. Prior to the Internet age, Galster, Freiberg and Houk (1987) examine data on the listing behavior from a single large real estate company in Milwaukee, WI and find that sellers in Black neighborhoods receive less advertising activity (fewer/shorter ads and fewer open houses) compared to those in predominantly white neighborhoods. More recently, Boeing (2020) analyzes the over- versus under-representation of vacant units on Craigslist, and Adu and Delmelle (2022) examine the differential use of exclusionary language depending upon the racial makeup of the neighborhood where a unit is located. Besbris, Schachter and Kuk (2021) focus on how advertisement language on Craigslist either emphasizes unit and neighborhood attributes or focuses on application criteria and logistics depending upon the neighborhood where the unit is located. Most directly related to our work, Humber and Matthews (2020) consider National Fair Housing Alliance v. Facebook, a case in which plaintiffs accused Facebook of allowing housing advertisers to target users based on protected characteristics such as age, sex, race, or zip code.

2.2 Experimental Approaches to Measuring Discrimination

Extensive research has been conducted on field experiment methods to reveal discrimination. Bertrand and Duflo (2017) offer a comprehensive overview, highlighting the differences between audit and correspondence studies. In an audit study, two testers —differing only by a specific characteristic like race—perform real-world tasks (such as inquiring about property availability) in person. These studies have been used to explore various markets, including bargaining at car dealerships (Ayres and Siegelman, 1995), gender discrimination in restaurant hiring (Neumark et al., 1996), and the combined effects of race and criminal records on employment (Pager, 2003). By contrast, correspondence studies involve fictitious applicants who interact solely via mail or online.

These methods were developed as alternatives to simple outcome studies, where discrimination is measured by regressing economic outcomes (e.g., wages) on productivity indicators and race. Such outcome studies may be biased by unobservable factors related to productivity and race. Audit and correspondence studies, with their controlled settings, are designed to mitigate this issue.

2.3 Paired-Tester Audit Studies

A significant body of research has examined discrimination in the process of searching for rental and sales properties, especially at the stage when potential buyers or renters inquire about

advertised units and receive recommendations or viewings. This phase is crucial as it helps shape the choice set available to the prospective tenant or buyer.

Historical data from HDS audits conducted in 1977, 1989, 2000, and 2012 shows a dramatic decrease in overt forms of housing discrimination, such as not showing an advertised property. However, it remains unclear whether more subtle forms of discrimination, like the number of properties shown, have also declined.

Research in this field often focuses on the likelihood that majority versus minority testers are given property viewings and opportunities to inspect. To understand the underlying mechanisms, studies typically test three hypotheses:

(i) Taste-based discrimination, where greater bias is expected from realtors with personal attributes that may make them more prejudiced;
(ii) Catering to white customers, where realtors may discriminate to avoid offending a prejudiced White clientele, especially in neighborhoods at risk of gentrification or where white customers have concerns about school integration; and
(iii) Statistical discrimination, where realtors base their behavior not on the individual characteristics of a minority customer but on the average attributes associated with that customer's race or class group.

Research in this area has largely focused on paired-tester audits, with notable studies including those conducted in Boston in 1981, as well as the HDS audits in 1989, 2000, and 2012. These studies share a common goal: measuring discrimination at the stage when realtors suggest rental units or homes for purchase and when customers are invited to inspect properties. However, they vary in their measures of discrimination and the minority groups they examine.

Yinger (1986), using data from the 1981 Boston audit, examined discrimination between white and Black testers. He advocated for the use of tester-pair fixed effects to account for unobservable factors specific to each audit pair (i.e., the two testers visiting a given realtor), a method that has since become standard in the field. Yinger's findings revealed that, on average, Black testers were informed of roughly 30 percent fewer rental units than their White counterparts, and White testers were invited to inspect 57 percent more apartments. Among the three hypotheses commonly explored in this literature, Yinger's study provided evidence supporting discrimination aimed at catering to a white customer base.

Page (1995) builds upon Yinger (1986) by using a Poisson model to account for the discrete and non-negative nature of the number of houses shown, as well as the heteroskedastic variance dependent on the total number of units available. Analyzing data from the 1989 HDS audit, Page finds that Black and Hispanic testers are shown 80 percent and 90 percent of the number of units shown to White testers, respectively. These results are consistent across both rental and sales properties, though the disparity is more pronounced in some cases. The findings are best explained by either white customer or statistical discrimination mechanisms, particularly for Black testers.

Analysis across HUD's Housing Discrimination Studies indicates that one of the most enduring forms of discrimination is the steering of minority households into minority neighborhoods during the search stage (Dymski, 2006; Galster and Godfrey, 2005; Yinger, 1995). Christensen and

Timmins (2022) observe significant differences in neighborhood characteristics—such as pollution, crime, poverty, and the skill levels of local residents—of properties shown by realtors to white, African American, Hispanic, and Asian testers in the 2012 HDS. Further, Christensen and Timmins (2023) use a correspondence study, involving online interactions with racially distinct names to assess rental markets in five major cities. They find that discrimination results in average welfare costs -- defined as an equivalent variation in income, or the amount of income that you would need to take away from individuals in the absence of discrimination to induce the same loss of welfare as caused by discriminatory constraints, to be 3.5 to 4.4 percent of annual income for renters of color, with African American renters experiencing higher welfare costs as their incomes increase.

There is a literature describing the limitations of audit studies.[4] For example, it may be difficult to test for particular types of bias, such as bias against individuals with certain disabilities. It is also 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 toward or against finding evidence of discrimination. While sacrificing some richness in the portrayal of a racial identity, the investigator retains more control in a correspondence study where identities are typically conveyed by a name on an application or resume and can therefore be more easily controlled.

2.4 Correspondence Studies

Correspondence studies have been employed to examine labor market discrimination based on race and ethnicity. One of the most well-known studies used fictitious resumes sent in response to job advertisements in Boston and Chicago newspapers, varying only by the racialized names (Bertrand and Mullainathan, 2004). The findings revealed that resumes with white-sounding names received 50 percent more callbacks, and that stronger observable resume attributes mitigated the negative impact of Black names, indicating statistical discrimination. Following this, correspondence studies have explored discrimination in various other labor market contexts, including race and ethnicity (McGinnity et al., 2009; Baert et al., 2015; Booth et al., 2012; Maurer-Fazio, 2012; Galarza et al., 2014), gender (Carlsson, 2011; Booth and Leigh 2010), caste and religion (Banerjee et al., 2009; Wright et al. 2013), previous unemployment spells (Eriksson and Rooth, 2014; Ghayad, 2013), and sexual orientation and appearance (Ahmed et al., 2013; Patacchini et al., 2015; Bailey et al., 2013; Rooth, 2009).

In housing rental markets, correspondence studies have analyzed the role of race and ethnicity (Carlsson and Eriksson, 2014; Ahmed and Hammarstedt, 2008; Ahmed et al., 2010; Ewens et al., 2014; Hanson and Hawley, 2011; Carpusor and Loges, 2006), sexual orientation (Ahmed and Hammarstedt, 2009), and immigrant status (Baldini and Federici, 2011; Bosch et al., 2010).

One problem that might arise in both audit and correspondence studies, specific to the internet age, is the potential for those being audited to check the online profile of the tester or fictitious applicant. To address this problem, Acquisti and Fong (2015) develop an online presence for their fictitious applicants in a correspondence study of labor market discrimination. Similarly, Bartoš et al. (2013) create websites for applicants and monitor their access rates. A separate set of problems may arise if those being audited actively pursue strategies to avoid detection.

[4] See, for example, Siegelman and Heckman (1993); Heckman (1998); Aranda (2015); Freiberg and Squires (2015).

2.5 Enforcement

Fair housing enforcement groups[5] have uncovered ample evidence that landlords and property managers are aware of the audit and correspondence studies described above and actively undertake strategies to avoid detection. Freiberg and Squires (2015) describe how property managers use word-of-mouth, referrals from existing tenants, real estate agents, and online platforms to find prospective applicants without listing vacant units. This allows them to screen applicants before making properties available. In one example, Freiberg and Squires (2015) note, "Although housing providers may have many reasons for using fewer public sources to reach prospective renters or buyers, discrimination is more likely to occur when providers restrict knowledge of, or access to, available housing by limiting advertising primarily to favored populations." They go on to say that "Recent enforcement testing suggests that contacts by testers to housing providers, as part of initial visits by matched paired testers, may not always capture the housing provider's practices in a way that adequately discloses or confirms whether fair and equal treatment is being provided."

While enforcement groups have developed strategies to document this sort of discriminatory behavior, these approaches are time-consuming and labor-intensive. The alternative strategy that we describe below takes a data-intensive approach to finding broad evidence of selective advertising and to learning about the contexts in which it is most likely to take place.

3. Data

Our data is constructed primarily from two sources: Dwellsy and InfoUSA. Listings, including United States Postal Service (USPS)-verified address and (if applicable) unit number, asking rent, listing date, delisting date, and the name of listing company, come from Dwellsy. Dwellsy is a listing platform that contracts with listing software companies and does not charge per listing. Property managers who use a platform that contracts with Dwellsy may choose to advertise their unit without cost to potential renters on Dwellsy's website.

Individual and household characteristics are from InfoUSA's Residential Historical Database, which compiles information on a large panel of individuals from a variety of public and proprietary sources. Variables included in the InfoUSA sample are USPS-verified address and a variety of imputed characteristics of the household, such as income and wealth, and characteristics of the individual, including imputed age, gender, and race/ethnicity.

In Sections 3.1 and 3.2, we provide more detail on the nature and coverage of the Dwellsy and InfoUSA data respectively, and in Section 3.3 we discuss the process of matching the two sources and identifying selective listings.

3.1 Dwellsy

Our data on rental listing come from Dwellsy, a rental listing platform. When a rental unit becomes available, the decision of whether to advertise it falls to the property manager, who may or may not also be the owner of the unit. The most common form of advertising is listing available properties on websites

[5] For example, see https://fairhousingjustice.org/about-fhjc/our-history/

that aggregate listings across managers, such as Apartments.com and Dwellsy. Professional property managers tend to use management software both to track their availability internally and to efficiently list on multiple websites at once. The number of listing websites available depends on whether those websites have contracted with the company that provides the management software, so the property manager need not have adopted software that is specific to Dwellsy or even have had knowledge of Dwellsy prior to the listing decision in order to enter our sample.

Pricing for management software varies by firm as well as the array of services provided,[6] the number of units under management, and contract specifics such as whether billing is annual or monthly. In general, a per-unit fee is applied, but the fee is lower for plans that require a higher number of units. Thus, a unit is more likely to be in our sample if they are managed by a company with a higher number of units under management. However, while most listing websites charge a fee per listing, which may induce selective listing on the part of the property manager, Dwellsy does not charge such a listing fee. We can therefore interpret an unlisted unit in a building whose manager has listed other units on Dwellsy within the same year to have been deliberately and selectively unlisted.

The Dwellsy data begin in January 2021 and end at year-end 2023. Before matching to InfoUSA, 430,728 unique units were listed in our sample of 27 cities during the sample period. For each listing, a company name is provided. This variable provides the name of the account holder for the software and is usually the name of an LLC that appears to be a management company. Although some large management companies may operate in multiple markets, we identify managers within markets to avoid erroneously identifying common listing company names such as Midtown Management or Total Property Management (or, in some cases, simply just first names) as multi-market firms.

One of the key advantages of Dwellsy's data over other online platform listing data is its accuracy, which is evident in several ways. First, Dwellsy provides data feeds directly from professional managers, ensuring accurate reporting. In contrast, existing studies that rely on similar listing data from online platforms often must scrape the data, which inevitably introduces recording errors.
Second, on some online platforms, only the number of available apartment units by type (e.g., two-bedroom and one-bathroom) is advertised. Some units are listed as teaser units to keep the apartment building visible on the market, while other rental listings remain active long after being leased out. These practices pose significant challenges for identifying the true fraction of unlisted units and for matching tenant information with the listed units, both of which are important for our identification strategy. However, Dwellsy differentiates itself in the online rental market by requiring managers to truthfully report which apartment units are available in the buildings they manage and to diligently check and update these units' status.

Although Dwellsy's focus on professionally managed rental buildings limits its broader coverage, its accuracy in reporting and monitoring listings, ensured by professional managers, makes it an ideal dataset for our empirical analysis. To characterize the share of properties for which units may be advertised on Dwellsy, we use three additional sources of data: rental registry records from Seattle, building-level listing data from CoStar, and listing data scraped from 10 online rental platforms.

[6] Most management software provides services beyond the management and advertisement of listings, such as the facilitation of rent payments or submission of maintenance requests.

Comparison with Rental Registry Records: First, we obtain a file of all rental properties registered with the city of Seattle as of year-end 2023 from the Seattle Department of Construction and Inspections (SDCI). Seattle has required all rental properties to be registered with the SDCI since 2017.7 In addition to reporting the address of the property, managers are required to report the number of rental units in the property, and the "contact" of the property is reported, often with the name of the management company.

Exhibit A1 displays Dwellsy's coverage of the Seattle rental market. While 19.3 percent of buildings registered as rentals in Seattle listed a unit on Dwellsy, these buildings accounted for nearly one-third of the city's registered rental units. Similarly, 34.7 percent (43.3 percent) of buildings (units) registered as rentals have a property manager contact that was also the contact of a building that listed a unit n Dwellsy. Note that the rental registry data covers the entire rental stock, while Dwellsy data reflects the flow of rental units listed on their platform between 2001-2003. Considering Dwellsy's focus on professionally managed properties and the possibility that a fraction of rental units do not go back to the market during the sample period, the 32 percent coverage of rental units and 44 percent coverage of managers offers strong confidence in the representativeness of the Dwellsy data for the Seattle market.

Comparison with CoStar Listings: Second, we use all multifamily properties in July and August 2023 in eight cities taken from the sample of CoStar Group, a commercial real estate data company. Unlike the Seattle rental registration sample, these data include vacancy information for each building. CoStar acquires its information about the existence, unit counts, and unit availability of multifamily properties from a variety of sources, including its subsidiary rental listing service Apartments.com, its investment in Commercial Mortgage-Backed Securities (CMBS) pools, interviews with property managers, other public listing platforms, and public records. CoStar's data can therefore be viewed as representing the universe of available rental stock—whether listed or not—from the buildings it monitors.

For each city, we use the "market" designation from CoStar, which is larger than the city level but smaller than a metropolitan area. To ensure that we appropriately evaluate Dwellsy's coverage within this area, we attempt to match every observation from Dwellsy within the entire census metropolitan area and drop any unmatched observations. As with the Seattle data, we match on street address alone and consider a building covered by Dwellsy if any listing from 2023 matched to a CoStar property with a vacancy.

Exhibit A2 displays the coverage statistics. We see that Dwellsy covers between 11.47 percent and 32.19 percent of buildings included in CoStar with vacancies. In terms of units, these values range between 8.05 percent and 55.31 percent.

Note that CoStar's data includes all available rental stock, whether listed or not. By contrast, Dwellsy only reports the portion of the available rental stock that is listed on the Dwellsy platform, with a strict focus on professionally managed properties. Given this focus, Dwellsy's 20 percent average coverage across cities seems quite reasonable.

Comparison with Scraped Listings: So far, we have compared Dwellsy data with the total rental stock from Seattle's Rental Registry and vacant rental stock from CoStar in selected cities. In both cases, Dwellsy rental listings represent a significant portion. To further verify whether this is indeed the case,

[7] All properties with at least 10 rental housing units were required to register beginning in July of 2014, with smaller rental properties being subject to registration requirements on a schedule that covered all units, with rare exceptions, by year-end 2016 (Seattle, Washington, Municipal Code §22.214.040).

we scraped rental listings from ten major online rental platforms between July and August 2023 in selected cities (Atlanta, Boston, DC, Minneapolis, Richmond, Seattle). These platforms include both popular well-known sites and other less well-known sites that target lower-income households. We collected data on the address, listing date, rent, and apartment characteristics for each listing, geocoded them, and compared them to Dwellsy listings from the same period, focusing only on buildings with at least one unit listed on Dwellsy. The goal was to see how many of these listings appeared on other rental websites but not on Dwellsy.

Exhibit A3 compares the number of units per building listed on Dwellsy versus the scraped websites. Panel A breaks this down by city. Across all six cities, the average number of units listed in Dwellsy buildings is generally close to that in the total scraped listings for almost all cities, with the exception of Washington, DC. The relatively large difference in Washington, DC is driven by one apartment building, which has 167 more units listed on a particular platform than on Dwellsy. A closer investigation reveals that this building was the result of a reporting error. To minimize the impact of outliers, the right panel shows the difference in listings per building between Dwellsy and the scraped sources. The difference is mostly zero at the 25th, 50th, and 75th percentiles across all cities, including Washington, DC. Panel B further breaks down the comparison by the source of the scraped data. When compared to each alternative rental platform, the number of units listed per building on Dwellsy is similar, with the difference again close to zero at the 25th, 50th, and 75th percentiles. On average, Dwellsy lists one unit fewer, likely due to its focus on professionally managed buildings and its diligent efforts to verify listings, avoid duplicates, and remove off-market listings.

Overall, this comparison gives us high confidence that Dwellsy's coverage of listings in Dwellsy-covered buildings is nearly universal. This aligns with the fact that Dwellsy does not charge per listing fees, allowing managers to advertise their listings at no additional cost once the initial software installation fee has been incurred.

3.2 InfoUSA

The InfoUSA Residential Historical Database is a large, annual panel of individuals and households owned by Data Axle. Information such as location, income, tenure status, age, and family composition are compiled from a set of both public (e.g., voter registration roles and land records) and private (e.g., marketing data sets) records. The coverage of the data is vast but non-universal; due to the relatively high quality of property ownership records and voter registration, unhoused and transient individuals are less likely to be included in the sample than homeowners and longtime residents.

The data also includes imputed racial and ethnic identity from the individual's full name and geography. Data Axle uses reference tables for ethnic backgrounds of names to infer an individual's identity beginning with their first name. When no unique inference is possible, the surname is used, then "expert rules" (e.g., all surnames ending with "oglu" are coded as Turkish), and middle names are used to break ties when two or more ethnic designations are possible. Demographics at the 9-digit zip code level are used to further resolve such ambiguities.

We aggregate the granular ethnicity variable into five exhaustive and mutually exclusive categories: Black, White, Hispanic, Asian, and Other.[8] Movers in the InfoUSA panel are identified by comparing their address (including unit number) in a given year with the prior year's address, or if InfoUSA indicates that they have lived in their unit for a year or less and they were most recently observed at their current address in the current year. Individuals are dropped from the InfoUSA sample if they lack an address, lack a unit number even though the address is known to be multi-unit, or lack an address in both the preceding two years.[9]

3.3 Identifying Listed and Unlisted Status of Turnover Units

We merge the Dwellsy and InfoUSA data on address to obtain a data set of renters in units that were either listed on Dwellsy or not. See **Exhibit 2** for a visual representation of how a unit that turns over during our sample period ends up in our sample and how it is categorized within our sample. Prior to a unit becoming available, the manager of the unit (which may or may not also be the landlord) decides whether to invest in a listing software. If they do not, or if they subscribe to a listing software that does not contract with Dwellsy, then the unit's eventual occupant is not in our sample, regardless of whether the unit is listed. If the unit manager does subscribe to a listing software that contracts with Dwellsy, then a necessary condition for the unit's eventual occupant being in our sample is that they are also included in the InfoUSA panel. If the unit rents to an individual in the InfoUSA panel, then the unit will be included in our panel in one of two cases: if the manager listed the unit on Dwellsy, then the unit is in our sample and coded as having been listed. If the manager did not list the unit on Dwellsy but within the same year listed other units, then the unit is included in our sample and coded as being unlisted.

We perform the merge by first subsetting each dataset by census metropolitan area, then merging on street address, zip code, and unit number (if one exists). Our sample comprises 27 cities across 25 metropolitan areas.[10] For units that were listed multiple times within the same calendar year, the most recent listing is retained.[11] Listings are presumed to have matched to a mover if they were deactivated in the year that InfoUSA observed the renter living in their current unit within a year after the initial listing date.

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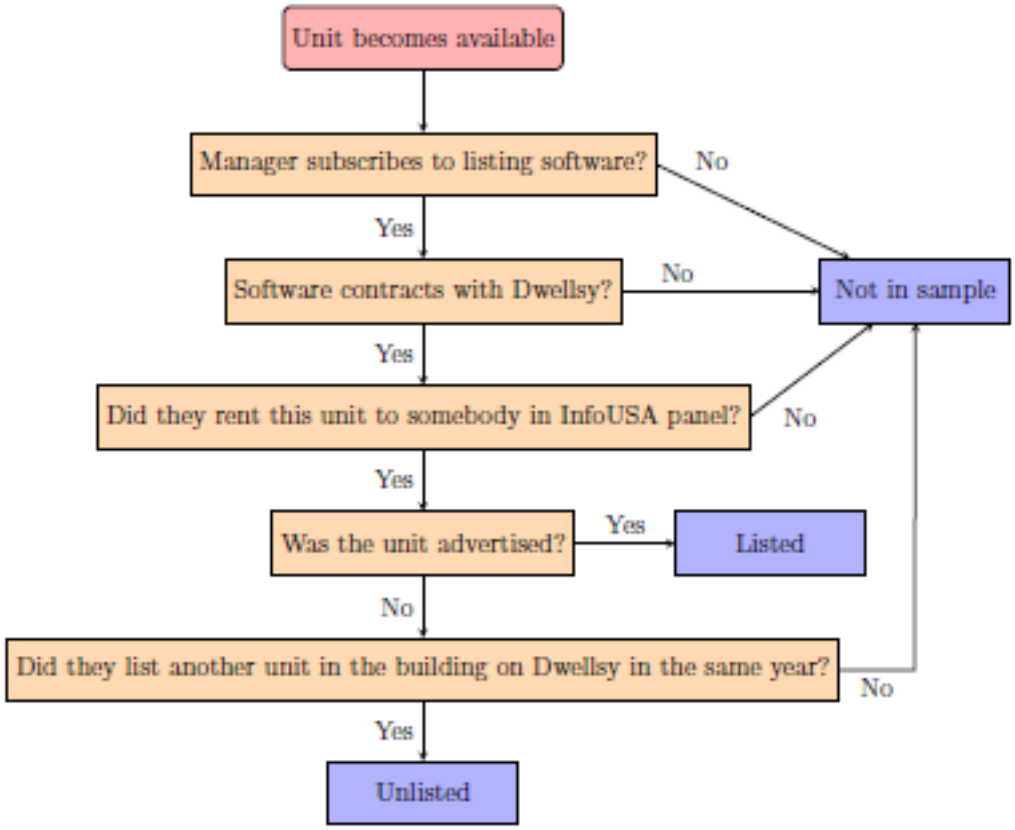
[8] White includes ethnicities classified as Western European, Scandinavian, Australian, New Zealander, Mediterranean, Jewish, and European Hispanic (i.e., Spanish and Portuguese). Black includes only African American. Asian includes all East Asian, South Asian, and Pacific ethnicities. Hispanic includes all non-European Hispanic ethnicities and Brazilians. Other includes all other categories, which in practice includes ethnicities classified as Caucasian (i.e., central Asian), Surinamese, Arab, and African (but not African American). To account for the possibility that Africans and African Americans experience comparable discrimination in the rental market, we test a racial coding that includes Africans in the Black designation and re-generate our primary results. InfoUSA includes missing ethnicity observations. These individuals are dropped from the sample. In cases where an individuals has multiple ethnic designations, InfoUSA uses both first and last name to assign ethnicity (e.g., Nguyen O'Brien is coded as Vietnamese).

[9] It is not uncommon for an individual to be absent from a single year of the InfoUSA data. If the individual lived in the same address both the following and prior year, the address is imputed to have been unchanged in the missing year. If their address was missing in the prior year but was not missing and different two years prior, they are assumed to have moved in the current year. These cases are noted so that they can be dropped as a robustness check.

[10] The sample includes all observations from the cities and respective metropolitan areas of Albuquerque, Atlanta, Baltimore, Boston, Chicago, Cleveland, Columbia (South Carolina), Dallas, Washington (D.C.), Detroit, Fort Worth, Houston, Kansas City, Los Angeles, Miami, Minneapolis, Newark, New York, Philadelphia, Pittsburgh, Providence, Riverside, San Antonio, San Diego, San Jose, Seattle, and Tampa.

[11] These cases are overwhelmingly due to changes in listing details, with re-listings occurring subsequently in a short period of time. For example, a change in the asking price is registered in the data as a re-listing.

Exhibit 2 | Process That Determines Whether a Turnover in a Unit is Included in the Sample and How it is Coded



Given the nature of Dwellsy's data generating process—managers may advertise a unit on Dwellsy's platform without cost as long as the listing is created in their software—we identify the unit inhabited by a mover in the InfoUSA panel as being selectively unadvertised if it was not listed on Dwellsy but is in a building that had other units listed on Dwellsy in the same year.

3.4 American Community Survey

To explore how selective advertising behavior varies with neighborhood attributes and to control for the probability that potential tenants of a given racial category would apply for a given unit, we obtain tract-level sociodemographic characteristics from the five-year American Community Survey (ACS). Although our data span 2022 and 2023, we use ACS data from the 2019 survey to avoid a five-year sample that includes the 2020 ACS data, which the U.S. Census Bureau chose not to release due to issues of potential non-response bias. In each tract, we retrieve the percentage of renters who are non-Hispanic white, Black, Hispanic (of any race), and Asian or Pacific Islander. We also obtain the percentage of households that are renters or have children and the percentage of the population that is in poverty or has a bachelor's degree or higher.

3.4 Sample Statistics

Exhibit 3 provides summary statistics at the neighborhood level for the merged Dwellsy-InfoUSA-ACS sample. The first six variables on listing status and tenant race are derived from individual-level unit and tenant information in the Dwellsy-InfoUSA sample. The remaining variables represent tract-level characteristics from the ACS.

Exhibit 3 | Summary Statistics for Variables Used in the Analysis

	Mean	SD	N
Individual-level variables			
Was the rental unit listed? (1=Yes)	0.177	0.382	411,895
Is the tenant white? (1=Yes)	0.610	0.488	411,895
Is the tenant Asian? (1=Yes)	0.109	0.311	411,895
Is the tenant Hispanic? (1=Yes)	0.145	0.353	411,895
Is the tenant Black? (1=Yes)	0.096	0.294	411,895
Is the tenant some other ethnicity? (1=Yes)	0.040	0.195	411,895
Census tract–level variables			
% of renters that are white	50.5	23.807	410,920
% of renters that are Black	16.9	21.664	410,920
% of renters that are Asian	10.3	10.253	410,920
% of renters that are Hispanic	19.8	19.342	410,920
% of renters from all other races/ethnicities	5.3	7.979	410,920
% Renters	64.3	20.762	410,920
% Households with children	36.7	13.262	410,920
% Bachelor's degree or higher	58.0	23.661	411,661
% Below poverty	14.6	10.566	410,921
PM 2.5	8.139	1.340	411,857
Toxic concentration (normalized)	0.026	0.742	411,857
Zip code–level variables			
ZORI Zip/Metro Index	106.13	22.136	399,808

Notes: The tract shares by race/ethnicity do not sum to 100 due to the double-counting of non-white Hispanic renters. The Zillow Observed Rent Index (ZORI) is a repeat-rent index of rental rates provided by listing company Zillow.com, released at both the zip code and metro area level each month. We divide the zip code–level index by the MSA-level index and multiply by 100 such that a value of 100 implies that the average rent in the zip code is exactly equal to the average rent in the metro area in a given month. PM 2.5 is the concentraction of PM 2.5 pollution in the census tract, and toxic concentration is measured using the EPA's Risk Screening Environmental Indicators (RSEI) data, which combines TRI data on the quantity of toxic chemicals released or transferred off site with information about the chemical's toxicity and its transport through the environment, to calculate a geographically precise measure of relative risk. We normalize toxic concentration by subtracting the MSA-wide mean and dividing by the MSA-wide standard deviation.

Exhibit 4 further presents the sample means of neighborhood characteristics by race. The average percentage of college-educated residents at the neighborhood level is 38.66 percent for Black renters, 48.27 percent for Hispanic renters, but 62.15 percent for White renters. Similarly, the mean neighborhood poverty rate is 23.04 percent for Black renters, 15.55 percent for Hispanic renters, and only 13.08 percent for White renters. These sharp differences are accompanied by the fact that 27.99 percent of Black renters, 20.08 percent of Hispanic renters, but only 16.72 percent of White renters and 12.05 percent of Asian renters reside in listed apartments. A natural question is how neighborhood amenities are distributed between listed and unlisted units, which we turn to next.

Exhibit 4 | Covariate Means by Race

	Asian	Black	Hispanic	Other	White
% of in-sample units that are listed	12.05	27.99	20.08	14.41	16.72
% of renters that are Black	11.90	55.86	14.86	15.68	12.32
% of renters that are white	51.92	26.01	41.34	51.02	56.24
% of renters that are Asian	16.51	4.68	9.07	11.66	10.27
% of renters that are Hispanic	16.95	11.83	32.63	19.08	18.56
% Population renters	68.62	64.55	62.93	65.01	63.71
% Households w/ children	33.84	40.23	39.73	36.41	35.93
% Bachelor's degree or higher	64.22	38.66	48.27	59.60	62.15
% in poverty	14.67	23.04	15.55	14.39	13.08
ZORI Zip Index (MSA Index = 100)	109.98	92.52	101.70	107.54	108.44
Toxic concentration (normalized)	0.12	0.04	-0.05	-0.02	0.03
PM 2.5	8.12	8.19	8.17	8.23	8.12

Notes: Values display the correlation between the variable named in the first column and a dummy variable that equals 1 if the tenant is of the race listed in the column header and equals zero otherwise. See the table notes for exhibit 3 for detailed variable labels and descriptions of ZORI, toxic concentration, and PM 2.5. All variables listed in the first column are defined at the tract level other than ZORI, which is defined at the zip code level.

3.5 Characterizing the Distribution of Unlisted Units

With each renter in the sample determined to be in a unit that is either listed or unlisted, we can observe which characteristics are more or less represented in neighborhoods with higher shares of unlisted units. **Exhibit 5** displays the pairwise Pearson correlation coefficient and its 95 percent confidence interval between the share of renters in each tract in the sample that live in unlisted units and each variable in a set of tract-level socio-demographic variables. **Exhibit 6** displays the histogram of each variable from **Exhibit 5** as well as the zip code-level Zillow Observed Rent Index (ZORI) (normalized by MSA-level ZORI) separately for renters in listed and unlisted units. The ZORI measures changes in asking rents over time, controlling for changes in the quality of the available rental stock.

Exhibit 5 | Tract-Level Pairwise Correlations between Different Covariates and Percent of In-Sample Renters Living in Unlisted Units

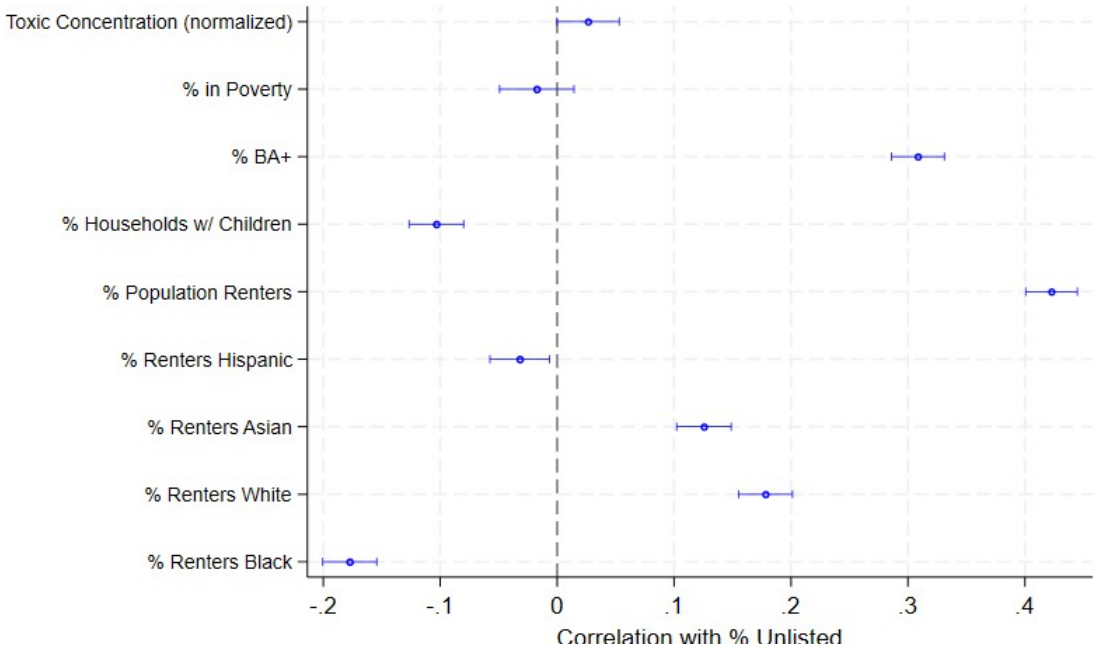
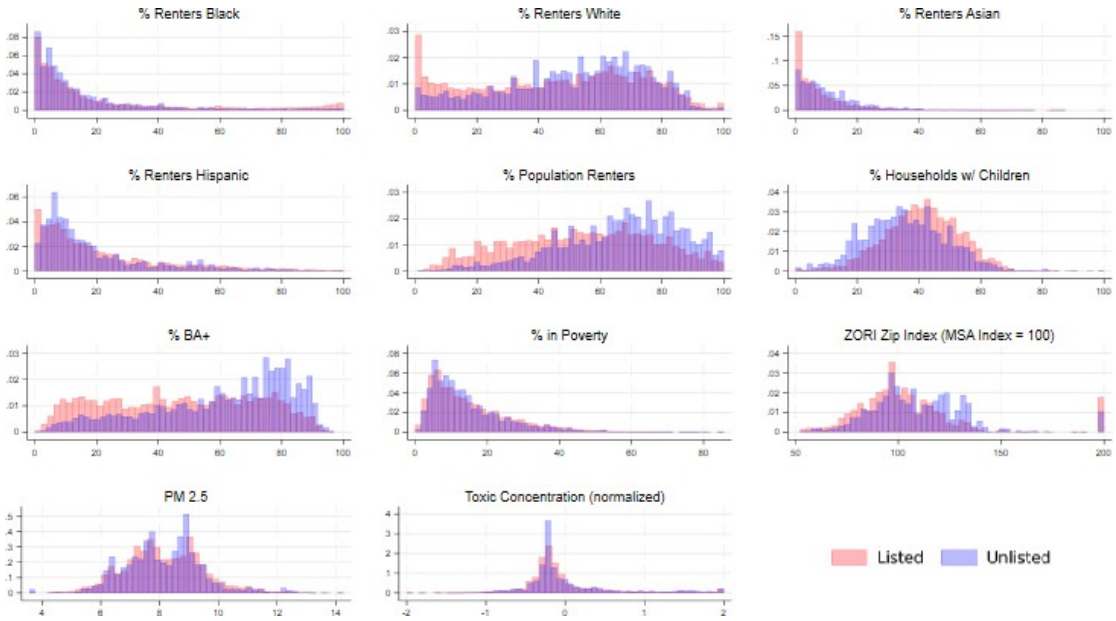


Exhibit 6 | Distribution of Different Covariates Based on the Listed Status of Renters in the Sample



Both figures suggest that unlisted units are more common in neighborhoods with larger shares of renters and people with at least a four-year college degree. Unlisted units are also more common in neighborhoods where a higher share of renters is white or Asian and less common in neighborhoods with higher shares of Black and Hispanic renters and households with children.

Simple correlations between tract attributes and share unlisted do not tell us about discrimination — learning about discrimination requires showing that a particular racial group is less likely to be in a particular unit because it was not listed, controlling for other tract characteristics that might increase or decrease that group's demand for that neighborhood in the first place.

Exhibit 7 provides an initial glimpse at the percentage of renters in listed apartment units across different race and ethnicity groups within principal cities. On average, 17.69 percent of tenants reside in listed apartment units, while the remainder live in unlisted apartments. The fact that approximately 18 percent of units are advertised in buildings where the fixed cost of advertising has already been incurred suggests that, unlike the owner-occupied market, most rental units are leased without being publicly advertised first. While this may seem surprising at first glance, it's important to consider that rental transactions are not officially recorded, whereas sales transactions are documented in the deeds office. This allows verification of whether an owner-occupied sale was publicly listed, but it is not feasible to do the same for rental records without tenant turnover data. As a result, landlords can choose not to list a rental property without considering the impact on equal information access for renters. Additionally, while the majority of sales transactions are listed by real estate agents who are almost always required to advertise properties on a centralized Multiple Listing Service (MLS), advertising requirements are much less stringent in the rental market.

One might be concerned that Dwellsy coverage does not capture the universe of online listings for a given property. In Section 3.1, we compared Dweslly listings with rental listings we scraped from ten major online rental platforms between July and August 2023 in selected cities (Atlanta, Boston, DC, Minneapolis, Richmond, Seattle). The results show that, among the professionally managed buildings covered by Dwellsy, very few listings would be listed in alternative listings appeared on other rental websites but not on Dwellsy. The comparison gives us high confidence that Dwellsy's coverage of listings in Dwellsy-covered buildings is nearly universal.

Another legitimate concern is that some buildings or managers may choose not to advertise units for valid reasons, even if they have access to the Dwellsy software. For instance, a building might be testing the effectiveness of different marketing methods, or some managers may rely on word-of-mouth to attract tenants with desirable characteristics unrelated to race, such as a strong record of paying rent. Regardless of these reasons, when not to advertise rental properties becomes a social norm, it grants landlords significant discretion in deciding whether to list units, making it a potential tool for targeting preferred tenants.

To detect discriminatory patterns in unadvertised units, we employ an econometric model to estimate the extent to which unlisted properties are disproportionately occupied by white tenants. This model controls for racial composition and a comprehensive set of neighborhood characteristics, as well as building-, tract-, and manager-specific fixed effects to address other factors that might influence racial sorting. For example, if word-of-mouth recommendations primarily come from tenants whom landlords "favor" and those tenants tend to recommend friends of the same race, we would expect the observed results only if landlords disproportionately favored white tenants. We will present the detail of this model in Section 4.

The average fraction of listed apartments may mask significant variability across cities. To explore this, **Exhibit A4** replicates **Exhibit 7** for each of the 27 cities in our sample. The percentage of renters in listed units ranges from 8 percent in Houston to 53 percent in Fort Worth, with a median of 25.16 percent. This fraction tends to be smaller in larger cities, likely due to the prevalence of moves arranged, for example, by corporations or through subleases within community networks—all of which reduce the likelihood of units being publicly advertised. However, if these were the only reasons units were not advertised before being occupied and if the tenants moving through subleases or in corporation-arranged transactions have similar racial composition as the neighborhood level population, we would expect white renters to be just as likely as Black renters to end up in listed apartments in our empirical setting.

Exhibit 7 | Share of Renters in Each Racial Group Occupying Units That Were Either Listed or Unlisted

	% in units that are:		
Renter Race	Listed	Unlisted	# Obs
Asian	12.05	87.95	44,723
Black	27.99	72.01	39,416
Hispanic	20.08	79.92	59,888
Other	14.41	85.59	16,372
White	16.72	83.28	251,400
Total	**17.69**	**82.31**	**411,895**

Exhibits 7 and **A4** suggest otherwise. **Exhibit 6** shows that about 28 percent of Black tenants and 20 percent of Hispanic tenants rent listed units, compared to 17 percent of white tenants. **Exhibit A4** further reveals that, across cities, the proportion of renters in listed units is typically highest among Black and Hispanic renters. For example, in Kansas City, 55 percent of Black tenants and 48 percent of Hispanic tenants live in listed units, compared to 40 percent of white and 30 percent of Asian renters. Similarly, in Cleveland, 47 percent of Hispanic tenants and 40 percent of Black tenants occupy listed units, compared to 33 percent of white and 22 percent of Asian renters. These diverse patterns across cities suggest that non-advertisement strategies may selectively affect different racial groups depending on the city.

These patterns could, of course, result from sorting based on differences in preferences across racial groups or neighborhood characteristics. In the empirical analysis below, we aim to systematically address this with a clean identification strategy.

4. Analysis

In this section, we describe our baseline statistical specification — a multinomial logit model of the probability that an individual of each racial group (white, Black, Asian, Hispanic, other) ends

up in a unit with attention paid to the role of the Listed attribute. We are particularly interested in how the role of Listed differs across racial groups. We show that listing matters more for a Black renter obtaining an apartment than for a white renter which suggests discrimination by selective advertising. Subsection 4.1 describes this model and Subsection 4.2 reports baseline parameter estimates. Subsection 4.3 describes how these estimates vary with neighborhood characteristics (i.e., rent level, white population share, and other metrics of discrimination) and other renter attributes (i.e., presence or absence of children). Subsection 4.4 reports results of a binary (e.g., Black versus all other races) linear probability model that allows for high-dimensional fixed effect controls.

4.1 Multinomial Logit

Our analysis undertakes a series of multinomial logit estimation procedures to explain the race of a resident of an apartment unit that turns over as a function of its listed/unlisted status. In particular, the probability of seeing a resident of race *j* in unit *i*

$$P(Y_{i,j}) = \frac{exp\{\alpha_j listed_i + X_i'\beta_j\}}{\sum_{j=1,\ldots,5} exp\{\alpha_k listed_i + X_i'\beta_k\}} \quad (1)$$

where:

- $Y_{i,j}$ = {white, Black, Asian, Hispanic, other}
- $listed_i$ = 1 if unit *i* is listed (= 0 if unlisted)
- X_i = Attributes of unit *i* and its neighborhood, including the ratio of quality-adjusted neighborhood rent to MSA-level rent, the fraction of renters, the racial composition of renters, the fraction of college graduates, the local poverty rate, and air quality indices.

The index underlying the multinomial logit is normalized to 0 for the white renter identity at each property *i*. One implicit assumption in the multinomial logit estimation model is the independence of irrelevant alternatives (IIA) assumption. It requires that the odds of the property manager selecting, for example, a white versus a Black occupant will not depend upon the presence of absence of a Hispanic or Asian renter alternative. The multivariate probit alternative relaxes this assumption but imposes a much greater computational burden on the model, requiring thousands of calculations of a high-dimensional integral. Asking whether our conclusions are robust to this assumption, we are encouraged by the results of our linear probability model (LPM) specifications, which come later in the paper and are used to show robustness to the inclusion of high-dimensional fixed effects. The LPM makes a binary comparison (i.e., the likelihood of a Black renter versus a non-Black renter being in a listed unity) and does not use the IIA assumption. Our results in that analysis are equally strong or stronger than the results found in our multinomial logit analysis.

We focus attention only on units in buildings that have any units listed on Dwellsy, as we know that the property managers of these buildings will have incurred the fixed costs required to list on the platform and that the practical costs of listing any marginal units will be minimal. This approach may be conservative in detecting discrimination, depending on the racial composition of tenants in apartments outside Dwellsy's market coverage. Landlords might leave entire buildings

unlisted to attract white tenants through referrals, which our method would miss. Conversely, if unlisted buildings were more frequently rented to Black tenants, our approach would overlook favorable treatment of minorities.

4.2 Baseline Multinomial Logit Estimates

Results are presented in **Exhibit 8**, where the dependent variables are Black, Hispanic, Asian, and other respectively, with non-Hispanic white as the reference category. **Exhibits A5–A8** report results of specifications showing how results vary with individual tract-level covariates. Our preferred specification uses both the percentage of renters in the census tract who are white along with the ZORI, measured by the zip code-level Zillow Observed Rent Index (ZORI) (normalized by MSA-level ZORI), for the corresponding zip code as controls. With those controls, we find significant evidence that Black renters are more likely to be found in listed units—that is, they are less likely than white renters (i.e., the excluded group) to appear in unlisted units. In particular, the listed odds ratio reveals that Black renters are about 12.5 percent more likely than their white counterparts to be in listed units. Similarly, Hispanics are 8.1 percent more likely than their white counterparts to be in listed units. Asian renters, by contrast, are significantly more likely than white renters to appear in unlisted units.

These estimates are robust to controls for a wide range of tract-level characteristics, including the percentage of white, Black, Asian, Hispanic renters, the overall renter population, the percentage of college-educated residents, the percentage of families with children, and apartment rent per square foot, as shown in **Exhibits A9–A10**.

Exhibit 8 | Multinomial Logit Model for Renters in Central Cities of MSAs

Outcome:	Asian	Black	Hispanic	Other
=1 if Unit is Listed	-0.434*** (0.0317)	0.118*** (0.0379)	0.078*** (0.0253)	-0.197*** (0.0291)
ZORI Zip/Metro Index	0.005*** (0.0014)	-0.016*** (0.0017)	-0.009*** (0.0007)	0.002** (0.0008)
% Renters White	-0.017*** (0.0007)	-0.056*** (0.0015)	-0.019*** (0.0006)	-0.012*** (0.0016)
Listed Odds Ratio	0.648	1.125	1.081	0.822
Log-likelihood: −339656 Observations: 340,080 MSA and Year FE included				

Outcome:	Asian	Black	Hispanic	Other
1(Listed)	-0.434*** (0.0317)	0.118*** (0.0379)	0.078*** (0.0253)	-0.197*** (0.0291)
ZORI Zip/Metro Index	0.005*** (0.0014)	-0.016*** (0.0017)	-0.009*** (0.0007)	0.002** (0.0008)
% Renters White	-0.017*** (0.0007)	-0.056*** (0.0015)	-0.019*** (0.0006)	-0.012*** (0.0016)
Listed Odds Ratio	0.648	1.125	1.081	0.822
Log-likelihood: −339656 Observations: 340,080 MSA and Year FE included				

4.3 Heterogeneity in Selective Advertising

So far, we have observed that Black and Hispanic renters are more likely to occupy listed units when compared to white renters. Conversely, this implies that white renters are more likely to reside in unlisted units, suggesting that the practice of not listing may be a form of racial segregation. In this section, we investigate which neighborhoods exhibit a higher propensity for using unlisted units to target white households along with another form of household heterogeneity (the presence of children), and heterogeneity in more direct forms of discrimination.

4.3.1 Heterogeneity in Neighborhoods with Varying Amenities

To assess differentiation in amenity levels, we introduce an interaction between the "listed" dummy variable and a dummy variable indicating whether the zip code-level ZORI is above its corresponding MSA-level ZORI. In a competitive market, neighborhood amenities are capitalized into local rents, so the ZORI dummy indicates neighborhoods with better-than-average local amenities. The results are presented in **Exhibit 9**.

We find evidence that Black renters are potentially being steered away from neighborhoods with better amenities. Listed apartment units are 37.4 percent more likely to be occupied by Black

tenants than their white counterparts in neighborhoods with above average rent compared to only 10.3 percent elsewhere. This suggests that access to these unlisted units is denied more often to Black renters in more desirable neighborhoods. The results below further show that such steering is more likely to occur in neighborhoods with lower poverty rates, improved air quality, and more college graduates. Thus, selective advertising not only limits Black renters' housing consumption but also restricts their access to better amenities.

On the other hand, the steering-away effect on Hispanic renters and the steering-in effect on Asian and other minority renters are similar in magnitude across neighborhoods, regardless of the level of local amenities as indicated by the ZORI. This suggests that the current practice of selective advertising may not result in uneven access to amenities for these racial groups.

Exhibit 9 | Interacting Listing Status with Indicator for Whether the Zip Code is Above the MSA Rent Price Average

Outcome:	Asian	Black	Hispanic	Other
=1 if Unit is Listed	-0.467*** (0.0478)	0.098 (0.0628)	0.085** (0.0376)	-0.229*** (0.0528)
(=1 if Unit is Listed)*(=1 if ZORI>100)	0.029 (0.0545)	0.219** (0.0905)-	-0.004 (0.0442)	0.046 (0.0599)
ZORI Zip/Metro Index	0.005*** (0.0012)	-0.018*** (0.0023)	-0.005*** (0.0012)	0.002** (0.0010)
% Renters White	-0.013*** (0.0011)	-0.052*** (0.0021)	-0.027*** (0.0007)	-0.013*** (0.0012)
Below-mean Listed Odds Ratio	0.627	1.103	1.089	0.796
Above-mean Listed Odds Ratio	0.646	1.374	1.084	0.833
Log-likelihood: −366958 Observations: 340,080 MSA and Year FE included				

Disparities in access to better amenities between Black and white households are not new and may be attributed to factors such as the correlation between race and income or sorting based on preferences for local public goods. However, a more troubling source of racial disparity in the rental market is landlords' discrimination against Black renters. For example, Christensen et al. (2022) find significantly lower levels of air toxics in the proximity of rental units where landlords do not respond to inquiries from Black and Hispanic identities but do respond to white identities. Our findings reveal that another form of discrimination, which contributes to unequal housing outcomes, occurs at the entry stage of the rental search process when landlords decide whether to advertise vacant units.

4.3.2 Heterogeneity in White Population Share

We further explore the heterogeneity in the degree of selective advertising based on the percentage of white population in a neighborhood and show where discrimination occurs. Doing so also helps us learn about why such discrimination occurs.

We augment the test of selective advertising by categorizing the percentage of the white population into 10 equal bins and interacting these with the Listed dummy. Two patterns emerge from **Exhibit 10**. First, as the percentage of the white population increases, the probability of leasing a unit to a minority decreases almost monotonically, and this trend holds across all minority racial groups—Asian, Black, Hispanic, and other— consistent with homophily effects.[12]

Exhibit 10 | Interacting Listing Status with White Population Share

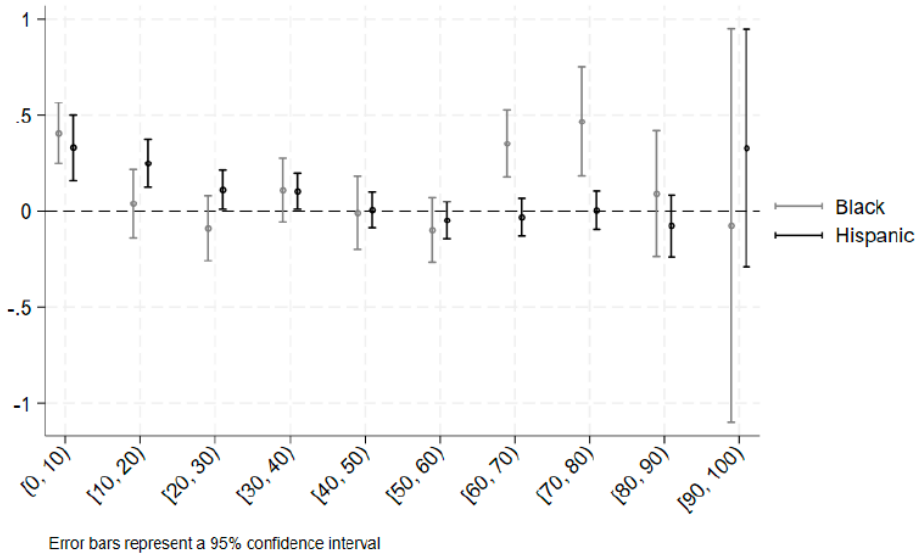
	Asian	Black	Hispanic	Other
=1 if Unit is Listed	-0.254* (0.1364)	0.406*** (0.0811)	0.331*** (0.0866)	0.027 (0.1084)
(=1 if Unit is Listed)×(=1 if 10 < % White < 20)	-0.108 (0.1326)	-0.366*** (0.1175)	-0.081 (0.0877)	-0.136 (0.1437)
(=1 if Unit is Listed)×(=1 if 20 < % White < 30)	-0.163 (0.1510)	-0.495*** (0.1181)	-0.219** (0.1060)	-0.122 (0.1400)
(=1 if Unit is Listed)×(=1 if 30 < % White < 40)	-0.312** (0.1490)	-0.296** (0.1168)	-0.227** (0.0929)	-0.356*** (0.1371)
(=1 if Unit is Listed)×(=1 if 40 < % White < 50)	-0.138 (0.1491)	-0.414*** (0.1280)	-0.324*** (0.0959)	-0.325** (0.1351)
(=1 if Unit is Listed)×(=1 if 50 < % White < 60)	-0.220 (0.1513)	-0.504*** (0.1181)	-0.377*** (0.0948)	-0.306** (0.1453)
(=1 if Unit is Listed)×(=1 if 60 < % White < 70)	-0.140 (0.1509)	-0.053 (0.1205)	-0.360*** (0.0970)	-0.162 (0.1385)
(=1 if Unit is Listed)×(=1 if 70 < % White < 80)	-0.119 (0.1487)	0.061 (0.1659)	-0.326*** (0.0974)	-0.199 (0.1281)
(=1 if Unit is Listed)×(=1 if 80 < % White < 90)	-0.073 (0.1570)	-0.314* (0.1819)	-0.407*** (0.1184)	-0.188 (0.1626)
(=1 if Unit is Listed)×(=1 if % White > 90)	-0.141 (0.4324)	-0.482 (0.5297)	-0.003 (0.3252)	0.096 (0.4348)
=1 if 10 < % White < 20	-0.329*** (0.0980)	-1.017*** (0.1097)	-0.401*** (0.0535)	-0.202** (0.0848)
=1 if 20 < % White < 30	-0.466*** (0.0977)	-1.616*** (0.1131)	-0.535*** (0.0559)	-0.258*** (0.0858)
=1 if 30 < % White < 40	-0.321*** (0.1166)	-2.225*** (0.1024)	-0.767*** (0.0533)	-0.302*** (0.0799)
=1 if 40 < % White < 50	-0.556***	-2.329***	-0.895***	-0.444***

[12] Here, we refer specifically to the coefficients in Exhibit 10 where percent white bins are not interacted with Listed. For each non-white race group, these results suggest that group is less likely to end up in the apartment the greater the percent white in the neighborhood, aside from any effects of listing. This result could reflect homophily preferences. Homophily refers to a tendency for individuals to prefer to live amongst others with similar attitudes, beliefs, social status, or demographic characteristics. Here we refer specifically to race — in particular, white renters may be more likely to seek out rental units in predominantly White neighborhoods.

	(0.1070)	(0.1274)	(0.0527)	(0.0827)
=1 if 50 < % White < 60	-0.525***	-2.510***	-0.990***	-0.421***
	(0.1165)	(0.1407)	(0.0524)	(0.0917)
=1 if 60 < % White < 70	-0.874***	-3.972***	-1.258***	-0.612***
	(0.1064)	(0.1402)	(0.0529)	(0.1180)
=1 if 70 < % White < 80	-1.252***	-4.514***	-1.399***	-0.834***
	(0.1052)	(0.1547)	(0.0524)	(0.1430)
=1 if 80 < % White < 90	-1.677***	-4.855***	-1.687***	-1.031***
	(0.1165)	(0.1437)	(0.0656)	(0.1534)
=1 if % White > 90	-1.666***	-4.771***	-1.735***	-1.168***
	(0.2968)	(0.3048)	(0.1521)	(0.2135)
ZORI Zip/Metro Index	0.005***	-0.014***	-0.009***	0.002*
	(0.0011)	(0.0015)	(0.0006)	(0.0009)
Log-likelihood: -337838 Observations: 340,551 MSA and year FE included				

Second, for Black renters, evidence of selective advertising—indicated by the absence of a significantly negative coefficient on the Listed dummy—becomes apparent when neighborhoods have approximately 60 to 80 percent white renters, or, 20 to 40 percent minority renters. This is apparent in **Exhibit 11**, where we plot the coefficients on Listed for Black and Hispanic renters, respectively, by the share of white population. Card et al. (2008) found that once minority share in a neighborhood exceeds a "tipping point," white residents tend to move out almost entirely. Using Census tract data from 1970 through 2000, the authors observed that white population flows exhibit tipping behavior in most cities, with tipping points for minority share ranging between 5 to 20 percent. Recognizing this, landlords may have incentives to prevent neighborhood tipping and could be more likely to discriminate in neighborhoods where the minority share is near this tipping point. Consistent with this, Page (1995) found increased discrimination in neighborhoods with exactly 20 percent African Americans; and Hanson and Hawley (2011) found that housing discrimination, measured by the landlords' response to email inquiries, was most severe in neighborhoods with a minority share between 5 to 20 percent. Our finding that selective advertising against Black renters is more severe in neighborhoods with 20 to 40 percent minority share suggests that this tipping behavior extends to discrimination at the entry stage of the rental search process.

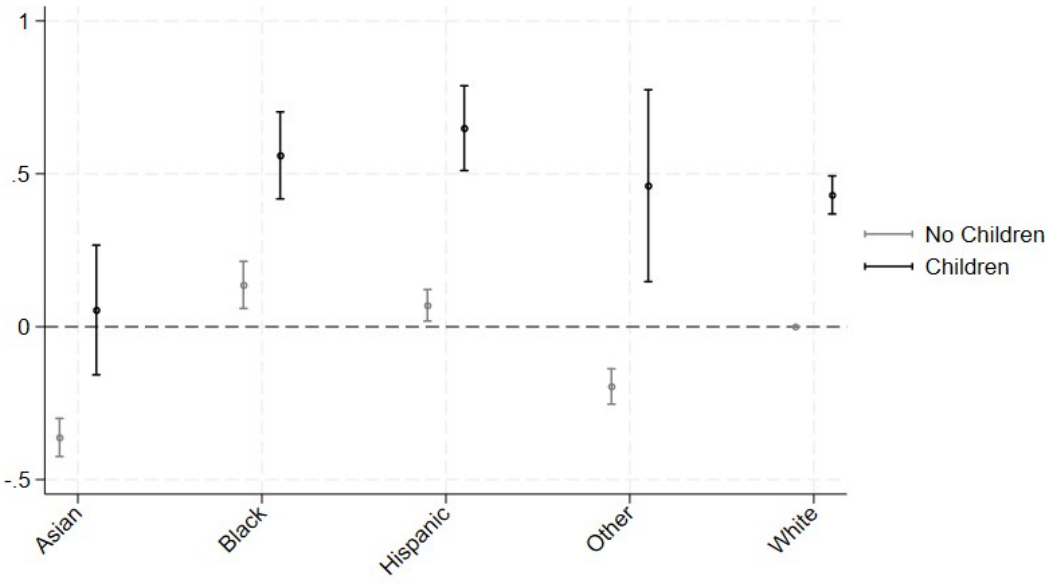
Exhibit 11 | Listed Coefficient by White Renter Share at the Tract Level



4.3.3 Heterogeneity Among Renters With and Without Children

We find that selective advertising targets not only minorities but also families with children. **Exhibit 12** displays the coefficients on Listed for each racial group, both with and without children, using white families without children as the reference category. Across all racial groups, families with children are more likely to rent listed units than those without children. Black, Hispanic, and other minority families face discrimination through selective advertising regardless of whether they have children, but the discrimination is significantly greater for those with children. Notably, the level of discrimination against white families with children is comparable to that experienced by Black, Hispanic, and other (but not Asian) minority families with children.

Exhibit 12 | Listed Coefficient for Each Group (Relative to White With no Children)



Error bars represent a 95% confidence interval; reference category is white households without children

4.3.4 Heterogeneity with Other Forms of Discrimination

We further explore the heterogeneity in selective advertising, particularly in relation to other forms of discrimination. We examine whether selective advertising serves as a substitute for or complement to more detectable forms of discrimination by analyzing how the degree of heterogeneity in selective advertising varies with discrimination as measured by landlords' response to email inquiries.

To do so, we merge our data with the city-level average within-property relative response rate difference to email inquiries from a white identity compared to a Black or Hispanic identity for a given listing, as imputed by Christensen et al. (2021) in their correspondence study on a major online rental platform. In each city, Christensen et al. (2021) recover an average response rate differential between white and Hispanic or Black identities, and we apply this as a form of heterogeneity to all houses in that city. A higher difference indicates greater discrimination, with landlords being less responsive to Black and Hispanic home seekers compared to white seekers.
We then augment our baseline estimation by interacting the Listed dummy with the white-Black response rate difference. Results are reported in **Exhibit 13**. As before, Black and Hispanic renters are more likely to occupy listed units, and this tendency increases as discrimination through response rates decreases. For example, in areas that are at the 75th percentile of the distribution of white-Black response rate differentials (i.e., where the difference in response rates is very high), the probability that a Black tenant lives in a listed unit is 32 percent higher than for a white tenant; this difference rises to 61 percent in areas where the difference is at the 25th percentile. Similarly, for Hispanic tenants, the probability of being in a listed unit is 13 percent higher than for white tenants in areas where the white-Hispanic response rate difference is at the 25th percentile, but this difference increases to 44 percent when the difference is at the 75th percentile.

Exhibit 13 | Interacting Listing Status with Differential Response Rate

Outcome:	Asian	Black	Hispanic	Other
(=1 if Unit is Listed)	-0.524***	0.511***	0.364***	-0.403***
	(0.0651)	(0.1094)	(0.0553)	(0.0650)
(=1 if Unit is Listed)*White-Black Correspondence Diff	-0.344	-2.584***	-2.744***	2.419***
	(0.6086)	(0.8926)	(0.3534)	(0.6114)
(=1 if Unit is Listed)*White-Hispanic Correspondence Diff	4.734***	-7.653***	-4.140***	0.203
	(0.7937)	(1.8122)	(1.4653)	(1.0188)
ZORI Zip/Metro Index	0.005***	-0.018***	-0.004***	0.002**
	(0.0012)	(0.0023)	(0.0012)	(0.0010)
% Renters White	-0.014***	-0.051***	-0.027***	-0.013***
	(0.0011)	(0.0022)	(0.0008)	(0.0012)
25% White-Black Diff Listed Odds Ratio	0.589	1.612	1.388	0.690
75% White-Black Diff Listed Odds Ratio	0.574	1.324	1.127	0.829
25% White-Hispanic Diff Listed Odds Ratio	0.592	1.667	1.439	0.668
75% White-Hispanic Diff Listed Odds Ratio	0.783	1.061	1.127	0.676
Log-likelihood: −350336 Observations: 323, 927 MSA and Year FE included				

Notes: The correspondence differences represent the difference in the share of rental applications responded to according to the apparent race of the applicant from Christensen and Timmins. (2023).

Outcome:	Asian	Black	Hispanic	Other
(=1 if Unit is Listed)	-0.524***	0.511***	0.364***	-0.403***
	(0.0651)	(0.1094)	(0.0553)	(0.0650)
(=1 if Unit is Listed)*White-Black Correspondence Diff	-0.344	-2.584***	-2.744***	2.419***
	(0.6086)	(0.8926)	(0.3534)	(0.6114)
(=1 if Unit is Listed)*White-Hispanic Correspondence Diff	4.734***	-7.653***	-4.140***	0.203
	(0.7937)	(1.8122)	(1.4653)	(1.0188)
ZORI Zip/Metro Index	0.005***	-0.018***	-0.004***	0.002**
	(0.0012)	(0.0023)	(0.0012)	(0.0010)
% Renters White	-0.014***	-0.051***	-0.027***	-0.013***
	(0.0011)	(0.0022)	(0.0008)	(0.0012)
25% White-Black Diff Listed Odds Ratio	0.589	1.612	1.388	0.690
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25% White-Hispanic Diff Listed Odds Ratio	0.592	1.667	1.439	0.668
75% White-Hispanic Diff Listed Odds Ratio	0.783	1.061	1.127	0.676
Log-likelihood: −350336 Observations: 323, 927 MSA and Year FE included				

Notes: The correspondence differences represent the difference in the share of rental applications responded to according to the apparent race of the applicant from Christensen and Timmins. (2023).

Overall, our findings suggest that when there is less callback discrimination by landlords, landlords may strategically shift to more subtle forms of discrimination. Unadvertised units are unlikely to be detected in audit or correspondence studies, thereby minimizing the risk of exposure. This gives landlords an incentive to avoid or minimize contact with unwanted populations by either not advertising at all or selectively advertising to reach only certain groups. For instance, the Fair Housing Justice Center recently completed an investigation involving a landlord who controls hundreds of rental units in a predominantly white Bronx neighborhood. The landlord avoided advertising available apartments, relying instead on referrals from existing white tenants to fill vacancies. [13]

The variation in selective advertising across areas with different response rates suggests that selective advertising, as a substitute for traditional forms of discrimination—like the number of units shown or landlords' response rates—may become increasingly popular in the housing search process if it goes undetected.

4.4 Linear Probability Model Estimation

One concern for our identification strategy is the potential presence of unobservable factors that simultaneously affect whether a property is listed on Dwellsy and the demographic composition of those searching in the neighborhood, particularly the percentage of Black searchers. In this case, a positive coefficient on the Listed dummy would not necessarily indicate evidence of discriminatory advertising. To address this concern, we employ the linear probability model (LPM) estimation, allowing us to control for granular fixed effects at the tract, building, or property manager level. The multinomial logit specification used above, while attractive in allowing for five different discrete outcomes, creates difficulties for the inclusion of large numbers of fixed effects. The linear probability model, while only permitting binary discrete outcomes, allows for any number of fixed effects. Our preferred identification strategy among the LPM specifications focuses on property manager fixed effects. These fixed effects control for any strategies aside from listing status used by the property manager across all their units that might appeal to one racial group more than another. By comparing the racial composition of tenants in listed versus unlisted units managed by the same property manager within the same year, we mitigate the confounding effects of any such strategies that might be correlated with discrimination across listed and unlisted units.

Exhibit 14 presents estimates from the LPM estimation where the dependent variable is an indicator for having a Black tenant. Unlike the baseline multinomial logit model, which uses white

[13] The enforcement literature (e.g., Freiberg and Squires 2015) notes that more complex testing procedures can be devised to uncover evidence of these alternative tools for intentional discrimination. This may involve the use of multiple testers interacting on multiple occasions with property managers. Given the resource requirements to implement such tests, having an indication of where selective advertising may be most prevalent, and which kind of renters it may be targeting most directly, will be useful. Our research provides this information.

renters as the reference category, the reference category here includes all non-Black racial groups. This changes the interpretation of the listed odds ratio compared to the baseline specification. However, the flexibility to include a rich set of fixed effects allows us to assess the robustness of the main findings.

Moving from left to right, columns add progressively richer sets of fixed effect controls. Adding MSA fixed effects and year fixed effects reduces the coefficient on "listed" from 6.112 to 4.939 (columns 1-2). Further inclusion of tract-level demographics decreases that estimate to 1.503 (column 3).

Exhibit 14 | Linear Probability Model for Black Renters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
=1 if Unit is Listed	6.455***	2.857***	2.869***	0.377***	0.270*	1.352***	1.217***	0.396***
	(0.1440)	(0.1315)	(0.5582)	(0.1248)	(0.1425)	(0.2488)	(0.2220)	(0.1223)
ZORI Zip/Metro Index		-0.098***	-0.065	-0.053**			-0.018	-0.052***
		(0.0021)	(0.0487)	(0.0204)			(0.0218)	(0.0170)
% Renters White		-0.384***	-0.416***				-0.288***	
		(0.0026)	(0.0695)				(0.0260)	
Mean Dep. Var.	9.40	9.40	9.40	9.38	8.54	9.29	9.29	9.27
Tract FE				✓				✓
Building FE					✓			
Manager MSA FE						✓	✓	✓
MSA FE			✓					
Year FE			✓	✓	✓	✓	✓	✓
Tract Covariates		✓	✓				✓	
Cluster level	None	None	MSA	Tract	Building	MSA	Manager	Tract
R^2	0.008	0.126	0.287	0.561	0.639	0.420	0.444	0.589
N	340,080	340,080	340,080	339,697	308,604	336,512	336,512	336,182

Notes: The dependent variable is a binary variable that equals one hundred if the renter is Black and zero otherwise. Sample includes only renters in central cities.

Another potential concern is that property managers may undertake other activities to recruit tenants aside from selective advertising that could contribute to a disproportionate racial composition with respect to listing status. To address this concern, we utilize manager-MSA fixed effects. Our identification assumption rests on the premise that once a manager adopts Dwellsy and lists a unit, there is no additional cost incurred to list additional units. Managers in our sample are typically professional commercial real estate managers who oversee multiple apartment buildings across various neighborhoods. Depending on the demographic makeup and property conditions within these neighborhoods, managers may have incentives to list vacant units in certain areas while opting not to list in others. In this case, observing a manager's decision to list some units but not others should reflect strategic incentives rather than the mere cost of using Dwellsy.

Furthermore, if listed units systematically attract Black renters more than unlisted units, such selective advertising practices could suggest discrimination against Black renters.

Returning to **Exhibit 14,** column 6 introduces property manager fixed effects alongside MSA and year fixed effects. The coefficient for Listed now stands at 1.352, significant at the 1 percent level, confirming the importance of controlling for manager-MSA fixed effects. In column 7, a further inclusion of tract-level demographics reduces the Listed coefficient to 1.217, although it remains statistically significant. Column 8 replaces observed tract-level demographics with tract fixed effects and the resulting coefficient for Listed is further reduced to 0.389, aligning with what we expected earlier.

Exhibit 14 highlights the differences between Black and non-Black renters, with the latter category including Hispanic renters. The baseline estimates show that both Black and Hispanic renters face discrimination. In **Exhibit 15**, we present LPM estimates where the dependent variable indicates whether a tenant is Black or Hispanic. The reference category includes all non-Black and non-Hispanic racial groups. The patterns are consistent with those in **Exhibit 14**, confirming that our main findings are robust to the inclusion of unobservables at the neighborhood, manager, and building levels.

Exhibit 15 | Linear Probability Model for Black and Hispanic Renters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
=1 if Unit is Listed	9.576***	4.272***	3.951***	0.370*	-0.160	1.895***	1.680***	0.274
	(0.1922)	(0.1771)	(0.5140)	(0.2176)	(0.2644)	(0.3184)	(0.3385)	(0.220)
ZORI Zip/Metro Index		-0.126***	-0.133***	-0.106***			-0.056**	-0.063**
		(0.0032)	(0.0497)	(0.0352)			(0.0309)	(0.0266)
% Renters White		-0.589***	-0.525***				-0.416***	
		(0.0032)	(0.0461)				(0.0247)	
Mean Dep. Var.	23.08	23.08	23.08	23.05	21.92	22.95	22.95	22.92
Tract FE				✓				✓
Building FE					✓			
Manager MSA FE						✓	✓	✓
MSA FE			✓					
Year FE			✓	✓	✓	✓	✓	✓
Tract Covariates		✓	✓				✓	
Cluster level	None	None	MSA	Tract	Building	MSA	Manager	Tract
R^2	0.008	0.137	0.171	0.301	0.412	0.230	0.256	0.333
N	340,080	340,080	340,080	339,697	308,604	336,512	336,512	336,182

Notes: The dependent variable is a binary variable that equals one hundred if the renter is Black or Hispanic and zero otherwise. Standard errors are clustered by building manager-MSA. Sample includes only renters in central cities.

5. External Validity

This section addresses a few concerns about the external validity of our results. The first concern about external validity is that within Dwellsy-covered buildings, landlords may use multiple channels to advertise available units. Therefore, a property not listed on Dwellsy might still be advertised elsewhere. To address this, we compared Dwellsy listings with rental listings scraped from major online platforms in selected cities. **Appendix A.1** shows that in Dwellsy-covered buildings, the number of units listed on Dwellsy closely matches the total number of units scraped from other sites. The difference is zero at the 25th, 50th, and 75th percentiles across all cities where data was scraped. On average, Dwellsy lists one fewer unit, likely due to its focus on professionally managed buildings and diligent efforts to verify listings, avoid duplicates, and remove off-market units. Overall, this comparison gives us high confidence that Dwellsy's online coverage of listed units in these buildings is nearly universal. In other words, very few units listed on other platforms are missing from Dwellsy. This aligns with the fact that Dwellsy does not charge per listing fees, allowing managers to advertise at no additional cost once the initial software installation fee is paid.

Another concern about external validity is how our findings from Dwellsy-covered buildings translate to the broader housing market. As discussed in Section 3.1, Dwellsy focuses on professionally managed rental buildings. In Seattle, Dwellsy-covered buildings represent at least one-third of the rental properties registered with the city, which reflects the universe of Seattle's rental market. When compared with the available rental stock, on average, Dwellsy listings cover 20 percent of the vacant rental units recorded in CoStar across cities like Atlanta, Chicago, DC, Minneapolis, Philadelphia, Pittsburgh, and Richmond. CoStar includes all vacant rental stock, listed or not, across multifamily properties, regardless of if they are professionally managed. In Chicago, Dwellsy's coverage of CoStar's vacant rental stock reaches 55.31 percent, reflecting the higher proportion of professionally managed properties and the increased turnover in larger cities, which leads to more units being listed on the market.

The extent to which our findings from the Dwellsy sample apply to the broader housing market depends on how similar the landlords, housing units, and neighborhoods in the Dwellsy sample are to the rest of the rental market. **Exhibit 3** shows that, on average, in neighborhoods covered by Dwellsy, 14.5 percent of the population live below the poverty line, 59 percent have college degrees or higher, and 64% are renters. These renters are 51.5 percent white, 16.4 percent Black, and 19.3 percent Hispanic. By contrast, the average Dwellsy-covered building has about 60 percent white renters, 9.5 percent Black renters, and 14.8 percent Hispanic renters. Thus, even within the Dwellsy sample, Dwellsy-covered buildings tend to have a lower fraction of Black and Hispanic renters relative to the rest of the neighborhood. While we can further compare the characteristics of neighborhoods and housing units between Dwellsy and the broader rental market, it is important to recognize the differences between professionally managed and non-professionally managed rental markets. We view our findings from Dwellsy as being most applicable to the professionally managed rental market, which constitutes a significant portion of the rental stock in large cities.

In non-professionally managed rental markets, there is not a central platform that covers nearly all rental listings. To extend our methodology to these markets, one approach could be to scrape listing data from all major rental websites available in each city and merge it with InfoUSA. This would

allow the detection of selective advertising by linking the racial characteristics of tenants to landlords' advertising choices, using the methodology we developed.

Third, our findings are based on a sample of 27 cities previously used by HUD in Housing Discrimination Studies. As such, we do not know how our results might apply to other cities or suburban rental markets. However, since Dwellsy covers 47 major metropolitan areas in the United States, one way to scale up this analysis would be to include all 47 metropolitan areas. For those interested in additional metropolitan areas, we recommend scraping rental listing data from those locations and merging it with InfoUSA, allowing the application of the methodology developed here.

Finally, some minorities may not use online platforms to search for rental housing and thus may not be subject to the discrimination associated with selective advertising. However, adapting search behavior to avoid discriminatory behavior still imposes costs on the housing seeker. Moreover, if landlords strategically withhold certain units from online platforms, they are likely to do the same with offline advertising channels, such as word of mouth.

6. Conclusion

Audit and correspondence studies have played a key role in a growing body of research highlighting the ongoing issue of racial discrimination in rental housing markets. However, these methods may miss more subtle forms of discrimination. In our analysis, we uncover evidence that selective advertising can be a source of discrimination, where landlords choose not to advertise certain units, instead reserving them for prospective renters they have met in person after an initial screening or through other offline channels.

Detecting this practice is challenging, complicating fair housing enforcement efforts. We present a novel method for identifying selective advertising and examine its impact on minorities' access to neighborhoods with better amenities. Our approach leverages a large marketing dataset to track apartment turnovers across 27 major U.S. metropolitan areas. We match this data with a rental listings dataset to spot turnover units that were not publicly advertised. Our empirical design takes a conservative approach, using only units in buildings where an online listing platform with low marginal costs for additional listings was known to be present. Future research could extend this work to include other listing services, allowing the analysis to incorporate a broader set of buildings, particularly smaller, non-professionally managed buildings.

By comparing the racial composition of actual occupants in listed versus 'hidden' units, we evaluate the extent of discrimination through selective advertising. Our findings reveal discrimination against Black and Hispanic renters through selective advertising that is both significant in magnitude and especially pronounced in neighborhoods with superior amenities, where other forms of discrimination are less common, and in areas approaching racial "tipping points."

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Appendix

Exhibit A1 | Dwellsy Rental Market Coverage in the City of Seattle

	Coverage Statistic	
	% Rental Buildings	% Rental Units
Building in Dwellsy	19.3	31.4
Property manager in Dwellsy	34.7	43.3

Notes: A building is determined to be in Dwellsy if a unit in it was listed on Dwellsy between January 2020 and July 2024. A property manager is determined to be in Dwellsy if they are listed as a contact of a building that had a unit listed on Dwellsy during the same period. The first column displays the share of buildings that are registered as rental properties in the city of Seattle in 2023 that are either in Dwellsy or have a property manager in Dwellsy. The second column displays the share of units in buildings that are registered as rental properties in 2023 that are either in Dwellsy or have a property manager in Dwellsy.

Exhibit A2 | Dwellsy Coverage in the Costar Multifamily Sample

City	Buildings with Vacancies		Units in Buildings with Vacancies	
	#	% Covered	#	% Covered
Atlanta	1,136	13.47	191,560	9.58
Chicago	233	32.19	24,031	55.31
Washington, DC	1,116	11.47	134,414	16.54
Minneapolis	903	26.25	63,510	16.79
Philadelphia	1,158	20.98	98,305	14.73
Pittsburgh	556	26.26	49,165	14.37
Richmond	363	16.80	44,131	8.05

Notes: The geographic area for each city is determined by CoStar "markets," which are generally larger than a central city but smaller than a metropolitan area. A building in the CoStar sample is considered to have a vacancy if it had a nonzero count of housing units marked as available when the full multifamily sample for its city was downloaded between July and August of 2023. A building is considered covered by the Dwellsy sample if any of its units were listed on Dwellsy in 2023.

Exhibit A3 | Listing Coverage in Dwellsy-Covered Buildings

	Mean Listed Units		Dwellsy Listings – Scraped Listings		
	Dwellsy	Scraped	25%ile	50%ile	75%ile
Panel A: All scraped sources, by city					
Atlanta	2.2	2.4	0	0	0
Boston	1.7	1.9	0	0	0
Washington, DC	2.7	5.5	-1	0	0
Minneapolis	2.8	3.7	-1	0	0
Richmond	1.7	2.0	0	0	0
Seattle	2.4	3.0	0	0	0
Panel B: All cities, by scraped source					
Platform #1	2.1	3.2	-1	0	0
Platform #2	1.6	2.0	-1	0	0
Platform #3	1.6	1.9	0	0	0
Platform #4	12.4	16.8	-6	-4	-3
Platform #5	1.0	1.0	0	0	0
Platform #6	3.0	1.0	2	2	2
Platform #7	3.3	3.7	0	0	2
Platform #8	2.5	4.1	0	0	0
Platform #9	3.0	4.2	-2	-1	0
Platform #10	2.4	2.9	0	0	0
Total	**2.4**	**3.4**	**0**	**0**	**0**

Exhibit A4 | Share of Renters in Listed Units by Racial Group and City

	% Renters in Group in Listed Units					
	Asian	Black	Hispanic	Other	White	Total
Albuquerque	27.01	37.50	32.85	30.70	32.03	**32.18**
Atlanta	11.19	22.55	12.83	11.82	12.34	**16.43**
Baltimore	16.52	38.46	22.26	20.85	28.46	**31.75**
Boston	7.28	23.96	11.94	7.89	11.00	**10.74**
Chicago	6.52	27.11	14.53	11.06	11.81	**12.78**
Cleveland	22.81	40.30	46.61	18.75	33.30	**36.17**
Columbia	28.57	37.84	35.94	35.00	28.82	**30.45**
Dallas	8.29	22.68	20.75	7.60	13.48	**14.83**
Washington, DC	10.15	20.36	12.44	10.73	13.15	**14.96**
Detroit	18.00	41.38	24.77	15.05	26.65	**37.85**
Fort Worth	53.80	45.17	56.14	58.97	52.04	**52.42**
Houston	9.38	14.79	12.39	6.90	6.46	**8.64**
Kansas City	29.91	54.63	47.97	33.70	40.55	**43.76**
Los Angeles	16.97	32.70	25.70	20.54	25.04	**23.92**
Miami	3.70	13.86	4.67	2.89	4.14	**4.47**
Minneapolis	14.86	26.57	20.20	21.74	22.14	**21.95**
New York	6.26	14.68	8.27	7.81	7.06	**7.50**
Newark	24.44	40.94	40.00	37.50	34.58	**39.08**
Philadelphia	17.00	38.60	29.87	27.52	22.13	**27.07**
Pittsburgh	21.48	37.94	25.37	26.32	38.05	**36.06**
Providence	8.16	17.86	32.26	17.50	19.08	**20.11**
Riverside	14.29	53.57	36.27	17.65	35.15	**33.97**
San Antonio	18.60	23.31	27.62	20.58	25.05	**25.66**
San Diego	23.51	20.38	27.14	22.86	25.10	**25.16**
San Jose	29.24	34.04	42.36	33.22	40.46	**37.12**
Seattle	13.45	22.70	22.57	16.61	24.16	**22.08**
Tampa	17.60	31.68	30.14	21.40	18.05	**21.17**
Mean	**12.05**	**27.99**	**20.08**	**14.41**	**16.72**	**17.69**
Median	**16.97**	**31.68**	**25.70**	**20.54**	**25.04**	**25.16**

Exhibit A5 | M

ultinomial Logit Results for Black Renters

	(1)	(2)	(3)	(4)	(5)
Outcome: Black					
=1 if Unit is Listed	0.674***	0.652***	0.321***	0.154***	0.118***
	(0.0662)	(0.0480)	(0.0356)	(0.0397)	(0.0379)
ZORI Zip/Metro Index			-0.054***		-0.016***
			(0.0016)		(0.0017)
% of Renters that are White				-0.063***	-0.056***
				(0.0013)	(0.0015)
MSA FE		✓	✓	✓	✓
Year FE		✓	✓	✓	✓
Listed Odds Ratio	1.963	1.920	1.379	1.166	1.125
Pseudo R^2	0.006	0.088	0.112	0.146	0.145
Log-likelihood	-410328	-376150	-353347	-351689	-339656
N	351,142	351,142	340,785	350,437	340,080

Exhibit A6 | Multinomial Logit results for Hispanic Renters

	(1)	(2)	(3)	(4)	(5)
Outcome: Hispanic					
=1 if Unit is Listed	0.297***	0.183***	0.117***	0.097***	0.078***
	(0.0517)	(0.0306)	(0.0286)	(0.0247)	(0.0253)
ZORI Zip/Metro Index			-0.019***		-0.009***
			(0.0007)		(0.0007)
% of Renters that are White				-0.023***	-0.019***
				(0.0005)	(0.0006)
MSA FE		✓	✓	✓	✓
Year FE		✓	✓	✓	✓
Listed Odds Ratio	1.345	1.200	1.124	1.102	1.081
Pseudo R^2	0.006	0.088	0.112	0.146	0.145
Log-likelihood	-410328	-376150	-353347	-351689	-339656
N	351,142	351,142	340,785	350,437	340,080

Exhibit A7 | Multinomial Logit Results for Asian Renters

	(1)	(2)	(3)	(4)	(5)
Outcome: Asian					
=1 if Unit is Listed	-0.434***	-0.408***	-0.405***	-0.446***	-0.434***
	(0.0298)	(0.0323)	(0.0337)	(0.0314)	(0.0317)
ZORI Zip/Metro Index			0.000		0.005***
			(0.0011)		(0.0014)
% of Renters that are White				-0.014***	-0.017***
				(0.0008)	(0.0007)
MSA FE		✓	✓	✓	✓
Year FE		✓	✓	✓	✓
Listed Odds Ratio	0.648	0.665	0.667	0.640	0.648
Pseudo R^2	0.006	0.088	0.112	0.146	0.145
Log-likelihood	-410328	-376150	-353347	-351689	-339656
N	351,142	351,142	340,785	350,437	340,080

Exhibit A8 | Multinomial Logit Results for Renters Who are Not White, Black, Asian, or Hispanic

	(1)	(2)	(3)	(4)	(5)
Outcome: Other					
=1 if Unit is Listed	-0.171***	-0.174***	-0.180***	-0.204***	-0.197***
	(0.0321)	(0.0296)	(0.0291)	(0.0288)	(0.0291)
ZORI Zip/Metro Index			-0.002		0.002**
			(0.0015)		(0.0008)
% of Renters that are White				-0.011***	-0.012***
				(0.0016)	(0.0016)
MSA FE		✓	✓	✓	✓
Year FE		✓	✓	✓	✓
Listed Odds Ratio	0.843	0.840	0.836	0.816	0.822
Pseudo R^2	0.006	0.088	0.112	0.146	0.145
Log-likelihood	-410328	-376150	-353347	-351689	-339656
N	351,142	351,142	340,785	350,437	340,080

Exhibit A9 | MNL Results with Covariates

Outcome:	Asian	Black	Hispanic	Other
=1 if Unit is Listed	-0.329***	0.089**	-0.081***	-0.259***
	(0.0343)	(0.0435)	(0.0255)	(0.0526)
ZORI Zip/Metro Index	0.002***	-0.007***	-0.005***	0.001
	(0.0008)	(0.0028)	(0.0008)	(0.0008)
% of Renters that are White	-0.017***	-0.023	-0.007*	-0.007
	(0.0045)	(0.0183)	(0.0036)	(0.0060)
% of Renters that are Black	0.004	0.032*	0.005	0.009
	(0.0045)	(0.0179)	(0.0034)	(0.0056)
% of Renters that are Asian	0.024***	-0.018	0.005	0.007
	(0.0050)	(0.0180)	(0.0036)	(0.0062)
% of Renters that are Hispanic	-0.004	-0.019	0.010***	-0.011*
	(0.0046)	(0.0193)	(0.0035)	(0.0056)
% Population Renters	0.003***	0.012***	-0.002***	-0.002
	(0.0009)	(0.0023)	(0.0006)	(0.0013)
% Households w/ Children	-0.006***	-0.010***	-0.001	-0.001
	(0.0013)	(0.0033)	(0.0010)	(0.0014)
% BA+	0.008***	-0.003	-0.004***	-0.005**
	(0.0018)	(0.0031)	(0.0014)	(0.0022)
Rent per sq ft	0.016	-0.285***	-0.124***	0.006
	(0.0215)	(0.0465)	(0.0151)	(0.0229)
Listed Odds Ratio	0.720	1.093	0.922	0.772
Log-likelihood: −208648 Observations: 211,395 MSA and Year FE included				

Exhibit A10 | MNL Results with All Race Covariates

Outcome:	Asian	Black	Hispanic	Other
=1 if Unit is Listed	-0.335***	0.072**	0.053**	-0.177***
	(0.0307)	(0.0349)	(0.0242)	(0.0296)
ZORI Zip/Metro Index	0.002***	-0.015***	-0.007***	0.001
	(0.0009)	(0.0017)	(0.0007)	(0.0008)
% of Renters that are White	-0.015***	-0.024**	-0.003	-0.004
	(0.0032)	(0.0104)	(0.0026)	(0.0040)
% of Renters that are Black	-0.001	0.035***	0.014***	0.015***
	(0.0031)	(0.0101)	(0.0025)	(0.0038)
% of Renters that are Asian	0.025***	-0.014	0.009***	0.010**
	(0.0036)	(0.0102)	(0.0026)	(0.0046)
% of Renters that are Hispanic	-0.010***	-0.014	0.019***	-0.005
	(0.0031)	(0.0107)	(0.0025)	(0.0038)
Listed Odds Ratio	0.715	1.075	1.055	0.838
Log-likelihood: −332722 Observations: 340,080 MSA and Year FE included				